#Import libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from xgboost import XGBRegressor
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor,
GradientBoostingRegressor
from sklearn.svm import SVR
from sklearn.neural_network import MLPRegressor
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler

import chardet

with open("car_purchasing.csv", 'rb') as f:
    result = chardet.detect(f.read())
    print(result)
```

```
{'encoding': 'ISO-8859-1', 'confidence': 0.73, 'language': ''}
```

#Data cleaning and preparation

```
df = pd.read_csv("car_purchasing.csv", encoding='ISO-8859-1')
df.head()
```

```
     customer name                                     customer e-mail
\
0    Martina Avila  cubilia.Curae.Phasellus@quisaccumsanconvallis.edu

1    Harlan Barnes                                  eu.dolor@diam.co.uk

2  Naomi Rodriquez  vulputate.mauris.sagittis@ametconsectetueradip...

3  Jade Cunningham                             malesuada@dignissim.com

4     Cedric Leach     felis.ullamcorper.viverra@egetmollislectus.net


        country  gender        age  annual Salary  credit card debt  \
0      Bulgaria       0  41.851720    62812.09301      11609.380910
1        Belize       0  40.870623    66646.89292       9572.957136
2       Algeria       1  43.152897    53798.55112      11160.355060
3  Cook Islands       1  58.271369    79370.03798      14426.164850
```

```
4        Brazil       1  57.313749    59729.15130       5358.712177
```

```
     net worth  car purchase amount
0  238961.2505          35321.45877
1  530973.9078          45115.52566
2  638467.1773          42925.70921
3  548599.0524          67422.36313
4  560304.0671          55915.46248
```

```
# Drop 'customer name' and 'customer e-mail' columns
df.drop(['customer name', 'customer e-mail'], axis=1, inplace=True)
df.head()
```

```
        country  gender        age  annual Salary  credit card debt  \
0      Bulgaria       0  41.851720    62812.09301      11609.380910
1        Belize       0  40.870623    66646.89292       9572.957136
2       Algeria       1  43.152897    53798.55112      11160.355060
3  Cook Islands       1  58.271369    79370.03798      14426.164850
4        Brazil       1  57.313749    59729.15130       5358.712177
```

```
     net worth  car purchase amount
0  238961.2505          35321.45877
1  530973.9078          45115.52566
2  638467.1773          42925.70921
3  548599.0524          67422.36313
4  560304.0671          55915.46248
```

```
# Convert float values to integer
for i in df.columns:
    if df[i].dtype == 'float64':
        df[i] = df[i].astype(int)
df.head()
```

```
        country  gender  age  annual Salary  credit card debt  net
worth  \
0      Bulgaria       0   41          62812             11609
238961
1        Belize       0   40          66646              9572
530973
2       Algeria       1   43          53798             11160
638467
3  Cook Islands       1   58          79370             14426
548599
4        Brazil       1   57          59729              5358
560304
```

```
   car purchase amount
0                35321
1                45115
2                42925
```

```
3                 67422
4                 55915
```

#Data analysis

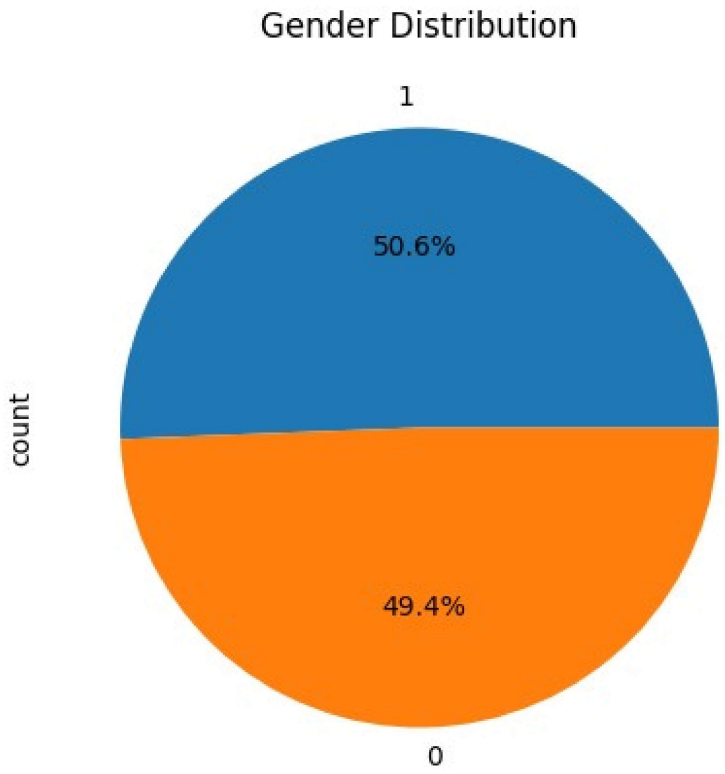
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 7 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   country              500 non-null    object
 1   gender               500 non-null    int64
 2   age                  500 non-null    int64
 3   annual Salary        500 non-null    int64
 4   credit card debt     500 non-null    int64
 5   net worth            500 non-null    int64
 6   car purchase amount  500 non-null    int64
dtypes: int64(6), object(1)
memory usage: 27.5+ KB
```

```
df['car purchase amount'].describe()
```

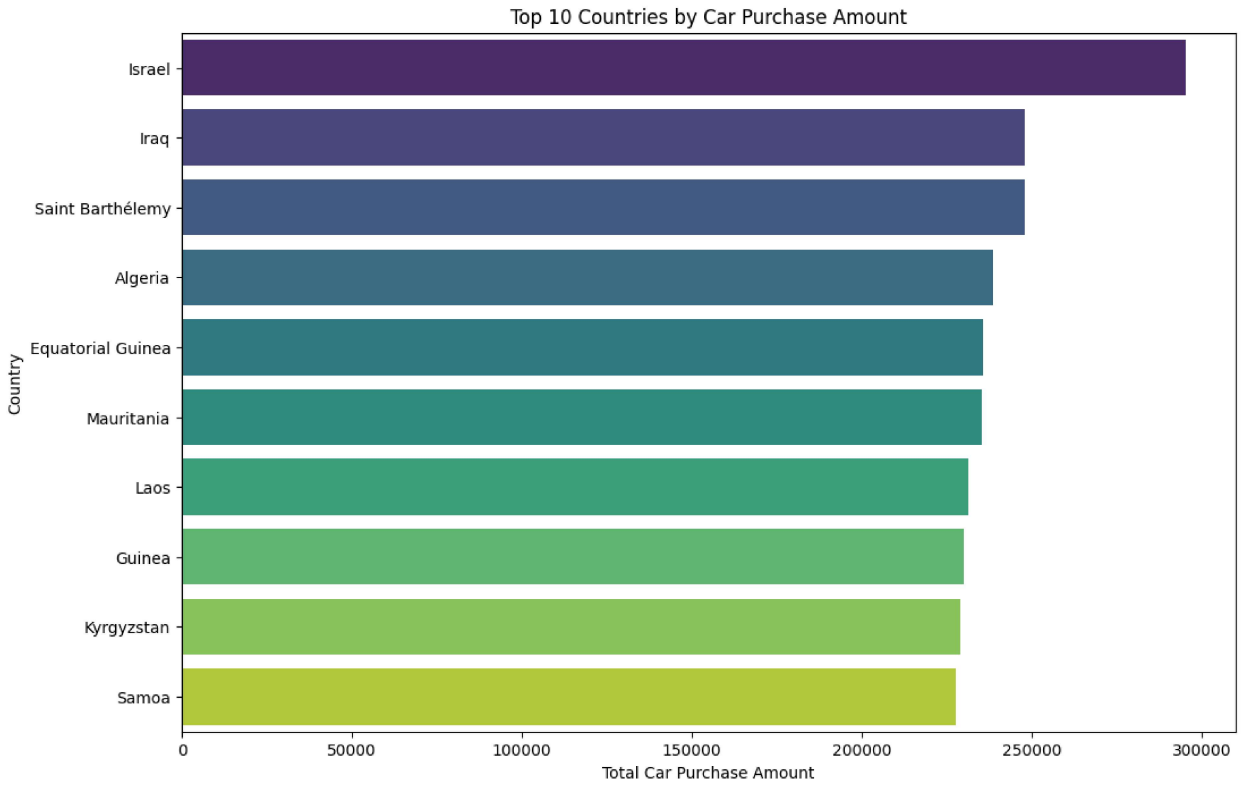
```
count      500.000000
mean     44209.292000
std      10773.182684
min       9000.000000
25%      37629.500000
50%      43997.500000
75%      51254.500000
max      80000.000000
Name: car purchase amount, dtype: float64
```

```
df['gender'].value_counts().plot(kind="pie", figsize=(5,5),
autopct='%1.1f%%')
plt.title('Gender Distribution')
plt.show()
```




```
country_sales = df.groupby('country')['car purchase amount'].sum()

# Sort in descending order and select the top 10 countries
top_10_countries = country_sales.sort_values(ascending=False).head(10)

plt.figure(figsize=(12, 8))
sns.barplot(x=top_10_countries.values, y=top_10_countries.index,
palette='viridis')
plt.xlabel('Total Car Purchase Amount')
plt.ylabel('Country')
plt.title('Top 10 Countries by Car Purchase Amount')
plt.show()
```

```
C:\Users\akshi\AppData\Local\Temp\ipykernel_7480\3814667738.py:9:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x=top_10_countries.values, y=top_10_countries.index,
palette='viridis')
```

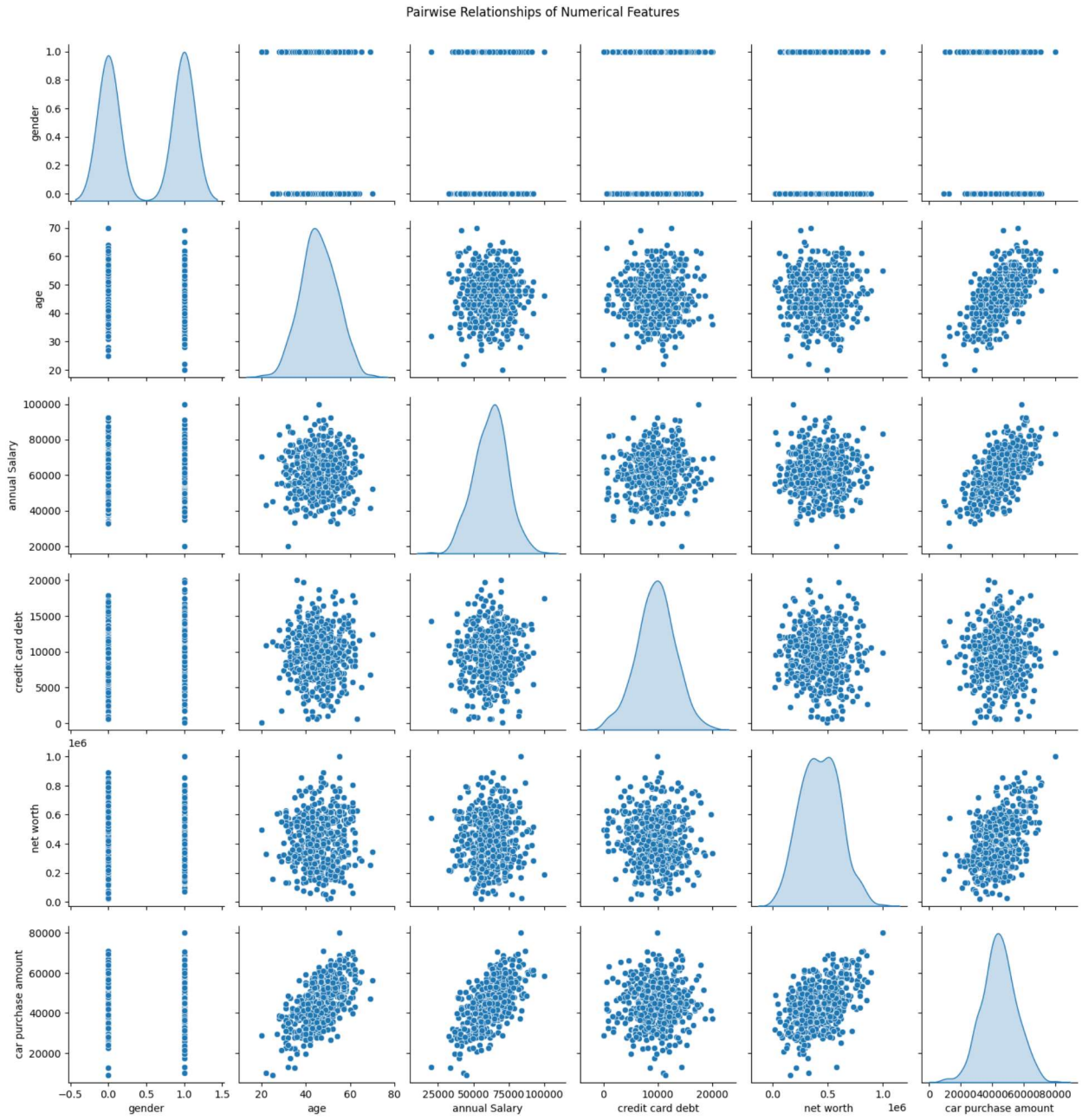



```
# Check skewness of numerical features
numerical_features = df.select_dtypes(include=['int64'])

if 'gender' in numerical_features.columns:
    numerical_features = numerical_features.drop(columns=['gender'])

skewness = numerical_features.skew()
print(skewness)
```

```
age                    0.013702
annual Salary         -0.087475
credit card debt      -0.063736
net worth              0.139755
car purchase amount   -0.030785
dtype: float64
```

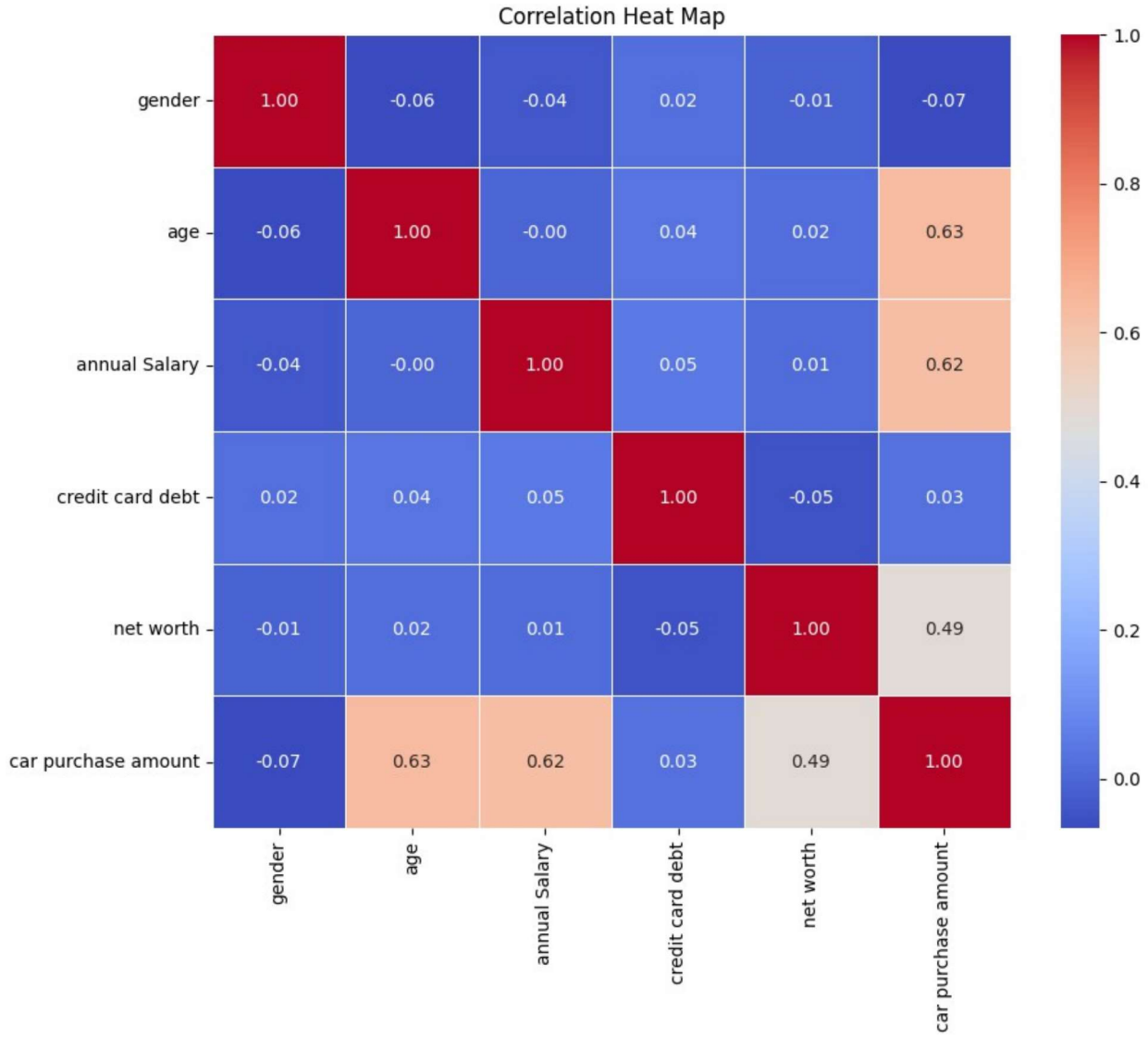
#Interaction features

```
#Pairplot
numerical_features = df[['gender', 'age', 'annual Salary', 'credit
card debt', 'net worth', 'car purchase amount']]

sns.pairplot(numerical_features, diag_kind='kde')
plt.suptitle('Pairwise Relationships of Numerical Features', y=1.02)
plt.show()
```




```
#Correlation heat map
plt.figure(figsize=(10,8))
num_cols = df.select_dtypes('int','float')
heatmap = sns.heatmap(num_cols.corr(), annot=True, cmap='coolwarm',
fmt=".2f", linewidths = .5)
heatmap.set_title('Correlation Heat Map')
```

```
Text(0.5, 1.0, 'Correlation Heat Map')
```



#Split the data

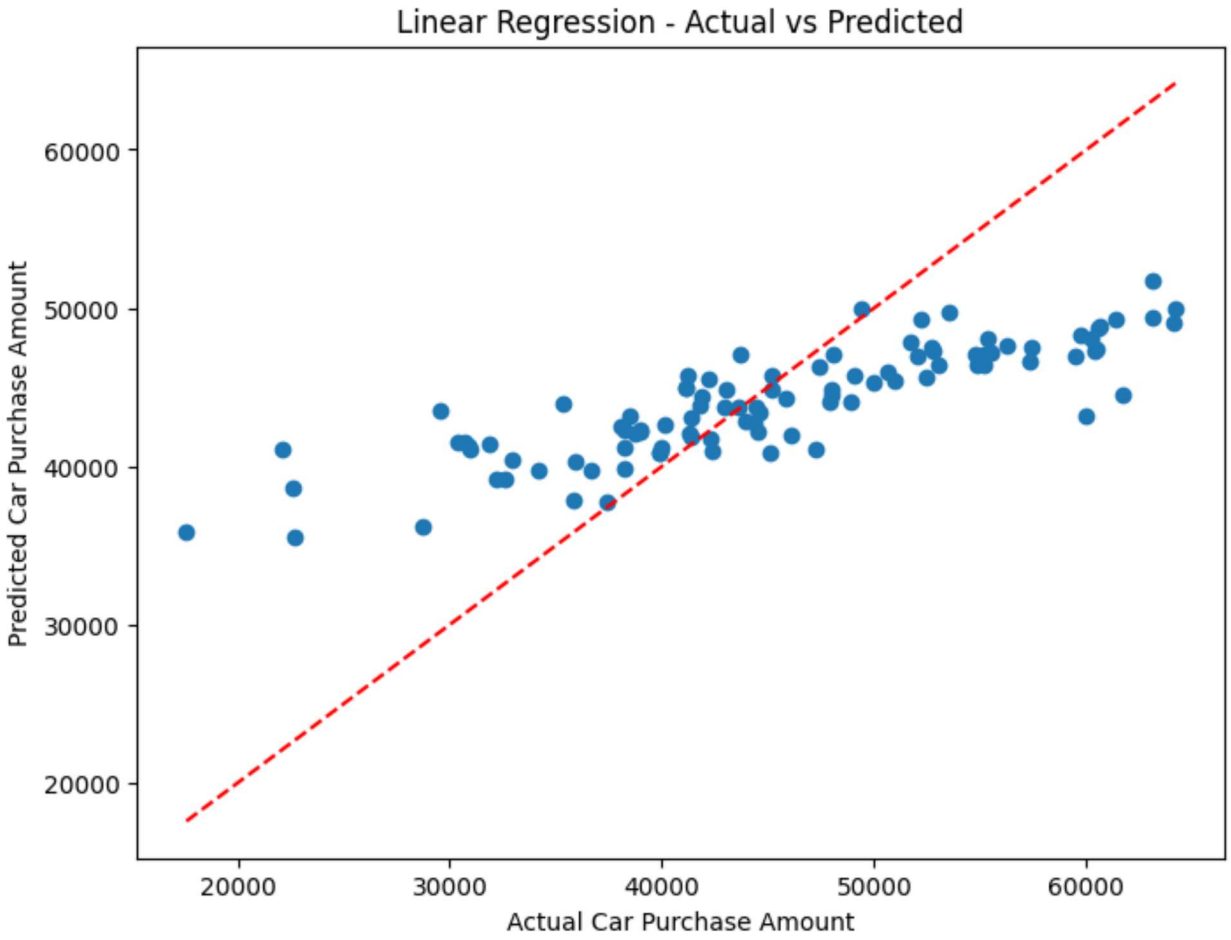
```
x = df.drop('car purchase amount', axis=1)
y = df['car purchase amount']
x_encoded = pd.get_dummies(x, drop_first=True)

X_train, X_test, y_train, y_test = train_test_split(x_encoded, y,
test_size=0.2, random_state=42)
```

#Standardize

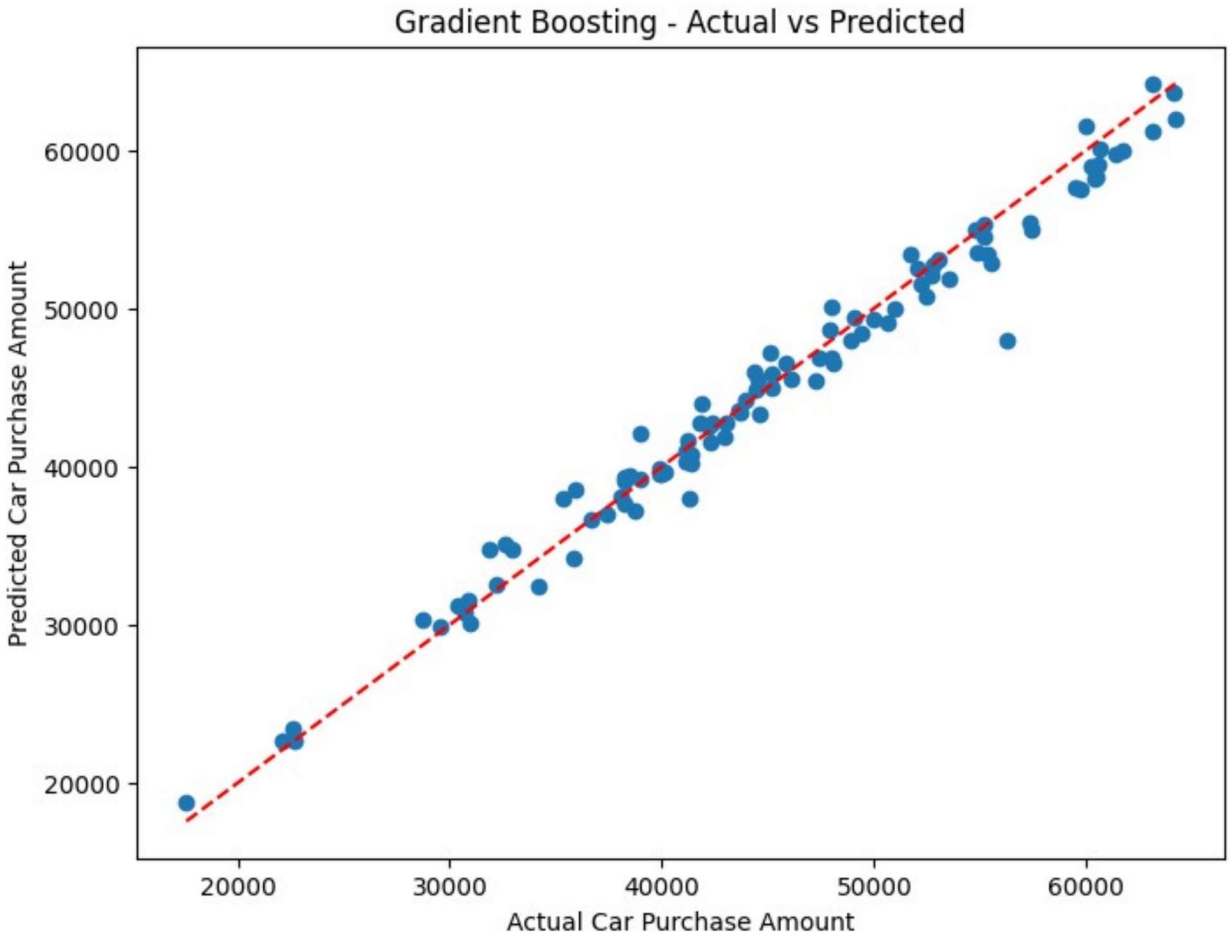
```
# Scale the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
models = {
    'Linear Regression': LinearRegression(),
    "Gradient Boosting": GradientBoostingRegressor(n_estimators=100,
random_state=42),
    'Support Vector Regression': SVR(kernel='rbf'),
    'Random Forest': RandomForestRegressor(random_state=42),
    'Neural Network': MLPRegressor(hidden_layer_sizes=(100,),
max_iter=500, random_state=42),
    'XGBoost': XGBRegressor(random_state=42)
}

for name, model in models.items():

    model.fit(X_train_scaled, y_train)

    y_pred = model.predict(X_test_scaled)

    mse = mean_squared_error(y_test, y_pred)
    mae = mean_absolute_error(y_test, y_pred)
    rmse = np.sqrt(mse)
    r2 = r2_score(y_test, y_pred)

    print(f"{name}:")
    print(f"  - Mean Squared Error (MSE): {mse}")
    print(f"  - Mean Absolute Error (MAE): {mae}")
    print(f"  - Root Mean Squared Error (RMSE): {rmse}")
    print(f"  - R Squared (R2): {r2}")

    # Plot actual vs predicted
    plt.figure(figsize=(8, 6))
    plt.scatter(y_test, y_pred)
    plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)],
'--', color='red')
    plt.xlabel('Actual Car Purchase Amount')
    plt.ylabel('Predicted Car Purchase Amount')
    plt.title(f'{name} - Actual vs Predicted')
    plt.show()
```

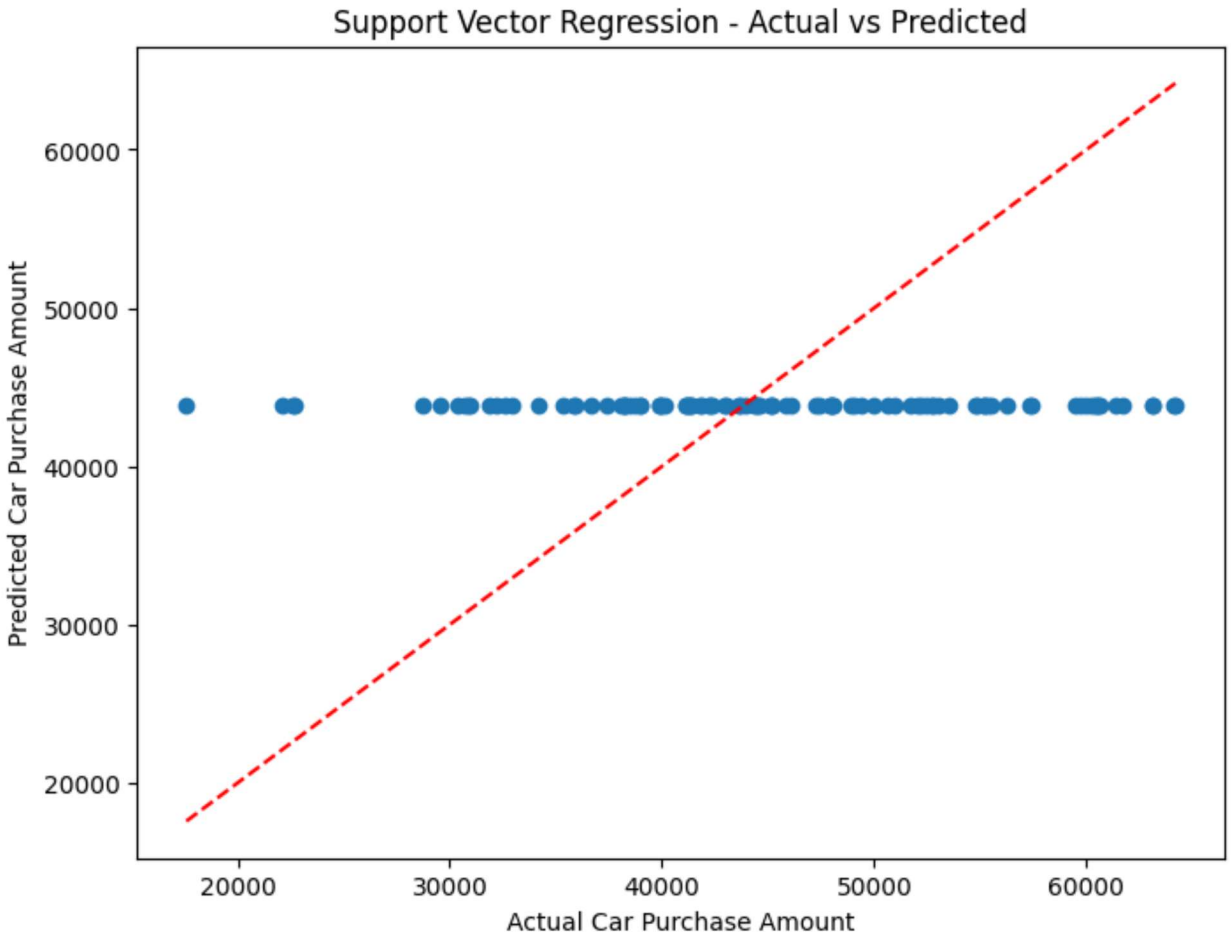
```
Linear Regression:
  - Mean Squared Error (MSE): 60635483.086599514
  - Mean Absolute Error (MAE): 6137.016865832602
  - Root Mean Squared Error (RMSE): 7786.878905350944
  - R Squared (R2): 0.4384207764299456
```



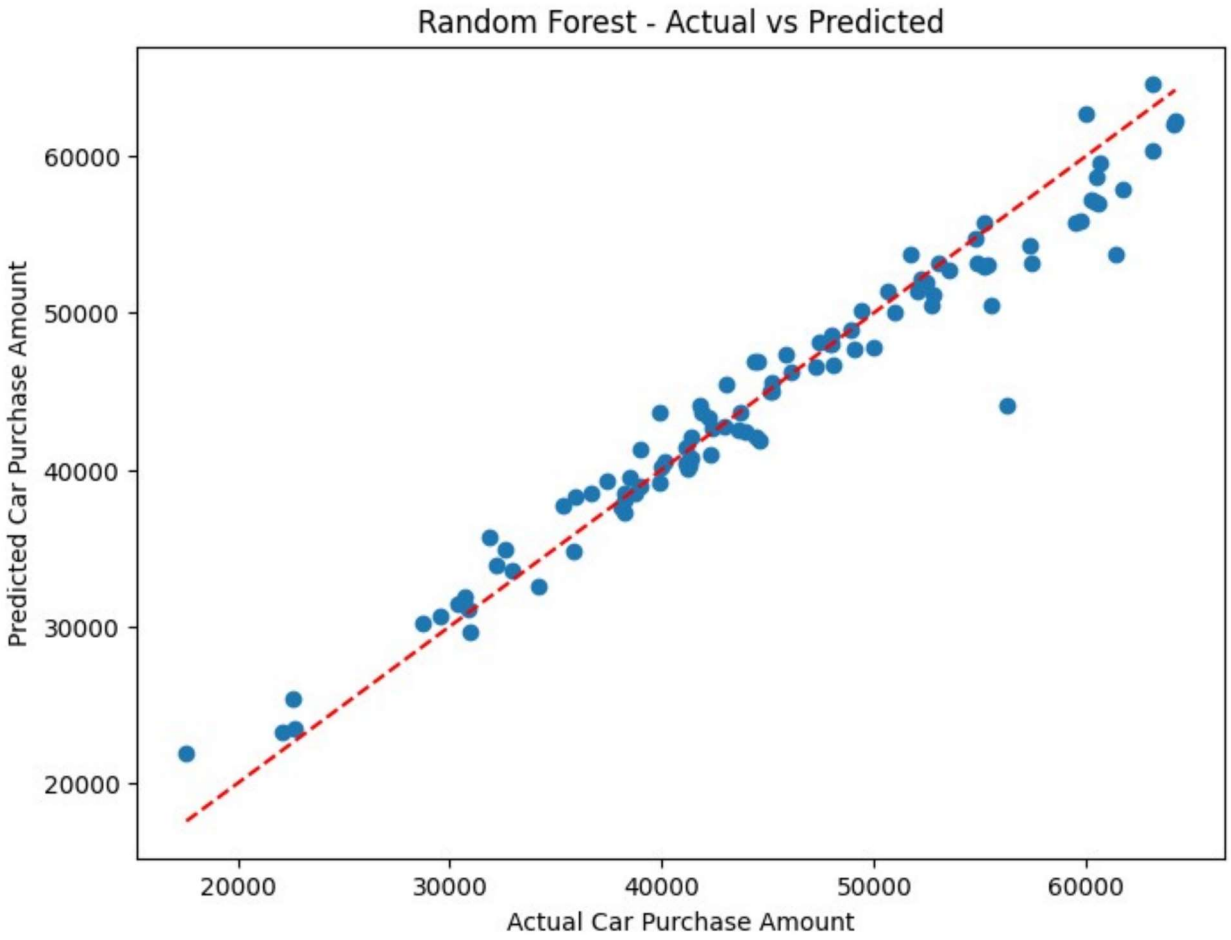

```
Gradient Boosting:
  - Mean Squared Error (MSE): 2530992.5278259073
  - Mean Absolute Error (MAE): 1177.1422392977029
  - Root Mean Squared Error (RMSE): 1590.9093399140968
  - R Squared (R2): 0.97655905838817
```



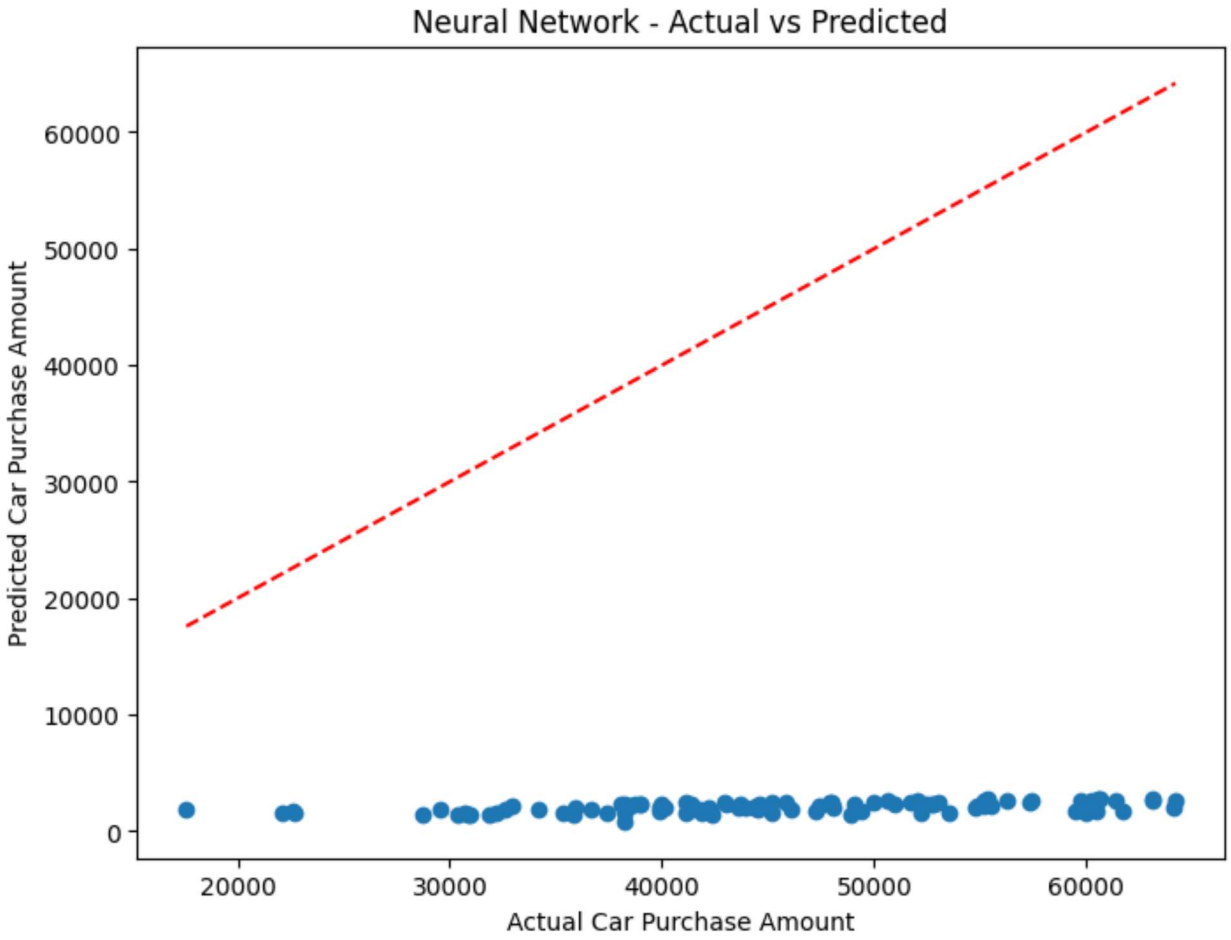

```
Support Vector Regression:
  - Mean Squared Error (MSE): 109890725.13076816
  - Mean Absolute Error (MAE): 8429.009730401938
  - Root Mean Squared Error (RMSE): 10482.877712287222
  - R Squared (R2): -0.01775965086894038
```



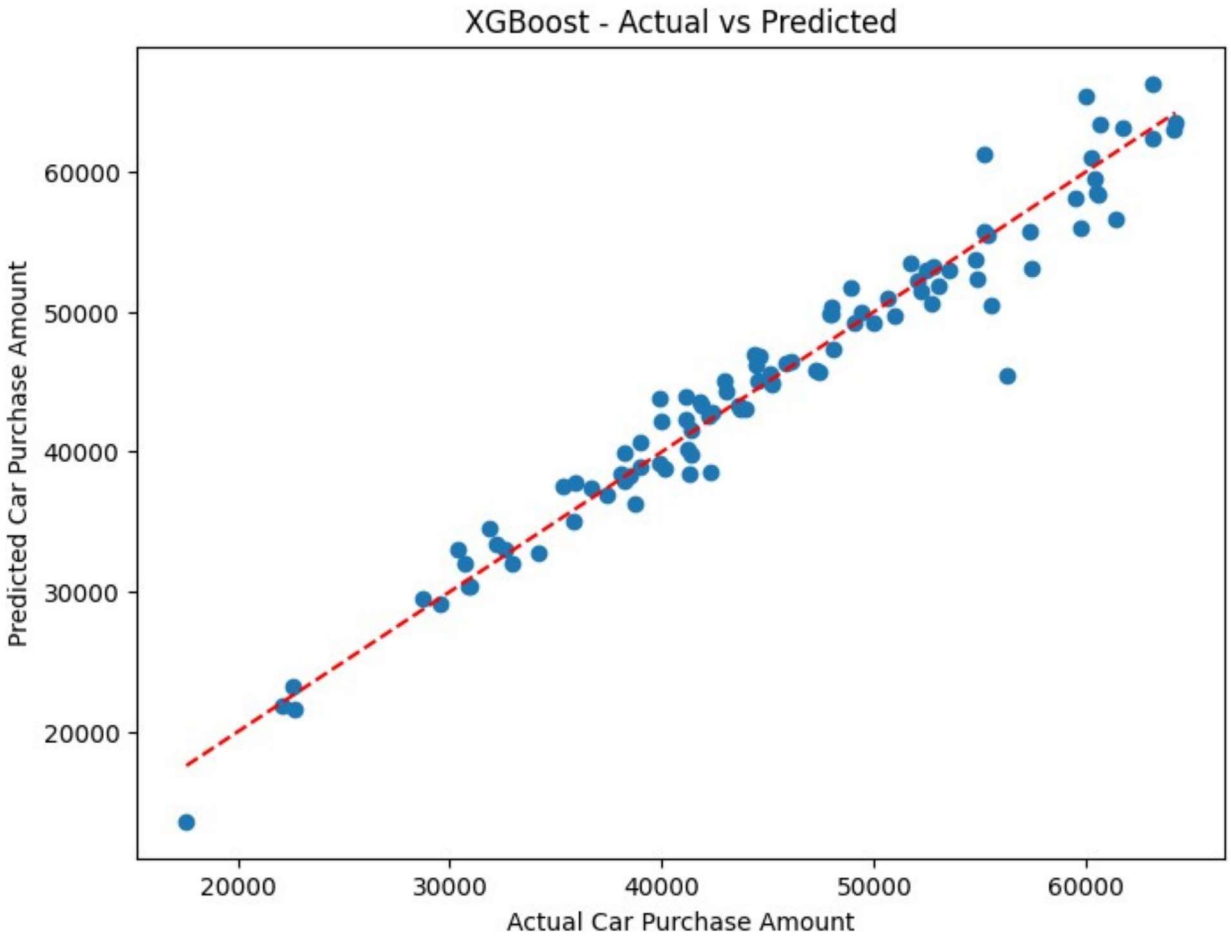

```
Random Forest:
  - Mean Squared Error (MSE): 5639933.306002016
  - Mean Absolute Error (MAE): 1668.0565104520024
  - Root Mean Squared Error (RMSE): 2374.854375746441
  - R Squared (R2): 0.9477654138180442
```




```
Neural Network:
  - Mean Squared Error (MSE): 1970032194.6135516
  - Mean Absolute Error (MAE): 43203.77331363553
  - Root Mean Squared Error (RMSE): 44385.0447179402
  - R Squared (R2): -17.24557328386468

c:\Users\akshi\AppData\Local\Programs\Python\Python312\Lib\site-
packages\sklearn\neural_network\_multilayer_perceptron.py:690:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (500)
reached and the optimization hasn't converged yet.
  warnings.warn(
```




```
XGBoost:
  - Mean Squared Error (MSE): 4945970.315879193
  - Mean Absolute Error (MAE): 1577.8810762093751
  - Root Mean Squared Error (RMSE): 2223.953757585619
  - R Squared (R2): 0.9541925943621975
```

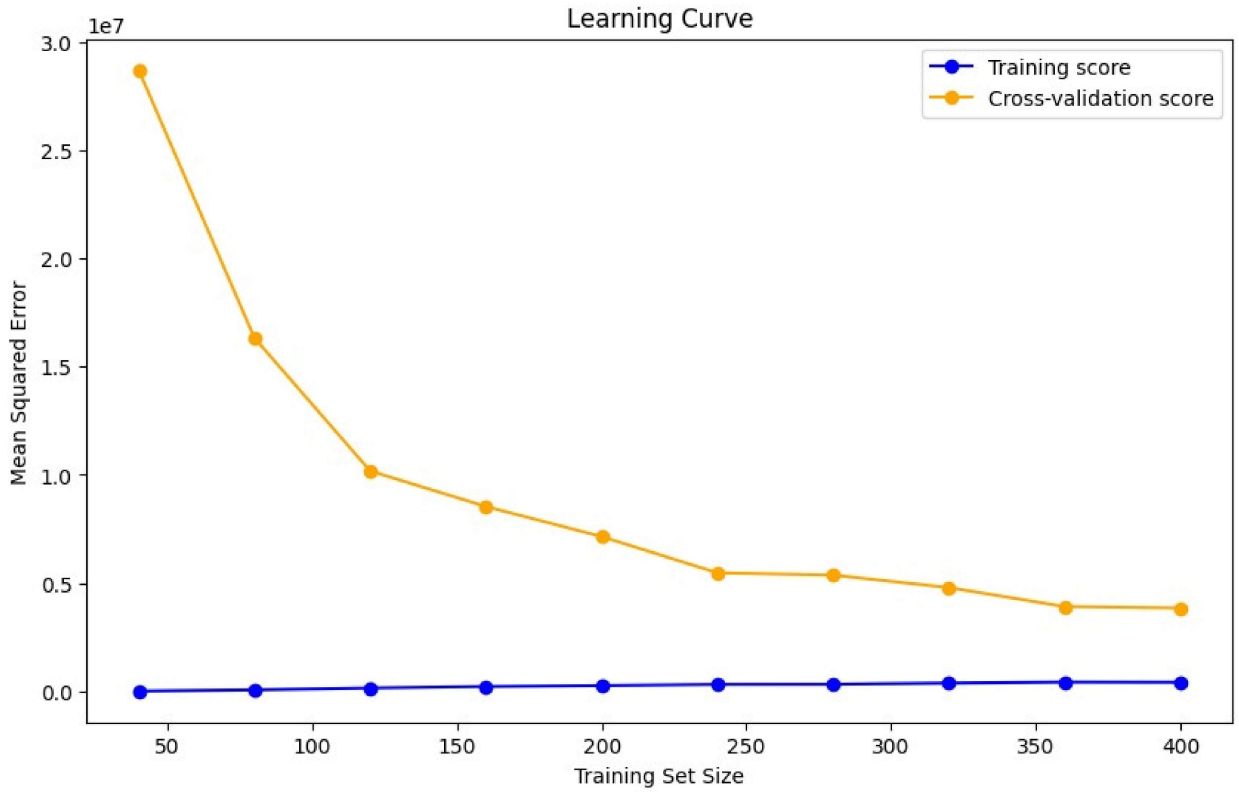


#Cross validation

```
# Cross-validate each model and calculate MSE
results = {}
for name, model in models.items():
    cv_mse = cross_val_score(model, X_train, y_train, cv=5,
scoring='neg_mean_squared_error')
    mean_cv_mse = -np.mean(cv_mse)

    results[name] = mean_cv_mse
    print(f"{name}: Cross-Validated MSE = {mean_cv_mse}")

Linear Regression: Cross-Validated MSE = 3.381289271129316
Gradient Boosting: Cross-Validated MSE = 4991153.847274978
Support Vector Regression: Cross-Validated MSE = 118258957.00225449
Random Forest: Cross-Validated MSE = 9529063.513659133
Neural Network: Cross-Validated MSE = 47578264.533180095
XGBoost: Cross-Validated MSE = 8281779.479076162
```

#Learning curve analysis

```
from sklearn.model_selection import learning_curve

model = GradientBoostingRegressor()

train_sizes, train_scores, test_scores = learning_curve(
    model, x_encoded, y, train_sizes=np.linspace(0.1, 1.0, 10), cv=5,
scoring='neg_mean_squared_error'
)
train_scores_mean = -train_scores.mean(axis=1)
test_scores_mean = -test_scores.mean(axis=1)

plt.figure(figsize=(10, 6))
plt.plot(train_sizes, train_scores_mean, 'o-', color='blue',
label='Training score')
plt.plot(train_sizes, test_scores_mean, 'o-', color='orange',
label='Cross-validation score')
plt.xlabel('Training Set Size')
plt.ylabel('Mean Squared Error')
plt.title('Learning Curve')
plt.legend()
plt.show()
```



Note:The gap between training and cross-validation errors, with training error being very low, suggests some level of overfitting. The model may be learning the specifics of the training data but is struggling to generalize to unseen data, as indicated by higher cross-validation error.