PROJECT REPORT
TITLE: ACCURATE BODY FAT PREDICTION

1. Introduction

1.1 Overview

Body fat prediction plays a crucial role in various fields, including health and fitness, sports performance, and medical research. Accurate estimation of body fat percentage is important for assessing overall health and monitoring progress in weight management programs.

We are using Random Forest Regressor, which belongs to the family of ensemble learning methods. Random Forest is a powerful technique that combines multiple decision trees to create a robust and accurate prediction model.

1.2 Purpose

Body fat percentage is closely linked to various health conditions such as obesity, cardiovascular disease, and diabetes. Predicting body fat percentage helps in assessing an individual's risk for these health issues. Body fat prediction is valuable in weight management programs. By accurately estimating body fat percentage, individuals can set realistic goals and track progress effectively. Body fat prediction contributes to scientific research in fields such as nutrition, epidemiology, and public health. It allows researchers to analyze large datasets, investigate the relationship between body fat and other health parameters.

2. Literature survey

2.1 Existing problem

One of the existing problems in body fat prediction is the accuracy and reliability of the prediction models. Although various methods and algorithms have been developed to estimate body fat percentage, there can still be significant variations and discrepancies between the predicted values and actual measurements.

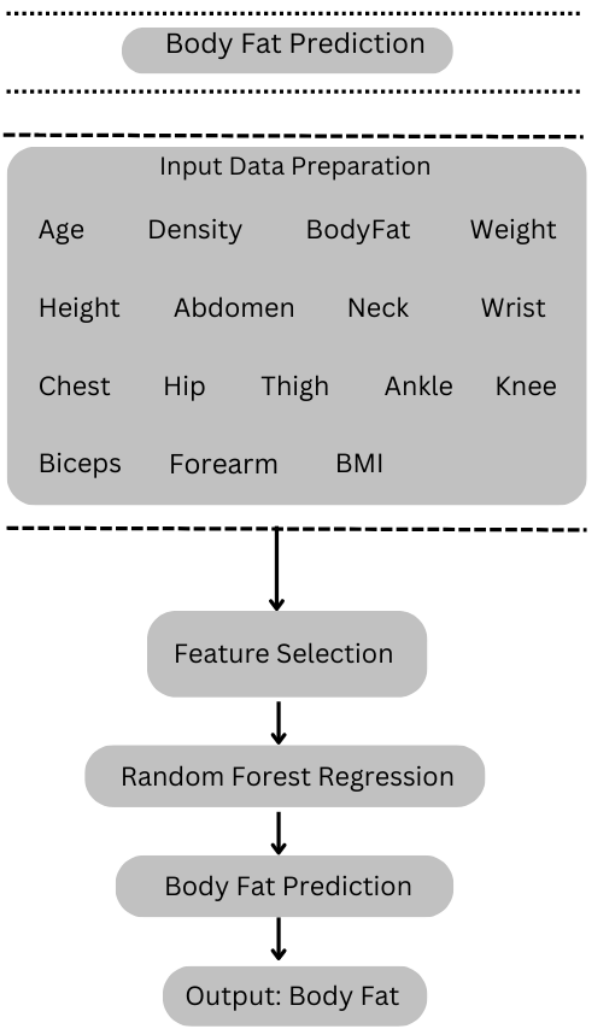
2.2 Proposed solution

We are proposing a solution by creating a model using Random Forest regressor. Random Forest has ability to handle high-dimensional datasets and

automatically select the most relevant features. This eliminates the need for manual feature selection and reduces the risk of overfitting. We are removing the outliers using IQR then we are scaling the data using standard scaler. We were able to achieve an accuracy of 99.8

3. Theoritical analysis

3.1 Block diagram



3.2 Hardware / Software designing

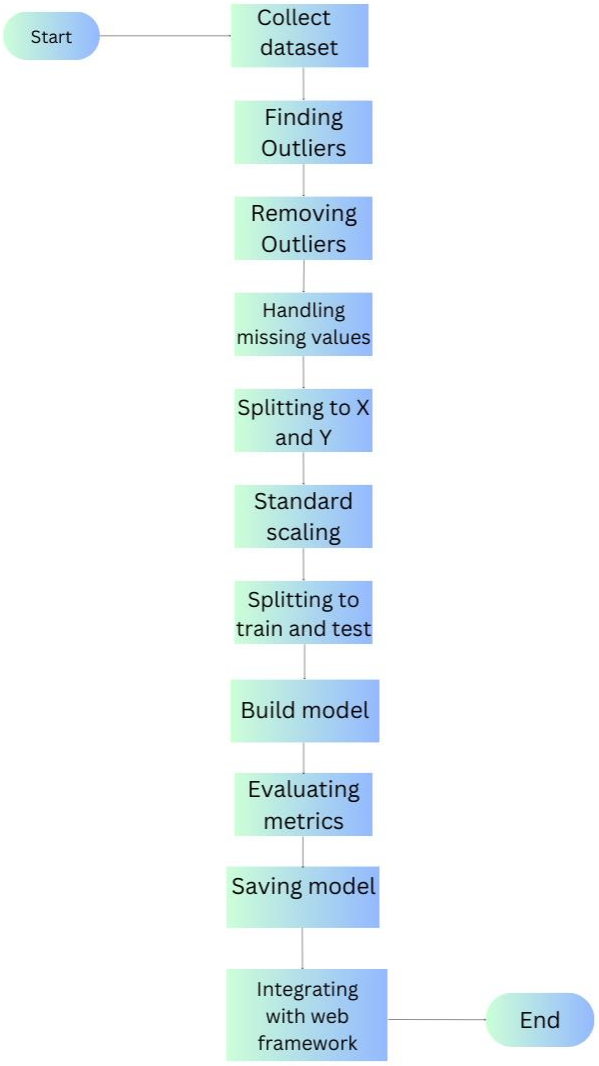
Hardware requirements: Computer or Server**,** Storage, Graphics Processing Unit, Memory (RAM)

Software requirements: Machine Learning Libraries, Data Preprocessing Tools, Development Environment like Jupyter notebook, Operating System

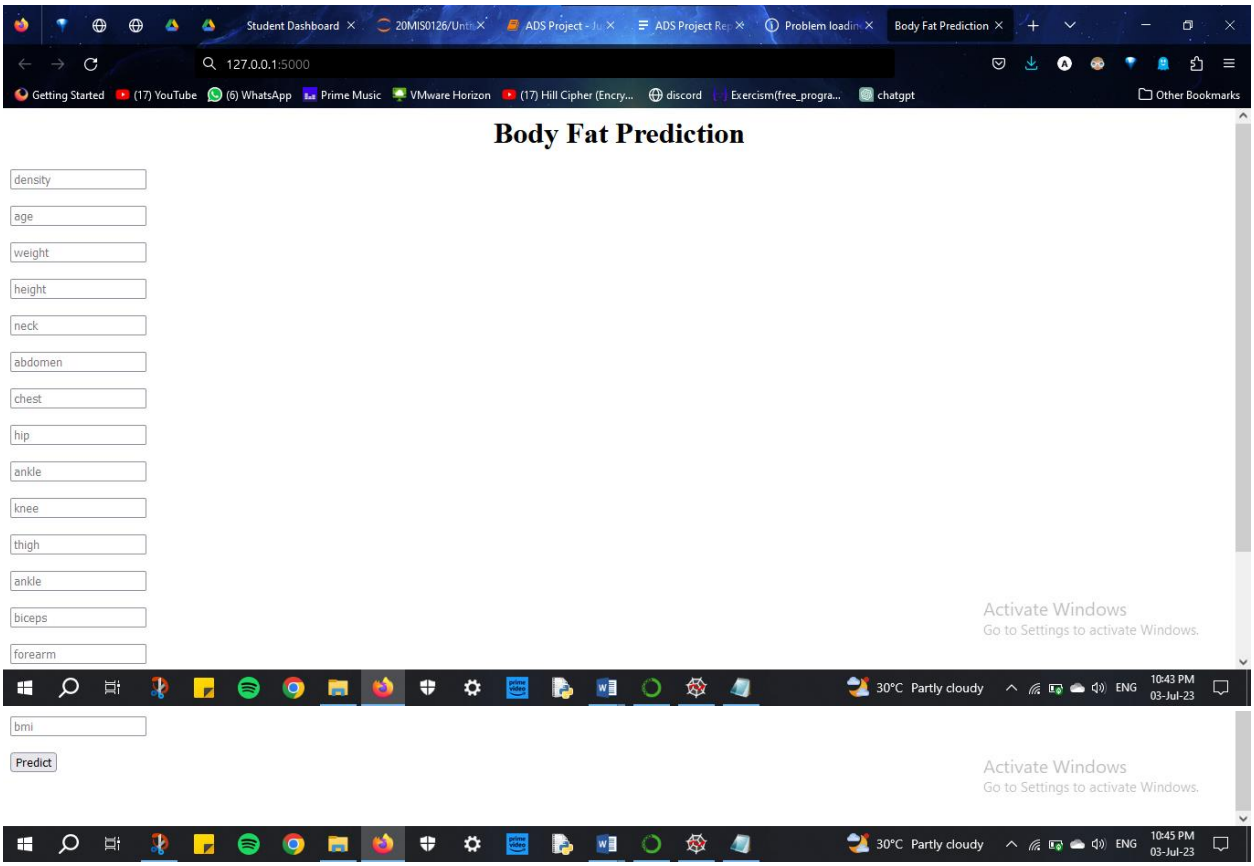
4. Experimental investigations

We have tried building the model using Linear Regression, Random Forest, Ridge and Lasso, Decision Tree Regressor and Knn. Out of all these algorithms we found that Random Forest gives the highest accuracy of 99.8%

5. Flowchart



6. Result



7. Advantages and disadvantages

Advantages of using Random Forest Regression for body fat prediction:

- Non-linear Relationships: It can handle complex patterns and interactions in the data, making it suitable for capturing the intricacies of body fat prediction.
- Robustness: Random Forest models are robust to outliers and noise in the data.
- Feature Importance: Random Forest models provide a measure of feature importance, which can help identify the most influential factors in predicting body fat percentage.
- Scalability: Random Forest can handle large datasets efficiently.

Disadvantages of using Random Forest Regression for body fat prediction:

- Model Interpretability: It may be difficult to explain the relationships between input features and body fat percentage.

- Overfitting: Although Random Forest is less prone to overfitting compared to individual decision trees, it can still overfit if the number of trees in the forest is too large or the model is not properly tuned.
- Limited Extrapolation Capability: Random Forest models are primarily designed for interpolation rather than extrapolation. Therefore, predictions for values outside the range of the training data may not be as reliable.

8. Applications

Key Areas where Body Fat Prediction is applied:

➔ Health and Fitness: Body fat prediction is widely used in the health and fitness industry for assessing an individual's overall health and fitness levels.

➔ Sports and Athletics: Body fat percentage to monitor and optimize body composition for improved performance.

➔ Nutritional Assessment: Body fat prediction is used to assess nutritional status and guide dietary interventions.

➔ Clinical Settings: Body fat prediction is valuable in clinical settings for assessing patients' health conditions and guiding treatment plans.

➔ Research and Epidemiology: Body fat prediction is used in research studies and epidemiological surveys to analyze population health data.

➔ Body Image and Cosmetics: Body fat prediction is also utilized in the cosmetics and body image industries.

9. Conclusion

In our project we have predicted body fat using random forest regressor. We have deployed the model using Flask application.

10. Future scope

Further research can focus on identifying and incorporating additional relevant features that may contribute to more accurate body fat prediction. This can include exploring new types of data, such as genetic or biomarker data. The development of personalized body fat prediction models can be explored. This involves considering individual characteristics, such as age, gender, activity level, and lifestyle factors, to tailor the prediction specifically to an individual's profile.

11. Bibliography

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https://stackabuse.com/decision-trees-in-python-with-scikit-learn/
https://stackabuse.com/random-forest-algorithm-with-python-and-scikit-learn/
https://machinelearningmastery.com/save-load-machine-learning-models-python-scikit-learn/

APPENDIX
Source code:

```
#importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
#dataset
data=pd.read_csv('bodyfat.csv')
data.head()
data.describe()
data.info()
#Finding Outliers
plt.figure(figsize=(20,14))
sns.boxplot(data=data)
plt.show()
data.isnull().sum()
#adding BMI to data
data['Bmi']=703*data['Weight']/(data['Height']*data['Height'])
data.head()
#Removing Outliers
q1=data.quantile(0.25)
q3=data.quantile(0.75)
IQR=q3-q1
data=data[~((data<(q1-1.5*IQR)) | (data>(q3+1.5*IQR)))]
data.describe()
data.isnull().sum()
```

```
sns.pairplot(data)
#handling missing values
data['Density'].fillna(data['Density'].mean(),inplace=True)
data['BodyFat'].fillna(data['BodyFat'].mean(),inplace=True)
data['Weight'].fillna(data['Weight'].mean(),inplace=True)
data['Height'].fillna(data['Height'].mean(),inplace=True)
data['Neck'].fillna(data['Neck'].mean(),inplace=True)
data['Chest'].fillna(data['Chest'].mean(),inplace=True)
data['Abdomen'].fillna(data['Abdomen'].mean(),inplace=True)
data['Hip'].fillna(data['Hip'].mean(),inplace=True)
data['Thigh'].fillna(data['Thigh'].mean(),inplace=True)
data['Knee'].fillna(data['Knee'].mean(),inplace=True)
data['Ankle'].fillna(data['Ankle'].mean(),inplace=True)
data['Biceps'].fillna(data['Biceps'].mean(),inplace=True)
data['Forearm'].fillna(data['Forearm'].mean(),inplace=True)
data['Wrist'].fillna(data['Wrist'].mean(),inplace=True)
data['Bmi'].fillna(data['Bmi'].mean(),inplace=True)
plt.figure(figsize=(20,14))
sns.boxplot(data=data)
plt.show()
#splitting to independent and dependent variables
Y=data['BodyFat']
X=data.drop(columns=['BodyFat'],axis=1)
#StandardScaler
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(X)
inputs_scaled = scaler.transform(X)
name=X.columns
X=pd.DataFrame(inputs_scaled,columns=name)
X
#splitting to test and train data
from sklearn.model_selection import train_test_split
X_train,X_test,Y_train,Y_test=train_test_split(X,Y,test_size=0.2,random_state=0)
X_train.head()
```

```
X_test.head()
print(X_train.shape)
print(X_test.shape)
print(Y_train.shape)
print(Y_test.shape)
#Building model using Linear Regression
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
from sklearn.linear_model import LinearRegression
lr=LinearRegression()
lr.fit(X_train,Y_train)
Y_pred=lr.predict(X_test)
Y_pred
E=Y_test-Y_pred
#evaluation metrics
from sklearn.metrics import r2_score
acc=r2_score(Y_pred,Y_test)
acc
#building model using Random Forest
X_train,X_test,Y_train,Y_test = train_test_split(X,Y, test_size=0.2,
random_state=42)
from sklearn.ensemble import RandomForestRegressor
rf = RandomForestRegressor(n_estimators = 100, random_state = 0)
rf.fit(X_train, Y_train)
pred=rf.predict(X_test)
#evaluation metrics
from sklearn.metrics import r2_score,mean_squared_error,mean_absolute_error
accuracy=r2_score(Y_test,pred)
accuracy
print('MAE: ', mean_absolute_error(Y_test,pred))
print('MSE: ', mean_squared_error(Y_test,pred))
#build model using Ridge and Lasso
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
r=Ridge()
l=Lasso()
```

```
r.fit(X_train,Y_train)
l.fit(X_train,Y_train)
pred1=r.predict(X_test)
pred2=l.predict(X_test)
#evaluation metrics
from sklearn import metrics
print(metrics.r2_score(Y_test,pred1))
print(metrics.r2_score(Y_test,pred2))
#MSE (Mean Square Error)
print(metrics.mean_squared_error(Y_test,pred1))
print(metrics.mean_squared_error(Y_test,pred2))
#RMSE(Root Mean Square Error)
print(np.sqrt(metrics.mean_squared_error(Y_test,pred1)))
print(np.sqrt(metrics.mean_squared_error(Y_test,pred2)))
#build model using decision tree
from sklearn.tree import DecisionTreeRegressor
df=DecisionTreeRegressor(random_state=0)
df=df.fit(X_train,Y_train)
pred=df.predict(X_test)
pred
#evaluation metrics
from sklearn.metrics import mean_squared_error, r2_score
print('Mean Absolute Error:', metrics.mean_absolute_error(Y_test,pred))
print('Mean Squared Error:', metrics.mean_squared_error(Y_test,pred))
print('Root Mean Squared Error:',
np.sqrt(metrics.mean_squared_error(Y_test,pred)))
r2 = r2_score(Y_test,pred)
r2
#building model using Knn
from sklearn.neighbors import KNeighborsRegressor
knn=KNeighborsRegressor()
knn.fit(X_train,Y_train)
pred=knn.predict(X_test)
#evaluating metrics
r2_score(Y_test,pred)
```

```
from sklearn.metrics import mean_absolute_error,mean_squared_error
from math import sqrt
mae = mean_absolute_error(Y_test,pred)
mse = mean_squared_error(Y_test,pred)
rmse = sqrt(mse)
mse
rmse
mae
from sklearn.ensemble import RandomForestRegressor
from sklearn.datasets import make_regression
import joblib
# Generate a random regression dataset for demonstration
X,Y = make_regression(n_samples=100, n_features=10, random_state=42)
# Create and fit the Random Forest model
rf_model = RandomForestRegressor()
rf_model.fit(X,Y)
# Save the trained model to a file
joblib.dump(rf_model, 'random_forest_model.pkl')
rf_model.predict(X)
loaded_model = joblib.load('random_forest_model.pkl')
```

NAME: JOSNA KJ
TEAM NO: 521
TITLE: ACCURATE BODY FAT PREDICTION USING MACHINE LEARNING