Description of the problem - machine learning libraries and packages experimental setup

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.svm import SVR
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.preprocessing import StandardScaler, MinMaxScaler
import seaborn as sns
import time

from zipfile import ZipFile
```

```
from sklearn.model_selection import RandomizedSearchCV
```

```
# configuring the path of Kaggle.json file
!mkdir -p ~/.kaggle
!cp kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json
```

```
# API to fetch the dataset from Kaggle
!kaggle datasets download -d dileep070/heart-disease-prediction-using-logistic-regression
```

```
Downloading heart-disease-prediction-using-logistic-regression.zip to /content
  0% 0.00/58.4k [00:00<?, ?B/s]
100% 58.4k/58.4k [00:00<00:00, 73.3MB/s]
```

```
# extracting the compessed Dataset
data = '/content/heart-disease-prediction-using-logistic-regression.zip'

with ZipFile(data,'r') as zip:
  zip.extractall()
  print('The dataset is extracted')
```

```
The dataset is extracted
```

```
!ls
```

```
framingham.csv  heart-disease-prediction-using-logistic-regression.zip  kaggle.json  sample_data
```

Choice of dataset Data Mining

```
# Load the dataset
data_path = '/content/framingham.csv'
framingham_data = pd.read_csv(data_path)

# Display the first few rows to confirm it's loaded correctly
print(framingham_data.head())
```

```
   male  age  education  currentSmoker  cigsPerDay  BPMeds  prevalentStroke  \
0     1   39        4.0              0         0.0     0.0                0
1     0   46        2.0              0         0.0     0.0                0
2     1   48        1.0              1        20.0     0.0                0
3     0   61        3.0              1        30.0     0.0                0
4     0   46        3.0              1        23.0     0.0                0

   prevalentHyp  diabetes  totChol  sysBP  diaBP    BMI  heartRate  glucose  \
0             0         0    195.0  106.0   70.0  26.97       80.0     77.0
1             0         0    250.0  121.0   81.0  28.73       95.0     76.0
2             0         0    245.0  127.5   80.0  25.34       75.0     70.0
3             1         0    225.0  150.0   95.0  28.58       65.0    103.0
4             0         0    285.0  130.0   84.0  23.10       85.0     85.0

   TenYearCHD
0           0
1           0
2           0
3           1
4           0
```

```
# drop the missing data
Heart_data = framingham_data.dropna()

# the shape after dropping the missing data
framingham_data.shape
```

```
(4238, 16)
```

```
print(framingham_data.isnull().sum())
```

```
male                 0
age                  0
education          105
currentSmoker        0
cigsPerDay          29
BPMeds              53
prevalentStroke      0
prevalentHyp         0
diabetes             0
totChol             50
sysBP                0
diaBP                0
BMI                 19
heartRate            1
glucose            388
TenYearCHD           0
dtype: int64
```

```
# drop the missing data
framingham_data = framingham_data.dropna()

# the shape after dropping the missing data
framingham_data.shape
```

```
(3656, 16)
```

```
print(framingham_data.isnull().sum().sort_values(ascending=False))
```

```
male               0
age                0
education          0
currentSmoker      0
cigsPerDay         0
BPMeds             0
prevalentStroke    0
prevalentHyp       0
diabetes           0
totChol            0
sysBP              0
diaBP              0
BMI                0
heartRate          0
glucose            0
TenYearCHD         0
dtype: int64
```

```
# Showing the data after Converting categorical values to numeric values
framingham_data.head()
```

	male	age	education	currentSmoker	cigsPerDay	BPMeds	prevalentStroke	prevalentHyp	diabetes	totChol	sysBP	diaBP	BMI	heartRate	glucose	TenYearCHD
0	1	39	4.0	0	0.0	0.0	0	0	0	195.0	106.0	70.0	26.97	80.0	77.0	0
1	0	46	2.0	0	0.0	0.0	0	0	0	250.0	121.0	81.0	28.73	95.0	76.0	0
2	1	48	1.0	1	20.0	0.0	0	0	0	245.0	127.5	80.0	25.34	75.0	70.0	0
3	0	61	3.0	1	30.0	0.0	0	1	0	225.0	150.0	95.0	28.58	65.0	103.0	1
4	0	46	3.0	1	23.0	0.0	0	0	0	285.0	130.0	84.0	23.10	85.0	85.0	0

Next steps: Generate code with `framingham_data` View recommended plots

```
# Displaying statistical information about the dataset
print(framingham_data.describe())
```

```
              male          age    education  currentSmoker   cigsPerDay  \
count  3656.000000  3656.000000  3656.000000    3656.000000  3656.000000
mean      0.443654    49.557440     1.979759       0.489059     9.022155
std       0.496883     8.561133     1.022657       0.499949    11.918869
min       0.000000    32.000000     1.000000       0.000000     0.000000
25%       0.000000    42.000000     1.000000       0.000000     0.000000
50%       0.000000    49.000000     2.000000       0.000000     0.000000
75%       1.000000    56.000000     3.000000       1.000000    20.000000
max       1.000000    70.000000     4.000000       1.000000    70.000000

            BPMeds  prevalentStroke  prevalentHyp     diabetes      totChol  \
count  3656.000000      3656.000000   3656.000000  3656.000000  3656.000000
mean      0.030361         0.005744      0.311543     0.027079   236.873085
std       0.171602         0.075581      0.463187     0.162335    44.096223
min       0.000000         0.000000      0.000000     0.000000   113.000000
25%       0.000000         0.000000      0.000000     0.000000   206.000000
```

```
50%       0.000000         0.000000      0.000000     0.000000   234.000000
75%       0.000000         0.000000      1.000000     0.000000   263.250000
max       1.000000         1.000000      1.000000     1.000000   600.000000

             sysBP        diaBP          BMI    heartRate      glucose  \
count  3656.000000  3656.000000  3656.000000  3656.000000  3656.000000
mean    132.368025    82.912062    25.784185    75.730580    81.856127
std      22.092444    11.974825     4.065913    11.982952    23.910128
min      83.500000    48.000000    15.540000    44.000000    40.000000
25%     117.000000    75.000000    23.080000    68.000000    71.000000
50%     128.000000    82.000000    25.380000    75.000000    78.000000
75%     144.000000    90.000000    28.040000    82.000000    87.000000
max     295.000000   142.500000    56.800000   143.000000   394.000000

        TenYearCHD
count  3656.000000
mean      0.152352
std       0.359411
min       0.000000
25%       0.000000
50%       0.000000
75%       0.000000
max       1.000000
```

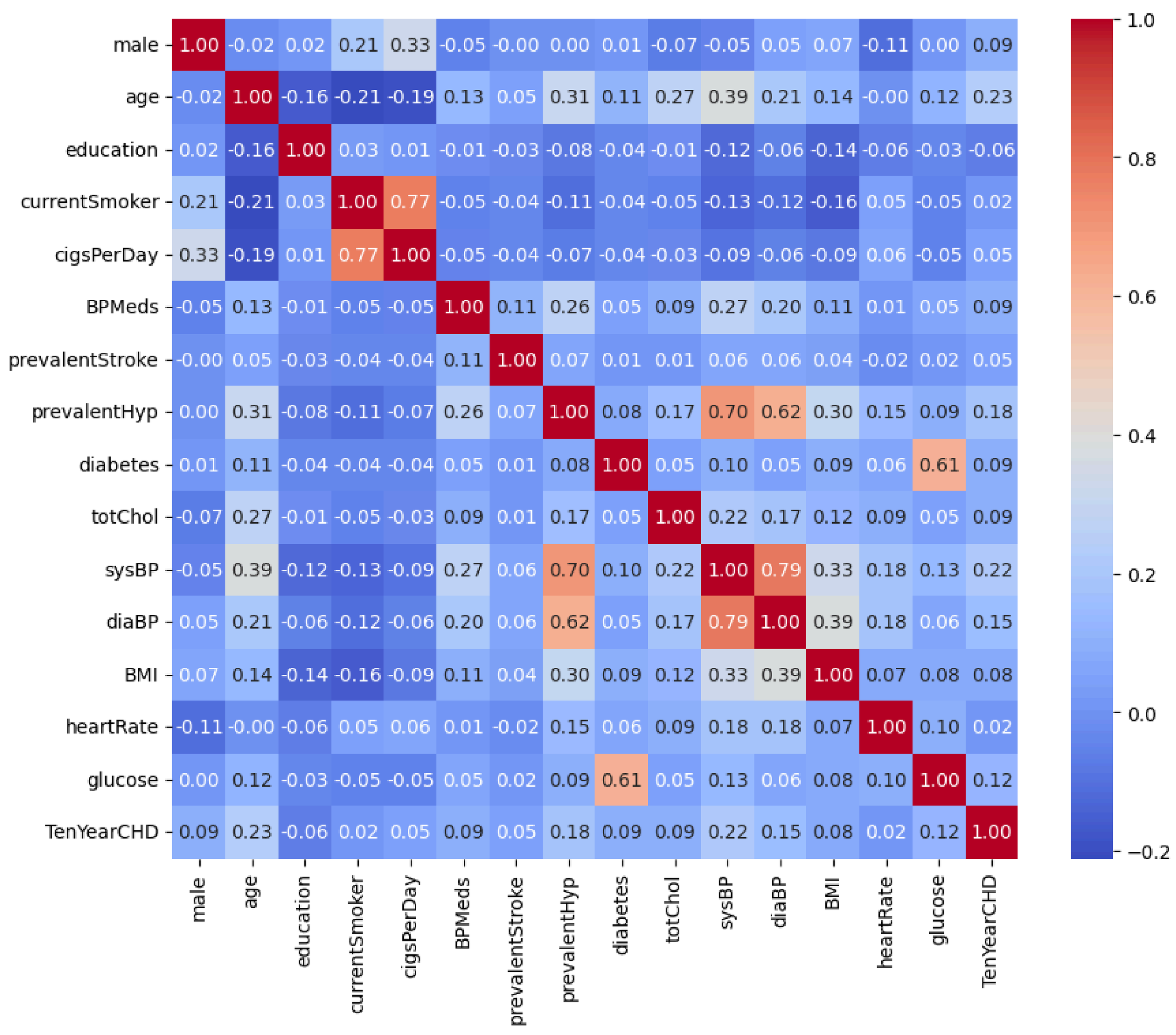
```
# Information about data types and non-null counts
print(framingham_data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3656 entries, 0 to 4237
Data columns (total 16 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   male             3656 non-null   int64  
 1   age              3656 non-null   int64  
 2   education        3656 non-null   float64
 3   currentSmoker    3656 non-null   int64  
 4   cigsPerDay       3656 non-null   float64
 5   BPMeds           3656 non-null   float64
 6   prevalentStroke  3656 non-null   int64  
 7   prevalentHyp     3656 non-null   int64  
 8   diabetes         3656 non-null   int64  
 9   totChol          3656 non-null   float64
 10  sysBP            3656 non-null   float64
 11  diaBP            3656 non-null   float64
 12  BMI              3656 non-null   float64
 13  heartRate        3656 non-null   float64
 14  glucose          3656 non-null   float64
 15  TenYearCHD       3656 non-null   int64  
dtypes: float64(9), int64(7)
memory usage: 485.6 KB
None
```

Correlation Analysis:

To check how each feature correlates with the target variable

```
# Calculate the correlation matrix
corr_matrix = framingham_data.corr()

# Use seaborn to create a heatmap to visualize the correlation matrix
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap='coolwarm', cbar=True)
plt.show()
```



Splitting the Data into Training and Testing Sets

```
# heartRate (Maximum Heart Rate Achieved) is the target variable
X = Heart_data.drop('heartRate', axis=1) # Features
y = Heart_data['heartRate']              # Target
```

```
# Splitting the dataset
X_train, X_test, Y_train, Y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Data Normalization

```
# Normalize features
scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Choice of machine learning techniques

Optimization/Parametrization

Models Training

1- Linear Regression

```
# Train the Linear Regression model
lin_reg = LinearRegression()
lin_reg.fit(X_train, Y_train)
```

```
▸ LinearRegression
LinearRegression()
```

2-Random Forest Regressor

```
# Random Forest Regressor
from sklearn.ensemble import RandomForestRegressor
rf_reg = RandomForestRegressor(random_state=42)
rf_reg.fit(X_train_scaled, Y_train)
```

```
▸       RandomForestRegressor
RandomForestRegressor(random_state=42)
```

3- Gradient Boosting Regressor

```
# Gradient Boosting Regressor
from sklearn.ensemble import GradientBoostingRegressor
gb_reg = GradientBoostingRegressor(random_state=42)
gb_reg.fit(X_train_scaled, Y_train)
```

```
▸       GradientBoostingRegressor
GradientBoostingRegressor(random_state=42)
```

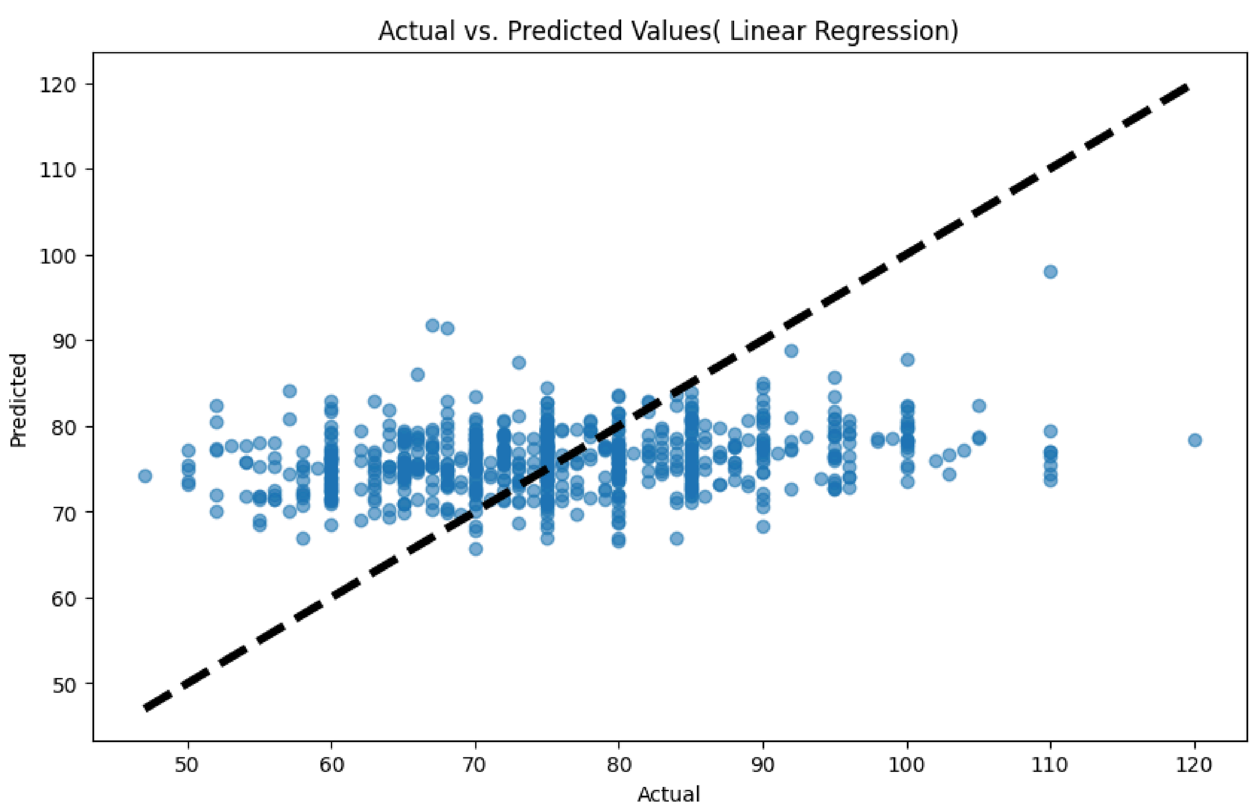
Evaluate the performance of the machine learning methods metrics

Evaluate Model

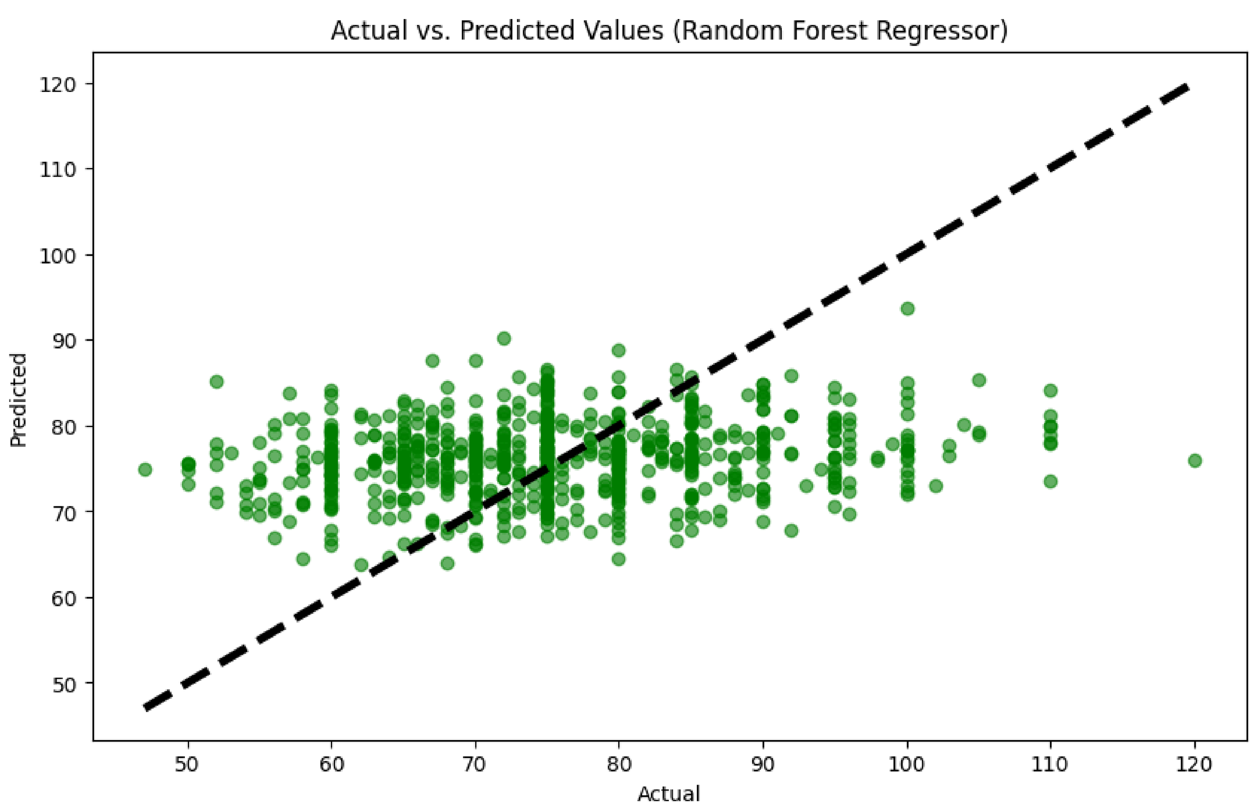
```
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

# Assuming rf_reg and gb_reg are already trained...

# Predictions
lin_predictions = lin_reg.predict(X_test)
rf_predictions = rf_reg.predict(X_test_scaled)
gb_predictions = gb_reg.predict(X_test_scaled)

# Calculate the metrics for each model
lin_mse = mean_squared_error(Y_test, lin_predictions)
lin_mae = mean_absolute_error(Y_test, lin_predictions)
lin_r2 = r2_score(Y_test, lin_predictions)

rf_mse = mean_squared_error(Y_test, rf_predictions)
rf_mae = mean_absolute_error(Y_test, rf_predictions)
rf_r2 = r2_score(Y_test, rf_predictions)

gb_mse = mean_squared_error(Y_test, gb_predictions)
gb_mae = mean_absolute_error(Y_test, gb_predictions)
gb_r2 = r2_score(Y_test, gb_predictions)

# Create a dictionary with the model names and their corresponding metrics
model_metrics = {
    'Model': ['Linear Regression', 'Random Forest Regressor', 'Gradient Boosting Regressor'],
    'MSE': [lin_mse, rf_mse, gb_mse],
    'MAE': [lin_mae, rf_mae, gb_mae],
    'R2': [lin_r2, rf_r2, gb_r2]
}

# Convert the dictionary to a DataFrame
comparison_df = pd.DataFrame(model_metrics)

# Display the DataFrame
print(comparison_df)
```

```
                         Model         MSE       MAE        R2
0            Linear Regression  137.609384  9.377027  0.059675
1      Random Forest Regressor  145.445384  9.691954  0.006129
2  Gradient Boosting Regressor  138.934627  9.465155  0.050619
```

```
plt.figure(figsize=(10, 6))
plt.scatter(Y_test, lin_predictions, alpha=0.6)
plt.plot([Y_test.min(), Y_test.max()], [Y_test.min(), Y_test.max()], 'k--', lw=4)  # Diagonal line
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Actual vs. Predicted Values( Linear Regression)')
plt.show()
```




```
plt.figure(figsize=(10, 6))
plt.scatter(Y_test, rf_predictions, alpha=0.6, color='green')  # Using green for differentiation
plt.plot([Y_test.min(), Y_test.max()], [Y_test.min(), Y_test.max()], 'k--', lw=4)  # Diagonal line
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Actual vs. Predicted Values (Random Forest Regressor)')
plt.show()
```




```
plt.figure(figsize=(10, 6))
plt.scatter(Y_test, gb_predictions, alpha=0.6, color='blue')  # Using blue for differentiation
plt.plot([Y_test.min(), Y_test.max()], [Y_test.min(), Y_test.max()], 'k--', lw=4)  # Diagonal line
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Actual vs. Predicted Values (Gradient Boosting Regressor)')
plt.show()
```