Report on how to solve a regression problem using different regression algorithms.

Introduction

1.1 Project Overview

This project focuses on solving a regression problem using various regression algorithms. The aim is to predict student performance based on several features and to compare the effectiveness of different regression techniques.

1.2 Objectives

- To understand the fundamentals of regression analysis.
- To implement and evaluate different regression algorithms.
- To compare the performance of these algorithms and determine the most effective one.

1.3 Importance of Regression Analysis

Regression analysis is a powerful statistical method that allows us to examine the relationship between two or more variables. It is essential for predicting outcomes and making informed decisions based on data.

1.4 Overview of Regression Algorithms

The project explores a variety of regression algorithms, including:

1.4.1 Linear Regression

Linear regression is the simplest form of regression analysis that models the relationship between a dependent variable and one or more independent variables using a linear equation.

1.4.2 Polynomial Regression

Polynomial regression is a type of regression analysis that models the relationship between the dependent and independent variables as an nth degree polynomial.

1.4.3 Ridge Regression

Ridge regression addresses multicollinearity issues by adding a degree of bias to the regression estimates, which helps in improving the model's prediction accuracy.

1.4.4 Lasso Regression

Lasso regression performs both variable selection and regularization to enhance the prediction accuracy and interpretability of the model it produces.

1.4.5 ElasticNet Regression

ElasticNet regression combines the properties of both Ridge and Lasso regression, aiming to retain the benefits of both techniques.

1.4.6 Decision Tree Regression

Decision tree regression models predict the target variable by learning decision rules inferred from the data features.

1.4.7 Random Forest Regression

Random forest regression is an ensemble method that uses multiple decision trees to improve the model's predictive accuracy and control overfitting.

1.4.8 Support Vector Regression (SVR)

Support vector regression uses support vector machines to perform regression tasks, maintaining all the main features that characterize the algorithm.

1.4.9 Gradient Boosting Regression

Gradient boosting regression builds an additive model in a forward stage-wise manner, allowing for the optimization of arbitrary differentiable loss functions.

1.5 Exploring Regression Analysis: Predictive Modeling Using Student Performance

Student Performance Dataset

Description: The Student Performance Dataset is designed to examine factors influencing academic student performance. It comprises 10,000 student records, each containing predictors and a performance index.

Variables:

- **Hours Studied:** Total hours spent studying by each student.
- **Previous Scores:** Scores from previous tests.
- **Extracurricular Activities:** Whether the student participates in extracurricular activities (Yes or No).
- **Sleep Hours:** Average hours of sleep per day for each student.
- **Sample Question Papers Practiced:** Number of sample question papers the student has practiced.

Target Variable:

- **Performance Index:** Rounded measure of each student's overall academic performance, ranging from 10 to 100. Higher values indicate better performance.

Dataset Purpose: The dataset aims to provide insights into how variables such as studying hours, previous scores, extracurricular activities, sleep patterns, and practice with sample question papers relate to student performance. It is a synthetic dataset created for illustrative purposes, offering a platform for researchers and data analysts to explore educational factors and their impacts.

Note: This dataset is synthetic, meaning it was generated artificially for illustrative purposes. Thus, while it facilitates analysis of educational influences, the relationships observed may not fully reflect real-world scenarios.

The data can be accessed from Student Performance Data-set (https://www.kaggle.com/datasets/nikhil7280/student-performance-multiple-linear-regression), which is a public resource.

The objective of using this dataset is to predict the `Performance` of Students based on the extracted features provided in `Student_Performance.csv`.

1.6 Setup

1.6.1 Installation

Ensure you have the necessary Python libraries installed. You can install them using pip:

```
pip install numpy pandas opendatasets matplotlib seaborn scikit-learn xgboost
```

1. Importing the Libraries

In [2]:
```
import numpy as np
import pandas as pd

import os
import opendatasets as od
import matplotlib.pyplot as plt
import matplotlib
%matplotlib inline
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression,RidgeCV,LassoCV,ElasticNetCV
from sklearn.preprocessing import StandardScaler, OneHotEncoder, MinMaxScaler
from sklearn.preprocessing import PolynomialFeatures
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR
from xgboost import XGBRegressor

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

In [3]:
```
# Customization for Visualisation of Graphs
sns.set_style('darkgrid')
matplotlib.rcParams['font.size'] = 14
matplotlib.rcParams['figure.figsize'] = (10,6)
matplotlib.rcParams['figure.facecolor'] = '#00000000'
```

2. Data Collection and Preprocessing

In [4]:
```
od.download('https://www.kaggle.com/datasets/nikhil7280/student-performance-multiple-linear-regression')
```

```
Skipping, found downloaded files in ".\student-performance-multiple-linear-regression" (use force=True to force downlo
ad)
```

In [5]:
```
os.listdir('student-performance-multiple-linear-regression')
```

Out[5]:
```
['Student_Performance.csv']
```

In [6]:
```python
df = pd.read_csv('student-performance-multiple-linear-regression/Student_Performance.csv')
df.head(5)
```

Out[6]:

	Hours Studied	Previous Scores	Extracurricular Activities	Sleep Hours	Sample Question Papers Practiced	Performance Index
0	7	99	Yes	9	1	91.0
1	4	82	No	4	2	65.0
2	8	51	Yes	7	2	45.0
3	5	52	Yes	5	2	36.0
4	7	75	No	8	5	66.0

In [7]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 6 columns):
 #   Column                            Non-Null Count  Dtype  
---  ------                            --------------  -----  
 0   Hours Studied                     10000 non-null  int64  
 1   Previous Scores                   10000 non-null  int64  
 2   Extracurricular Activities        10000 non-null  object 
 3   Sleep Hours                       10000 non-null  int64  
 4   Sample Question Papers Practiced  10000 non-null  int64  
 5   Performance Index                 10000 non-null  float64
dtypes: float64(1), int64(4), object(1)
memory usage: 468.9+ KB
```

In [8]:
```python
# Check for null value
df.isna().sum()
```

Out[8]:
```
Hours Studied                       0
Previous Scores                     0
Extracurricular Activities          0
Sleep Hours                         0
Sample Question Papers Practiced    0
Performance Index                   0
dtype: int64
```

In [9]:
```
df.describe()
```

Out[9]:

	Hours Studied	Previous Scores	Sleep Hours	Sample Question Papers Practiced	Performance Index
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	4.992900	69.445700	6.530600	4.583300	55.224800
std	2.589309	17.343152	1.695863	2.867348	19.212558
min	1.000000	40.000000	4.000000	0.000000	10.000000
25%	3.000000	54.000000	5.000000	2.000000	40.000000
50%	5.000000	69.000000	7.000000	5.000000	55.000000
75%	7.000000	85.000000	8.000000	7.000000	71.000000
max	9.000000	99.000000	9.000000	9.000000	100.000000

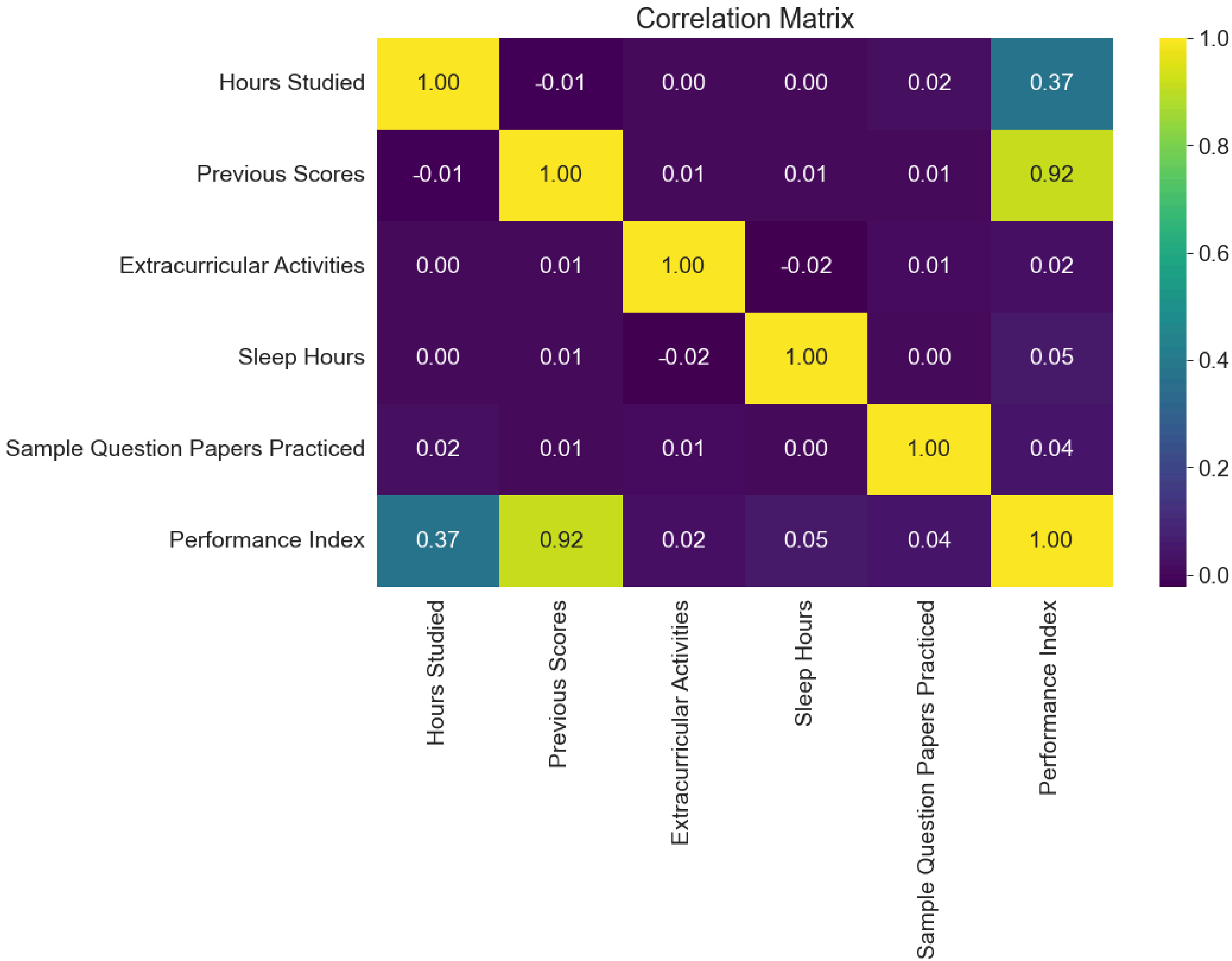
In [10]:
```
df['Extracurricular Activities'] = df['Extracurricular Activities'].map({'Yes':1, 'No':0})
df.head(5)
```

Out[10]:

	Hours Studied	Previous Scores	Extracurricular Activities	Sleep Hours	Sample Question Papers Practiced	Performance Index
0	7	99	1	9	1	91.0
1	4	82	0	4	2	65.0
2	8	51	1	7	2	45.0
3	5	52	1	5	2	36.0
4	7	75	0	8	5	66.0

2.1 Data Exploration and Visualization

In [11]:
```
# Check for Correleation of each columns
corr = df.corr()
plt.title("Correlation Matrix")
sns.heatmap(corr, annot=True, fmt=".2f",cmap='viridis', cbar=True)
plt.show()
```


Correlation Matrix
Hours Studied
Previous Scores
Extracurricular Activities
Sleep Hours
Sample Question Papers Practiced
Performance Index
1.00
-0.01
0.00
0.00
0.02
0.37
-0.01
1.00
0.01
0.01
0.01
0.92
0.00
0.01
1.00
-0.02
0.01
0.02
0.00
0.01
-0.02
1.00
0.00
0.05
0.02
0.01
0.01
0.00
1.00
0.04
0.37
0.92
0.02
0.05
0.04
1.00
1.0
0.8
0.6
0.4
0.2
0.0

2.2 Data Splitting

In [12]:
```
# Input column is X and Target column is y
X = df[['Hours Studied','Previous Scores']]
y = df['Performance Index']
```

In [13]:
```
# Splitting the dataset into the Training set and Test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 42)
```

In [14]:
```
# using StandardScaler
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

3. Modelling

In [15]:
```python
def evaluate_model(model, X_train, y_train, X_test, y_test):
    # Train the model
    model.fit(X_train, y_train)

    # Predict on training and testing data
    y_train_pred = model.predict(X_train)
    y_test_pred = model.predict(X_test)

    # Calculate R^2 scores
    train_r2 = r2_score(y_train, y_train_pred)*100
    test_r2 = r2_score(y_test, y_test_pred)*100

    # Calculate RMSE
    train_rmse = np.sqrt(mean_squared_error(y_train, y_train_pred))
    test_rmse = np.sqrt(mean_squared_error(y_test, y_test_pred))

    # Print the scores
    print(f"Training Score (R^2): {train_r2}")
    print(f"Testing Score (R^2): {test_r2}")
    print(f"Training RMSE: {train_rmse}")
    print(f"Testing RMSE: {test_rmse}")

    return test_r2, test_rmse

# Initialize a list to store the results
results = []
```

3.1 Linear Regression

In [16]:
```python
linear_model = LinearRegression()
print("LinearRegression")
test_r2, test_rmse = evaluate_model(linear_model, X_train, y_train, X_test, y_test)
results.append(['Linear Regression', test_r2, test_rmse])
```

```
LinearRegression
Training Score (R^2): 98.58696583934669
Testing Score (R^2): 98.5855014245765
Training RMSE: 2.2824274304787613
Testing RMSE: 2.289524227116088
```

3.2 Polynomial Regression

In [17]:
```
# Create a polynomial features object of degree 2
poly = PolynomialFeatures(degree=2)
X_train_poly = poly.fit_transform(X_train)
X_test_poly = poly.transform(X_test)

# Create a linear regression model
model = LinearRegression()

# Evaluate the model
print("Polynomial Regression:")
test_r2, test_rmse = evaluate_model(model, X_train_poly, y_train, X_test_poly, y_test)
results.append(['Polynomial Regression', test_r2, test_rmse])
```

```
Polynomial Regression:
Training Score (R^2): 98.58760527867469
Testing Score (R^2): 98.58563492759195
Training RMSE: 2.281910939422129
Testing RMSE: 2.289416179781838
```

3.3 Ridge Regression

In [18]:
```
alphas = [0.005, 0.05, 0.1, 0.3, 1, 3, 5, 10, 15, 30, 80]

# Initialize RidgeCV model with specified alphas and cross-validation folds
ridgeCV = RidgeCV(alphas=alphas, cv=4)
print("Ridge Model:")
test_r2, test_rmse = evaluate_model(ridgeCV, X_train, y_train, X_test, y_test)
results.append(['Ridge Regression', test_r2, test_rmse])
print(f"Best alpha: {ridgeCV.alpha_}")
```

```
Ridge Model:
Training Score (R^2): 98.5869658237001
Testing Score (R^2): 98.5854836257077
Training RMSE: 2.2824274431154676
Testing RMSE: 2.2895386318012028
Best alpha: 0.1
```

3.4 Lasso Regression

In [19]:
```
alphas2 = np.array([1e-5, 5e-5, 0.0001, 0.0005, 0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1])

# Initialize LassoCV model with specified alphas, maximum iterations, and cross-validation folds
lassoCV = LassoCV(alphas=alphas2, max_iter=50000, cv=3)
print("Lasso Model:")
test_r2, test_rmse = evaluate_model(lassoCV, X_train, y_train, X_test, y_test)
results.append(['Lasso Regression', test_r2, test_rmse])
print(f"Best alpha: {lassoCV.alpha_}")
```

```
Lasso Model:
Training Score (R^2): 98.58696583929184
Testing Score (R^2): 98.58550064139607
Training RMSE: 2.282427430523067
Testing RMSE: 2.2895248609485868
Best alpha: 1e-05
```

3.5 ElasticNet

In [20]:
```
alphas2 = np.array([1e-5, 5e-5, 0.0001, 0.0005, 0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1])
l1_ratios = np.linspace(0.1, 0.9, 9)

# Initialize ElasticNetCV model with specified alphas, l1_ratios, maximum iterations, and cross-validation folds
elasticNetCV = ElasticNetCV(alphas=alphas2, l1_ratio=l1_ratios, max_iter=10000)
print("ElasticNet Model:")
test_r2, test_rmse = evaluate_model(elasticNetCV, X_train, y_train, X_test, y_test)
results.append(['ElasticNet Regression', test_r2, test_rmse])
print(f"Best alpha: {elasticNetCV.alpha_}, Best l1_ratio: {elasticNetCV.l1_ratio_}")
```

```
ElasticNet Model:
Training Score (R^2): 98.58696581252097
Testing Score (R^2): 98.58548012328893
Training RMSE: 2.282427452144111
Testing RMSE: 2.2895414663099527
Best alpha: 0.0001, Best l1_ratio: 0.9
```

3.6 Decision Tree Regressor

In [21]:
```
# Initialize Decision Tree Regressor with best parameters
dt_model = DecisionTreeRegressor(max_depth=30, min_samples_leaf=10, random_state=42)

print("Decision Tree:")
test_r2, test_rmse = evaluate_model(dt_model, X_train, y_train, X_test, y_test)
results.append(['Decision Tree Regression', test_r2, test_rmse])
```

```
Decision Tree:
Training Score (R^2): 98.66587276390435
Testing Score (R^2): 98.5134820738645
Training RMSE: 2.2177841362213067
Testing RMSE: 2.347086317315597
```

3.7 Random Forest Regression

In [22]:
```
rf_model = RandomForestRegressor(n_estimators=500, max_depth=8, min_samples_leaf=5, n_jobs=-1, random_state=42)

print("Random Forest:")
test_r2, test_rmse = evaluate_model(rf_model, X_train, y_train, X_test, y_test)
results.append(['Random Forest Regression', test_r2, test_rmse])
```

```
Random Forest:
Training Score (R^2): 98.65789930384949
Testing Score (R^2): 98.52494368757101
Training RMSE: 2.224401597439517
Testing RMSE: 2.3380203477472805
```

3.8 Support Vector Regression (SVR)

In [23]:
```
svr_model = SVR(C=15, epsilon=0.02, kernel='linear')

print("Support Vector Regressor:")
test_r2, test_rmse = evaluate_model(svr_model, X_train, y_train, X_test, y_test)
results.append(['Support Vector Regression', test_r2, test_rmse])
```

```
Support Vector Regressor:
Training Score (R^2): 98.58651770152879
Testing Score (R^2): 98.58780127282756
Training RMSE: 2.282789332898403
Testing RMSE: 2.2876621890573148
```

3.9 Gradient Boosting Regression

In [24]:
```
# Initialize XGB Regressor
xgb_model = XGBRegressor(n_jobs=-1, random_state=42, n_estimators=500,
                    learning_rate=0.1, max_depth=15, subsample=0.8,
                    colsample_bytree=0.7)

# Evaluate the best model
print("XGBoost Regressor:")
test_r2, test_rmse = evaluate_model(xgb_model, X_train, y_train, X_test, y_test)
results.append(['Gradient Boosting Regression', test_r2, test_rmse])
```

```
XGBoost Regressor:
Training Score (R^2): 98.5964268827699
Testing Score (R^2): 98.58065440528469
Training RMSE: 2.274773541659338
Testing RMSE: 2.2934435939470137
```

4. Comparison of Models

In [25]:
```
# Create a DataFrame from the results
results_df = pd.DataFrame(results, columns=['Regressor', 'Test Score R²', 'Test RMSE'])
print(results_df)  # Print the results
```

```
                    Regressor  Test Score R²  Test RMSE
0           Linear Regression      98.585501   2.289524
1       Polynomial Regression      98.585635   2.289416
2            Ridge Regression      98.585484   2.289539
3            Lasso Regression      98.585501   2.289525
4       ElasticNet Regression      98.585480   2.289541
5    Decision Tree Regression      98.513482   2.347086
6    Random Forest Regression      98.524944   2.338020
7   Support Vector Regression      98.587801   2.287662
8  Gradient Boosting Regression    98.580654   2.293444
```

5. Actual vs Predicted

In [26]:
```python
# For Support Vector Regression
y_test_pred  = svr_model.predict(X_test)

pred_df= pd.DataFrame({'Actual': np.round(y_test, 0),
                       'Predicted': np.round(y_test_pred, 0)})
pred_df
```

Out[26]:

	Actual	Predicted
6252	51.0	55.0
4684	20.0	23.0
1731	46.0	47.0
4742	28.0	30.0
4521	41.0	44.0
...	...	...
6412	45.0	47.0
8285	66.0	62.0
7853	16.0	17.0
1095	65.0	63.0
6929	47.0	46.0

2000 rows × 2 columns

7. Model Performance Comparison

- **Linear Regression**
  - **Test R^2 Score**: 98.585%
  - **Test RMSE**: 2.289

- **Polynomial Regression**
  - **Test R^2 Score**: 98.585%
  - **Test RMSE**: 2.289

- **Ridge Regression**
  - **Test R^2 Score**: 98.585%
  - **Test RMSE**: 2.289

- **Lasso Regression**
  - **Test R^2 Score**: 98.585%
  - **Test RMSE**: 2.289

- **ElasticNet Regression**
  - **Test R^2 Score**: 98.585%
  - **Test RMSE**: 2.289

- **Decision Tree Regression**
  - **Test R^2 Score**: 98.513%
  - **Test RMSE**: 2.347

- **Random Forest Regression**
  - **Test R^2 Score**: 98.525%
  - **Test RMSE**: 2.338

- **Support Vector Regression (SVR)**
  - **Test R^2 Score**: 98.588%
  - **Test RMSE**: 2.287

- **Gradient Boosting Regression**
  - **Test R^2 Score**: 98.581%
  - **Test RMSE**: 2.293

Overall Conclusion

- **SVR Performance:** SVR demonstrates high accuracy with a Test Score R^2 of **98.588%** and low RMSE of **2.287**. This indicates that SVR fits the data well and generalizes effectively, similar to other linear regression-based models such as Ridge, Lasso, and ElasticNet.
- **Tree-Based Models:** Decision Tree and Random Forest perform well but show slightly lower R^2 scores and marginally higher RMSE compared to linear models. This could be attributed to their tendency to overfit.
- **Gradient Boosting Regression:** Stands out by achieving comparable performance to linear models, indicating effective ensemble learning and boosting.

Recommendation

- **For Predictive Tasks:**
  - **Interpretability and Simplicity:** Linear regression-based models (including Ridge, Lasso, ElasticNet, and SVR) are suitable choices due to their high accuracy and ease of interpretation.
  - **Complex Relationships:** If capturing more complex relationships or benefiting from ensemble learning is necessary, Gradient Boosting Regression is recommended for its robust performance.

```
In [ ]:
```