Exploratory Analysis of the 2023 World Happiness Report

Talha Iqbal - 217967951

EECS3401

Dr. Ruba Alomari

3/24/2024

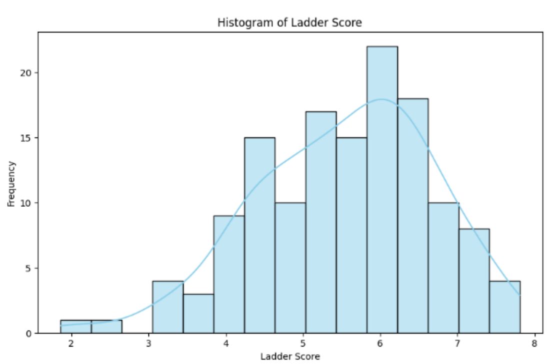
Framing the problem and looking at the big picture

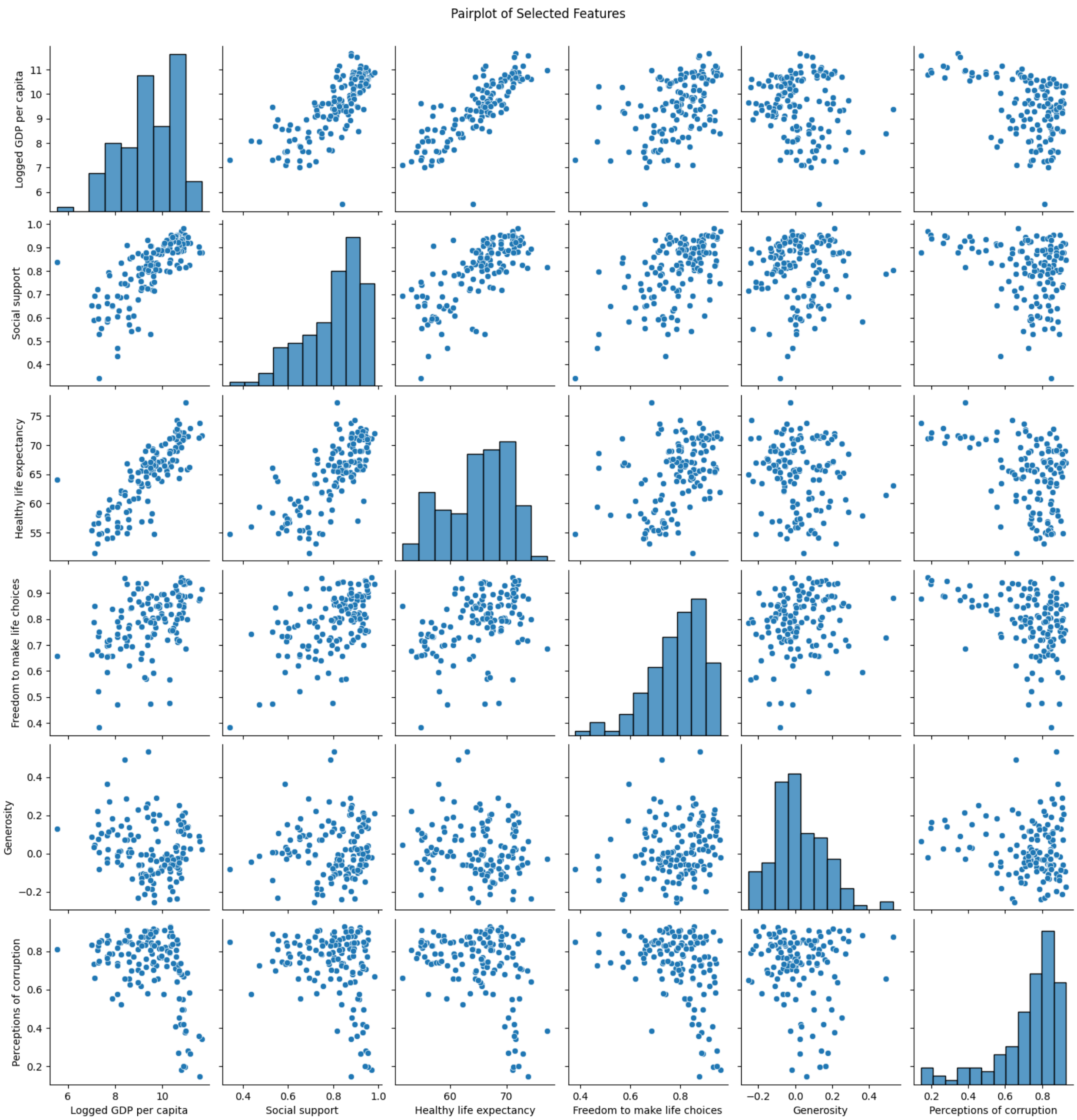
- This problem requires supervised learning.
- It is a regression task.
- Batch learning is required.

- The problem: Create a model that will predict a country's happiness given a series of factors as well as determine the most influential factors.
- Benefit of solution: The benefit of finding a solution to this problem is that understanding the factors driving happiness aids companies and governments in Corporate Social Responsibility efforts and making policies that favour the happiness of their clients or citizens.

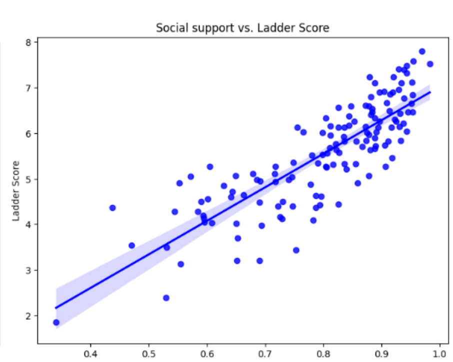
Description of the dataset and 3+ graphs of EDA

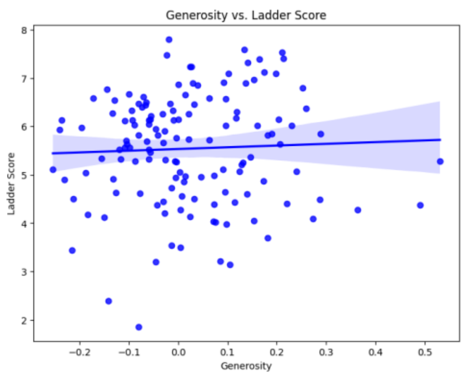
The World Happiness Report is a landmark survey of the state of global happiness . The report continues to gain global recognition as governments, organizations and civil society increasingly use happiness indicators to inform their policy-making decisions. Leading experts across fields – economics, psychology, survey analysis, national statistics, health, public policy and more – describe how measurements of well-being can be used effectively to assess the progress of nations. The reports review the state of happiness in the world today and show how the new science of happiness explains personal and national variations in happiness. (https://www.kaggle.com/datasets/ajaypalsinghlo/world-happiness-report-2023?resource=download)

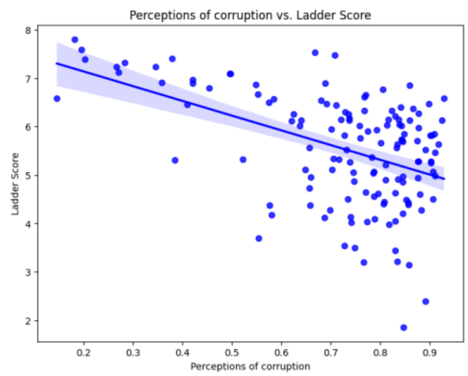


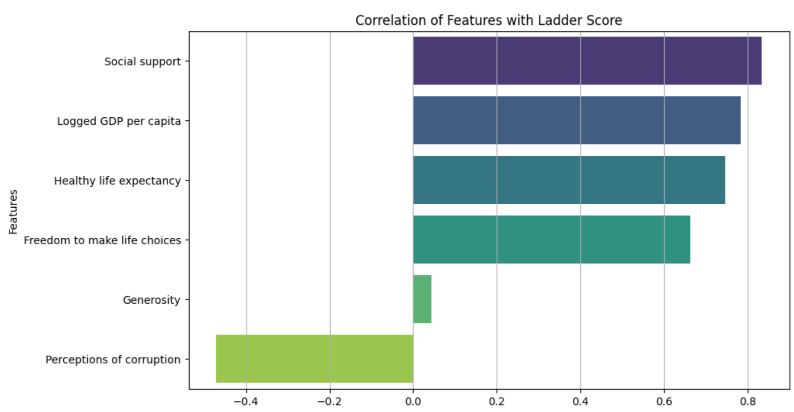

Pairplot of Selected Features
Logged GDP per capita
Social support
Healthy life expectancy
Freedom to make life choices
Generosity
Perceptions of corruption


Logged GDP per capita vs. Ladder Score
Ladder Score
Logged GDP per capita


Social support vs. Ladder Score
Ladder Score
Social support







Data cleaning and preprocessing

```
# Split features and target variable
X = data.drop(['Ladder score', 'Country name'], axis=1)
y = data['Ladder score']

# Splitting the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)
```

```
# Preprocessing pipeline
numeric_features = X.select_dtypes(include=['float64']).columns

numeric_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler())
])

preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numeric_features)
    ])
```

Training and evaluation of three machine learning algorithms

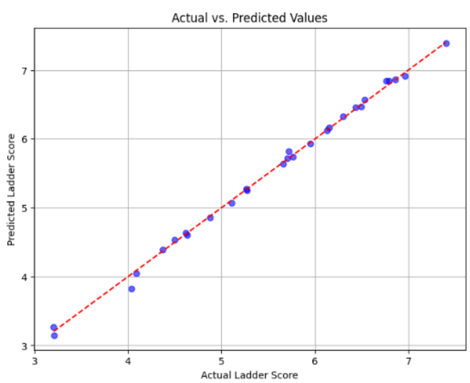
```
# Train and evaluate models
for name, model in models:
    model_pipeline = Pipeline(steps=[
        ('preprocessor', preprocessor),
        ('model', model)
    ])
    model_pipeline.fit(X_train, y_train)
    y_pred = model_pipeline.predict(X_test)
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)
    results.append((name, mse, r2))

# Display results
results_df = pd.DataFrame(results, columns=['Model', 'Mean Squared Error', 'R-
squared'])
print("Performance Metrics:")
print(results_df)

# Identify the best-performing algorithm
best_model_idx = results_df['Mean Squared Error'].idxmin()
best_model_name = results_df.loc[best_model_idx, 'Model']
best_model = models[best_model_idx][1]
print(f"\nBest performing algorithm: {best_model_name}")

# Train the best model on the entire dataset
best_model_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
```

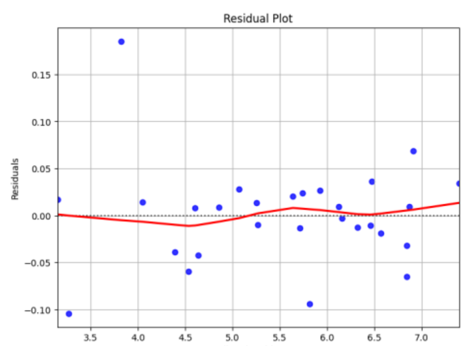
```
    ('model', best_model)
])
best_model_pipeline.fit(X, y)
```

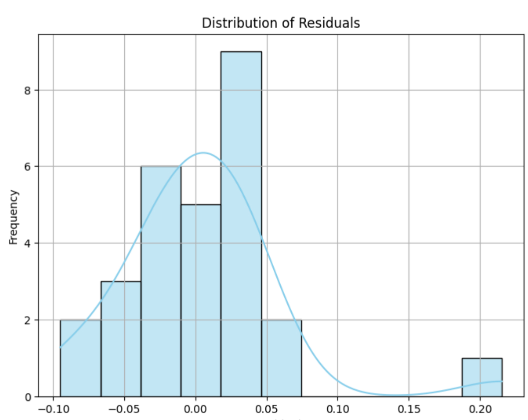
The 3 models where fairly close when it came to regression. However, linear regression ultimately won. It had smallest least error.

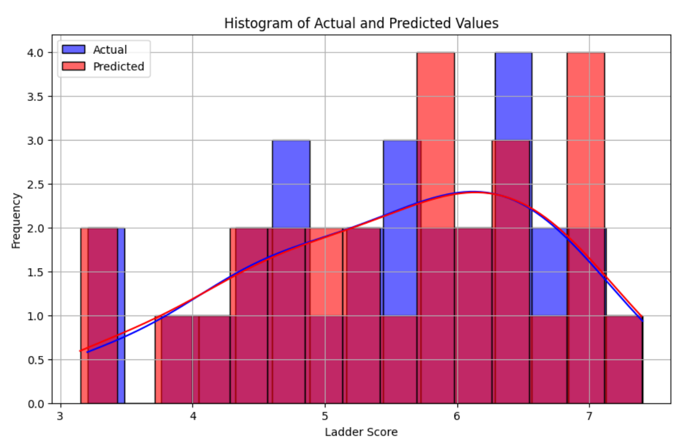
```
Performance Metrics:
                          Model  Mean Squared Error  R-squared
0             Linear Regression        1.461316e-07   1.000000
1      Random Forest Regression        2.356780e-03   0.998101
2  Gradient Boosting Regression        3.098134e-03   0.997504
```

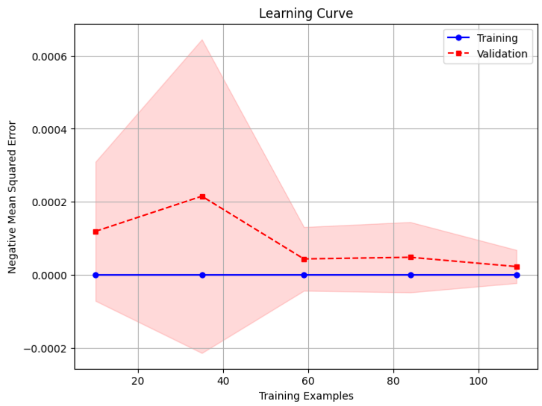
2+ graphs for the best performing algorithm











Limitations

These models are limited to taking only the 6 factors and cant take other factors such as crime rate.

Next steps

Add various other factors by using combining datasets.

Appendix 1

Dataset link

https://www.kaggle.com/datasets/ajaypalsinghlo/world-happiness-report-2023?resource=download

Github link

https://github.com/Iqbal-Talha/aiProject

Appendix 2

Importing Data from Kaggle

```
# IMPORTANT: RUN THIS CELL IN ORDER TO IMPORT YOUR KAGGLE DATA SOURCES
# TO THE CORRECT LOCATION (/kaggle/input) IN YOUR NOTEBOOK,
# THEN FEEL FREE TO DELETE THIS CELL.
# NOTE: THIS NOTEBOOK ENVIRONMENT DIFFERS FROM KAGGLE'S PYTHON
# ENVIRONMENT SO THERE MAY BE MISSING LIBRARIES USED BY YOUR
# NOTEBOOK.

import os
import sys
from tempfile import NamedTemporaryFile
from urllib.request import urlopen
from urllib.parse import unquote, urlparse
from urllib.error import HTTPError
from zipfile import ZipFile
import tarfile
import shutil

CHUNK_SIZE = 40960
DATA_SOURCE_MAPPING = 'world-happiness-report-
2023:https%3A%2F%2Fstorage.googleapis.com%2Fkaggle-data-
sets%2F3031959%2F5212373%2Fbundle%2Farchive.zip%3FX-Goog-
Algorithm%3DGOOG4-RSA-SHA256%26X-Goog-Credential%3Dgcp-kaggle-
com%2540kaggle-
161607.iam.gserviceaccount.com%252F20240324%252Fauto%252Fstorage%252Fgoog4
_request%26X-Goog-Date%3D20240324T223645Z%26X-Goog-Expires%3D259200%26X-
Goog-SignedHeaders%3Dhost%26X-Goog-
Signature%3D45e491d310cff8be628f9a64ede66ca545217536b018d2aaa8769e57f8e963b
a70512cada41556ab00d21b88ab574fe894fd6b849d16a0985c4c6ccbdcab025b5c868e35
3d0ee8632f555d076283e0ca9c2c55518172df562e49999ed68380cdddda16b6fa1dace946
1b79d72c0a013628e45fb8a44c3411c8611f66daac4d7064c055e9724a7f00e59906bd2f99
18006ca53bcf7543c99869ccaf30fa236bcd8c49e749818ef9e0116d008413e942306d823f4
52fcae1b31544d8a67516875fb14aae4d989e4cdb5091f8f11cbdae0742e6db88766616ec3
ed6a42ecb7fd3123bc4fdee6015677428b0f4c645b6804d460f831ff53b7d770e7a5a458286
d871'

KAGGLE_INPUT_PATH='/kaggle/input'
KAGGLE_WORKING_PATH='/kaggle/working'
KAGGLE_SYMLINK='kaggle'
```

```
!umount /kaggle/input/ 2> /dev/null
shutil.rmtree('/kaggle/input', ignore_errors=True)
os.makedirs(KAGGLE_INPUT_PATH, 0o777, exist_ok=True)
os.makedirs(KAGGLE_WORKING_PATH, 0o777, exist_ok=True)

try:
  os.symlink(KAGGLE_INPUT_PATH, os.path.join("..", 'input'), target_is_directory=True)
except FileExistsError:
  pass
try:
  os.symlink(KAGGLE_WORKING_PATH, os.path.join("..", 'working'),
target_is_directory=True)
except FileExistsError:
  pass

for data_source_mapping in DATA_SOURCE_MAPPING.split(','):
    directory, download_url_encoded = data_source_mapping.split(':')
    download_url = unquote(download_url_encoded)
    filename = urlparse(download_url).path
    destination_path = os.path.join(KAGGLE_INPUT_PATH, directory)
    try:
        with urlopen(download_url) as fileres, NamedTemporaryFile() as tfile:
            total_length = fileres.headers['content-length']
            print(f'Downloading {directory}, {total_length} bytes compressed')
            dl = 0
            data = fileres.read(CHUNK_SIZE)
            while len(data) > 0:
                dl += len(data)
                tfile.write(data)
                done = int(50 * dl / int(total_length))
                sys.stdout.write(f"\r[{'=' * done}{' ' * (50-done)}] {dl} bytes downloaded")
                sys.stdout.flush()
                data = fileres.read(CHUNK_SIZE)
            if filename.endswith('.zip'):
              with ZipFile(tfile) as zfile:
                zfile.extractall(destination_path)
            else:
              with tarfile.open(tfile.name) as tarfile:
                tarfile.extractall(destination_path)
            print(f'\nDownloaded and uncompressed: {directory}')
    except HTTPError as e:
        print(f'Failed to load (likely expired) {download_url} to path {destination_path}')
        continue
    except OSError as e:
```

```
        print(f'Failed to load {download_url} to path {destination_path}')
        continue

print('Data source import complete.')
```

Importing Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.metrics import accuracy_score
import seaborn as sns
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import FunctionTransformer
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
```

Loading Dataset

```
data = pd.read_csv("/kaggle/input/world-happiness-report-2023/WHR2023.csv")
```

EDA Graphs

```
# Correlation Table
selected_features = ['Logged GDP per capita', 'Social support', 'Healthy life expectancy',
            'Freedom to make life choices', 'Generosity', 'Perceptions of corruption']
correlation_table = data[selected_features].corr(numeric_only=True)
print(correlation_table)

# Histogram of Ladder Score
plt.figure(figsize=(10, 6))
sns.histplot(data['Ladder score'], bins=15, kde=True, color='skyblue')
plt.title('Histogram of Ladder Score')
plt.xlabel('Ladder Score')
plt.ylabel('Frequency')
plt.show()

# Pairplot of Selected Features
sns.pairplot(data[selected_features])
plt.suptitle('Pairplot of Selected Features', y=1.02)
```

```
plt.show()


# Plot features
for feature in selected_features:
    plt.figure(figsize=(8, 6))
    sns.regplot(x=feature, y='Ladder score', data=data, color='blue')
    plt.title(f'{feature} vs. Ladder Score')
    plt.xlabel(feature)
    plt.ylabel('Ladder Score')
    plt.show()

# Plot correlation values for each feature
plt.figure(figsize=(10, 6))
correlation_table = data[selected_features].corrwith(data['Ladder
score']).sort_values(ascending=False)
sns.barplot(x=correlation_table.values, y=correlation_table.index, palette='viridis')
plt.title('Correlation of Features with Ladder Score')
plt.xlabel('Correlation')
plt.ylabel('Features')
plt.grid(axis='x')
plt.show()

# Sort correlation values in descending order
sorted_correlation = correlation_table.abs().sort_values(ascending=False)

# Select the top 3 highly correlated features
top_3_features = sorted_correlation.index[:3].tolist()

# Print the top 3 highly correlated features along with their correlation values
print("Top 3 highly correlated features:")
for feature in top_3_features:
    correlation_value = correlation_table.loc[feature]
    print(f"{feature}: {correlation_value}")
```

Preprocessing and Regression model training

```
# Split features and target variable
X = data.drop(['Ladder score', 'Country name'], axis=1)
y = data['Ladder score']

# Splitting the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Preprocessing pipeline
```

```
numeric_features = X.select_dtypes(include=['float64']).columns

numeric_transformer = Pipeline(steps=[
  ('imputer', SimpleImputer(strategy='median')),
  ('scaler', StandardScaler())
])

preprocessor = ColumnTransformer(
  transformers=[
    ('num', numeric_transformer, numeric_features)
  ])

# Define models
models = [
  ('Linear Regression', LinearRegression()),
  ('Random Forest Regression', RandomForestRegressor(random_state=42)),
  ('Gradient Boosting Regression', GradientBoostingRegressor(random_state=42))
]

results = []

# Train and evaluate models
for name, model in models:
  model_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('model', model)
  ])
  model_pipeline.fit(X_train, y_train)
  y_pred = model_pipeline.predict(X_test)
  mse = mean_squared_error(y_test, y_pred)
  r2 = r2_score(y_test, y_pred)
  results.append((name, mse, r2))

# Display results
results_df = pd.DataFrame(results, columns=['Model', 'Mean Squared Error', 'R-squared'])
print("Performance Metrics:")
print(results_df)

# Identify the best-performing algorithm
best_model_idx = results_df['Mean Squared Error'].idxmin()
best_model_name = results_df.loc[best_model_idx, 'Model']
best_model = models[best_model_idx][1]
print(f"\nBest performing algorithm: {best_model_name}")
```

```
# Train the best model on the entire dataset
best_model_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('model', best_model)
])
best_model_pipeline.fit(X, y)

# Graph 1: Scatter plot of actual vs. predicted values
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred, color='blue', alpha=0.6)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red', linestyle='--')
plt.title('Actual vs. Predicted Values')
plt.xlabel('Actual Ladder Score')
plt.ylabel('Predicted Ladder Score')
plt.grid(True)
plt.show()

# Graph 2: Residual plot
residuals = y_test - y_pred
plt.figure(figsize=(8, 6))
sns.residplot(x=y_pred, y=residuals, lowess=True, color='blue', line_kws={'color': 'red'})
plt.title('Residual Plot')
plt.xlabel('Predicted Ladder Score')
plt.ylabel('Residuals')
plt.grid(True)
plt.show()

# Graph 3: Distribution plot of residuals
plt.figure(figsize=(8, 6))
sns.histplot(residuals, kde=True, color='skyblue')
plt.title('Distribution of Residuals')
plt.xlabel('Residuals')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()

# Graph 4: Histogram of actual and predicted values
plt.figure(figsize=(10, 6))
sns.histplot(y_test, bins=15, kde=True, color='blue', alpha=0.6, label='Actual')
sns.histplot(y_pred, bins=15, kde=True, color='red', alpha=0.6, label='Predicted')
plt.title('Histogram of Actual and Predicted Values')
plt.xlabel('Ladder Score')
plt.ylabel('Frequency')
plt.legend()
```

```
plt.grid(True)
plt.show()

# Graph 5: Learning curve
from sklearn.model_selection import learning_curve

train_sizes, train_scores, test_scores = learning_curve(best_model_pipeline, X, y, cv=5,
scoring='neg_mean_squared_error')
train_mean = -np.mean(train_scores, axis=1)
train_std = np.std(train_scores, axis=1)
test_mean = -np.mean(test_scores, axis=1)
test_std = np.std(test_scores, axis=1)

plt.figure(figsize=(8, 6))
plt.plot(train_sizes, train_mean, color='blue', marker='o', markersize=5, label='Training')
plt.fill_between(train_sizes, train_mean + train_std, train_mean - train_std, alpha=0.15,
color='blue')
plt.plot(train_sizes, test_mean, color='red', linestyle='--', marker='s', markersize=5,
label='Validation')
plt.fill_between(train_sizes, test_mean + test_std, test_mean - test_std, alpha=0.15,
color='red')
plt.title('Learning Curve')
plt.xlabel('Training Examples')
plt.ylabel('Negative Mean Squared Error')
plt.legend()
plt.grid(True)
plt.show()
```