```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score, confusion_matrix
from sklearn.feature_selection import f_regression
from xgboost import XGBRegressor
from keras.models import Sequential
from keras.layers import Dense
import joblib
import seaborn as sns
```

```
# Load the dataset
data_path = 'world_happiness_report_csv.csv'
import codecs

with codecs.open(data_path, 'r', encoding='ISO-8859-1') as f:
    df = pd.read_csv(f)
```

```
df.head(10)
```

	Year	Rank	Country name	Ladder score	upperwhisker	lowerwhisker	Explained by: Log GDP per capita	Explain b Soci suppo
0	2024	1	Finland	7.736	7.810	7.662	1.749	1.7
1	2023	143	Afghanistan	1.721	1.775	1.667	0.628	0.0
2	2022	137	Afghanistan	1.859	1.923	1.795	0.645	0.0
3	2021	146	Afghanistan	2.404	2.469	2.339	0.758	0.0
4	2020	150	Afghanistan	2.523	2.596	2.449	0.370	0.0
5	2019	153	Afghanistan	2.567	2.628	2.506	0.301	0.3
6	2018	154	Afghanistan	3.203	NaN	NaN	NaN	N
7	2017	145	Afghanistan	3.632	NaN	NaN	NaN	N
8	2016	141	Afghanistan	3.794	NaN	NaN	NaN	N
9	2015	154	Afghanistan	3.360	NaN	NaN	NaN	N

```
# Define the new column names
new_column_names = {
    "Ladder score": "Happiness_Score",
    "Explained by: Log GDP per capita": "GDP_per_capita",
    "Explained by: Social support": "Social_Support",
    "Explained by: Healthy life expectancy": "Healthy_Life_Expectancy",
    "Explained by: Freedom to make life choices": "Freedom_to_Choose",
    "Explained by: Generosity": "Generosity_Score",
    "Explained by: Perceptions of corruption": "Corruption_Perception"
}

# Rename the columns
df = df.rename(columns=new_column_names)
```

```
df.columns
```

```
Index(['Year', 'Rank', 'Country name', 'Happiness_Score', 'upperwhisker',
       'lowerwhisker', 'GDP_per_capita', 'Social_Support',
       'Healthy_Life_Expectancy', 'Freedom_to_Choose', 'Generosity_Score',
       'Corruption_Perception', 'Dystopia + residual'],
      dtype='object')
```

```
df.shape
```

```
(1969, 13)
```

Preprocessing the Data

```
# Check for missing values
df.isnull().sum()
```

	0
Year	0
Rank	0
Country name	0
Happiness_Score	0
upperwhisker	1094
lowerwhisker	1094
GDP_per_capita	1097
Social_Support	1097
Healthy_Life_Expectancy	1099
Freedom_to_Choose	1098
Generosity_Score	1097
Corruption_Perception	1098
Dystopia + residual	1101

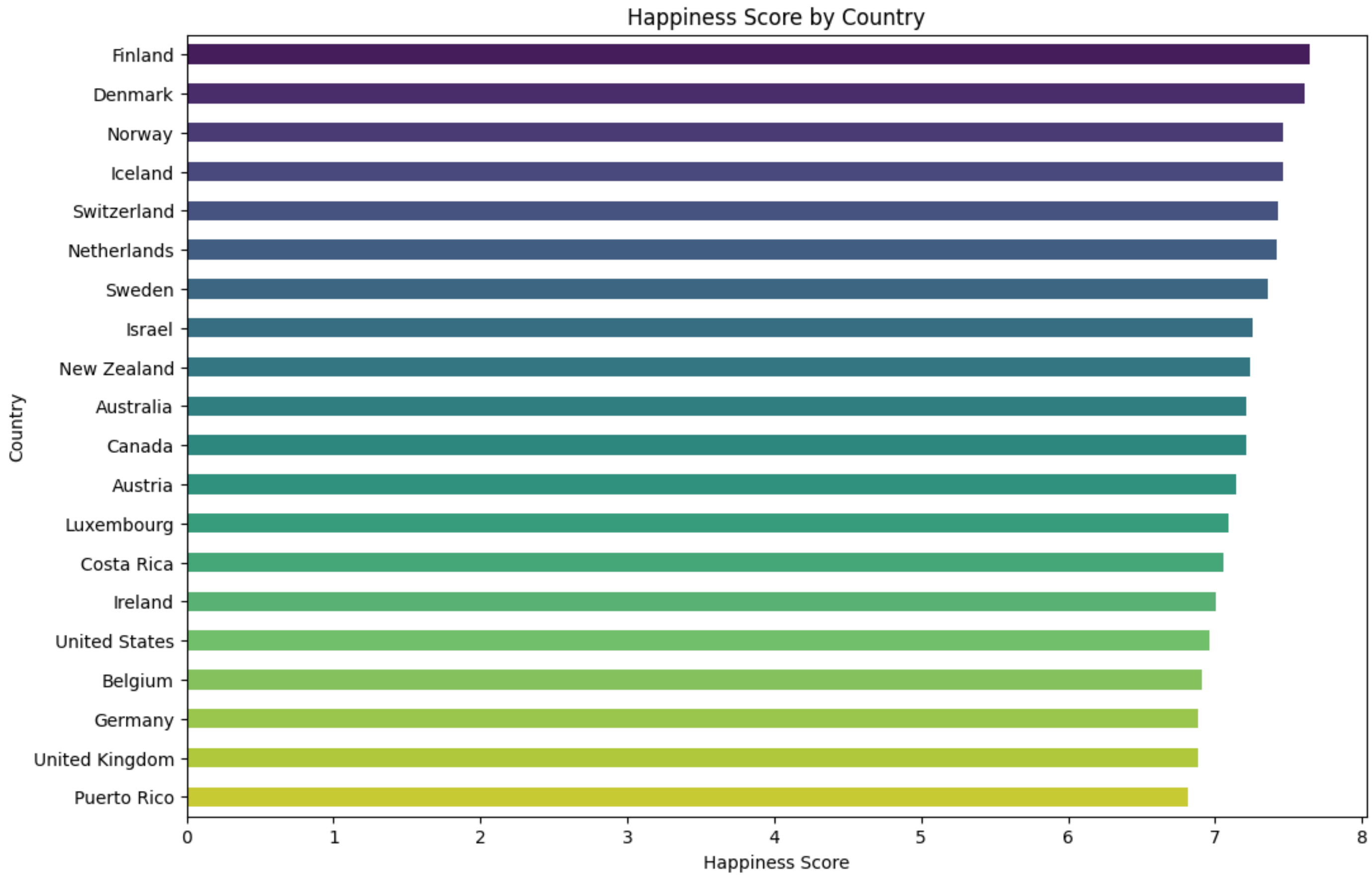
dtype: int64

```
# Group by country and calculate the average happiness score (if multiple rows ex
df_unique = df.groupby('Country name', as_index=False)['Happiness_Score'].mean()

# Sort the dataframe by Happiness_Score in descending order
df_sorted = df_unique.sort_values(by='Happiness_Score', ascending=False)
df_sorted.head(20)
```

	Country name	Happiness_Score
49	Finland	7.646923
40	Denmark	7.605462
112	Norway	7.462154
64	Iceland	7.460231
146	Switzerland	7.429538
105	Netherlands	7.415615
145	Sweden	7.356846
70	Israel	7.252692
106	New Zealand	7.233769
6	Australia	7.213077
25	Canada	7.211769
7	Austria	7.141769
87	Luxembourg	7.094077
33	Costa Rica	7.057615
69	Ireland	7.003077
161	United States	6.965923
12	Belgium	6.911769
54	Germany	6.886000
160	United Kingdom	6.879846
121	Puerto Rico	6.816000

```
df_unique_top_20 = df_sorted.head(20)

# Create the barplot again
plt.figure(figsize=(12, 8))
sns.barplot(x='Happiness_Score', y='Country name', data=df_unique_top_20, palette=

# Add labels and title
plt.xlabel('Happiness Score')
plt.ylabel('Country')
plt.title('Happiness Score by Country')

# Show the plot
plt.show()
```

```
<ipython-input-184-53ccffb19260>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed ir

  sns.barplot(x='Happiness_Score', y='Country name', data=df_unique_top_20, pa
```




```
#Plot Happiness Score by GDP
df_not_null = df.dropna(subset=['GDP_per_capita'])

# Sort the dataframe by Happiness_Score in descending order
df_sorted = df_not_null.sort_values(by='Happiness_Score', ascending=False)

df_sorted.head(20)
```

	Year	Rank	Country name	Happiness_Score	upperwhisker	lowerwhisker	GDP_pe
567	2020	2	Finland	7.842	7.904	7.780	
566	2021	1	Finland	7.821	7.886	7.756	
568	2019	1	Finland	7.809	7.870	7.748	
565	2022	1	Finland	7.804	7.875	7.733	
564	2023	1	Finland	7.741	7.815	7.667	
0	2024	1	Finland	7.736	7.810	7.662	
460	2019	2	Denmark	7.646	7.711	7.580	
458	2021	2	Denmark	7.636	7.710	7.563	
459	2020	3	Denmark	7.620	7.687	7.552	
457	2022	2	Denmark	7.586	7.667	7.506	
456	2023	2	Denmark	7.583	7.665	7.500	
1688	2020	4	Switzerland	7.571	7.643	7.500	
1689	2019	3	Switzerland	7.560	7.629	7.491	
738	2021	3	Iceland	7.557	7.651	7.464	
739	2020	5	Iceland	7.554	7.670	7.438	
737	2022	3	Iceland	7.530	7.625	7.434	
736	2023	3	Iceland	7.525	7.618	7.433	
13	2024	2	Denmark	7.521	7.611	7.431	
26	2024	3	Iceland	7.515	7.606	7.425	
1687	2021	4	Switzerland	7.512	7.586	7.437	

```
# Group by country and calculate the average happiness score (if multiple rows ex
df_unique = df_sorted.groupby('Country name', as_index=False)[['Happiness_Score',

# Sort the dataframe by Happiness_Score in descending order
df_sorted = df_unique.sort_values(by='Happiness_Score', ascending=False)
df_sorted.head(20)
```

	Year	Rank	Country name	Happiness_Score	upperwhisker	lowerwhisker	GDP_pe
567	2020	2	Finland	7.842	7.904	7.780	
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565	2022	1	Finland	7.804	7.875	7.733	
564	2023	1	Finland	7.741	7.815	7.667	
...	...	...	...	...	...	...	
3	2021	146	Afghanistan	2.404	2.469	2.339	
969	2022	136	Lebanon	2.392	2.479	2.305	
2	2022	137	Afghanistan	1.859	1.923	1.795	
1	2023	143	Afghanistan	1.721	1.775	1.667	
1956	2024	147	Afghanistan	1.364	1.427	1.301	

872 rows × 13 columns

```
plt.figure(figsize=(12, 8))
sns.barplot(x='Happiness_Score', y='GDP_per_capita', data=df_sorted, palette='vir

# Add labels and title
plt.xlabel('Happiness Score')
plt.ylabel('Country')
plt.title('Happiness Score by Country')

# Show the plot
plt.show()
```

```
# Drop the 'Country' and "Rank" column as we don't need it for modeling
df = df.drop(columns=["Country name"])
```

```
# Fill NaN values with the mean of each column (numerical columns)
df = df.fillna(df.mean(numeric_only=True))
```

```
df.corr()['Happiness_Score'].sort_values(ascending=False)
```

	Happiness_Score
Happiness_Score	1.000000
lowerwhisker	0.665514
upperwhisker	0.665492
GDP_per_capita	0.458434
Social_Support	0.456223
Healthy_Life_Expectancy	0.437363
Freedom_to_Choose	0.360348
Corruption_Perception	0.287307
Dystopia + residual	0.275491
Year	0.057769
Generosity_Score	0.029380
Rank	-0.984096

dtype: float64

```
# Define the target and features
X = df.drop("Happiness_Score", axis=1)
y = df["Happiness_Score"]
```

```
X
```

	Year	Rank	upperwhisker	lowerwhisker	GDP_per_capita	Social_Support	He
0	2024	1	7.810000	7.662000	1.74900	1.783000	
1	2023	143	1.775000	1.667000	0.62800	0.000000	
2	2022	137	1.923000	1.795000	0.64500	0.000000	
3	2021	146	2.469000	2.339000	0.75800	0.000000	
4	2020	150	2.596000	2.449000	0.37000	0.000000	
...	...	...	...	...	...	...	
1964	2016	138	5.648687	5.418737	1.22028	1.078529	
1965	2015	131	5.648687	5.418737	1.22028	1.078529	
1966	2014	115	5.648687	5.418737	1.22028	1.078529	
1967	2012	103	5.648687	5.418737	1.22028	1.078529	
1968	2011	142	5.648687	5.418737	1.22028	1.078529	

1969 rows × 11 columns

```
# Display basic information
print(df.info(verbose=False))
print(df.describe())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1969 entries, 0 to 1968
Columns: 12 entries, Year to Dystopia + residual
dtypes: float64(10), int64(2)
memory usage: 184.7 KB
None
              Year         Rank  Happiness_Score  upperwhisker  lowerwhisker
count  1969.000000  1969.000000      1969.000000   1969.000000   1969.000000
mean   2017.714068    76.430168         5.451904      5.648687      5.418737
std       3.964913    43.942744         1.121865      0.735676      0.759088
min    2011.000000     1.000000         1.364000      1.427000      1.301000
25%    2015.000000    38.000000         4.596000      5.648687      5.418737
50%    2018.000000    76.000000         5.456000      5.648687      5.418737
75%    2021.000000   114.000000         6.295000      5.648687      5.418737
max    2024.000000   158.000000         7.856000      7.904000      7.780000

       GDP_per_capita  Social_Support  Healthy_Life_Expectancy  \
count     1969.000000     1969.000000              1969.000000
mean         1.220280        1.078529                 0.542917
std          0.308317        0.236207                 0.148150
min          0.000000        0.000000                 0.000000
25%          1.220280        1.078529                 0.542917
50%          1.220280        1.078529                 0.542917
75%          1.220280        1.078529                 0.542917
max          2.209000        1.840000                 1.138000

       Freedom_to_Choose  Generosity_Score  Corruption_Perception  \
count        1969.000000       1969.000000            1969.000000
mean            0.563723          0.154259               0.144356
std             0.119814          0.057703               0.079978
min             0.000000          0.000000               0.000000
25%             0.563723          0.153000               0.125000
50%             0.563723          0.154259               0.144356
75%             0.563723          0.154259               0.144356
max             1.018000          0.570000               0.587000

       Dystopia + residual
count          1969.000000
mean              1.832778
std               0.417360
min              -0.110000
25%               1.832778
50%               1.832778
75%               1.832778
max               3.482000
```

Data Preprocessing

```
#Feature Importance from a Model

from sklearn.ensemble import RandomForestRegressor

model = RandomForestRegressor()
model.fit(X, y)

importances = pd.Series(model.feature_importances_, index=X.columns)
importances.sort_values(ascending=False)
```

	0
Rank	0.976595
upperwhisker	0.011122
lowerwhisker	0.007056
Year	0.003451
Freedom_to_Choose	0.000548
Social_Support	0.000317
Corruption_Perception	0.000249
Dystopia + residual	0.000218
GDP_per_capita	0.000210
Healthy_Life_Expectancy	0.000134
Generosity_Score	0.000099

dtype: float64

```
# f_regression
f_scores, p_values = f_regression(X, y)
feature_scores = pd.DataFrame({'Feature': X.columns, 'F-Score': f_scores, 'P-Valu
print(feature_scores.sort_values(by='F-Score', ascending=False))
```

```
                    Feature       F-Score        P-Value
1                      Rank  60370.174596   0.000000e+00
3             lowerwhisker   1563.842308  3.546556e-252
2             upperwhisker   1563.654749  3.736896e-252
4            GDP_per_capita    523.384630  6.628832e-103
5            Social_Support    517.024443  8.236918e-102
6   Healthy_Life_Expectancy    465.257056   8.501307e-93
7         Freedom_to_Choose    293.531819   1.937463e-61
9     Corruption_Perception    176.975552   9.910702e-39
10     Dystopia + residual    161.547144   1.255792e-35
0                      Year      6.586430   1.034933e-02
8          Generosity_Score      1.699357   1.925246e-01
```

```
# Data scaling
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
y_scaled = scaler.fit_transform(y.values.reshape(-1, 1))
```

```
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y_scaled, test_size
# Check the shapes of the splits
X_train.shape, X_test.shape
```

```
((1575, 11), (394, 11))
```

```
# Linear Regression
lr = LinearRegression()
lr.fit(X_train, y_train)
y_pred_lr = lr.predict(X_test)
```

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

# Evaluate the model
mae = mean_absolute_error(y_test, y_pred_lr)
mse = mean_squared_error(y_test, y_pred_lr)
r2 = r2_score(y_test, y_pred_lr)

print(f"Mean Absolute Error: {mae}")
print(f"Mean Squared Error: {mse}")
print(f"R-squared: {r2}")
```

```
Mean Absolute Error: 0.11747702146259696
Mean Squared Error: 0.02811347144174125
R-squared: 0.9707277802260325
```

```
# Random Forest with hyperparameter tuning
rf = RandomForestRegressor(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)
y_pred_rf = rf.predict(X_test)
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/base.py:1389: DataConversionWa
  return fit_method(estimator, *args, **kwargs)
```

```
# XGBoost with hyperparameter tuning
xgb = XGBRegressor(random_state=42)
xgb_params = {'n_estimators': [100, 200], 'learning_rate': [0.05, 0.1], 'max_dept
xgb_grid = GridSearchCV(xgb, xgb_params, cv=3, scoring='r2')
xgb_grid.fit(X_train, y_train)
y_pred_xgb = xgb_grid.best_estimator_.predict(X_test)
```

```
# Deep Learning Model
dnn = Sequential()
dnn.add(Dense(64, input_dim=X_train.shape[1], activation='relu'))
dnn.add(Dense(32, activation='relu'))
dnn.add(Dense(1))
dnn.compile(optimizer='adam', loss='mean_squared_error')
dnn.fit(X_train, y_train, epochs=100, batch_size=10, verbose=1)
y_pred_dnn = dnn.predict(X_test).flatten()
```

```
from sklearn.svm import SVR
# Create and train the SVR model
svr = SVR(kernel='rbf')
svr.fit(X_train, y_train)
y_pred_svr = svr.predict(X_test)

# Evaluate the model
mae = mean_absolute_error(y_test, y_pred_svr)
mse = mean_squared_error(y_test, y_pred_svr)
r2 = r2_score(y_test, y_pred_svr)

print(f"Mean Absolute Error: {mae}")
print(f"Mean Squared Error: {mse}")
print(f"R-squared: {r2}")
```

```
Mean Absolute Error: 0.07010709275575486
Mean Squared Error: 0.01633034791775674
R-squared: 0.9829965668158581
/usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:1408: Data
  y = column_or_1d(y, warn=True)
```

```
# Evaluation function
def evaluate_model(name, y_true, y_pred):
    rmse = np.sqrt(mean_squared_error(y_true, y_pred))
    r2 = r2_score(y_true, y_pred)
    print(f"{name} - RMSE: {rmse:.3f}, R^2: {r2:.3f}")

# Evaluate all models
evaluate_model("Linear Regression", y_test, y_pred_lr)
evaluate_model("Random Forest", y_test, y_pred_rf)
evaluate_model("XGBoost", y_test, y_pred_xgb)
evaluate_model("Deep Learning", y_test, y_pred_dnn)
```

```
Linear Regression - RMSE: 0.168, R^2: 0.971
Random Forest - RMSE: 0.048, R^2: 0.998
XGBoost - RMSE: 0.038, R^2: 0.999
Deep Learning - RMSE: 0.041, R^2: 0.998
```

```
# Import necessary libraries for metrics
from sklearn.metrics import mean_squared_error, r2_score

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_s
```

```
# Initialize models
models = {
    'Linear Regression': LinearRegression(),
    'Random Forest': RandomForestRegressor(),
    'XGBoost': XGBRegressor(),
    'Neural Network': Sequential([
        Dense(64, input_dim=X_train.shape[1], activation='relu'),
        Dense(32, activation='relu'),
        Dense(1)
    ])
}

# Train models and make predictions
mse_scores = {}
r2_scores = {}

for name, model in models.items():
    if name == 'Neural Network':
        # Compile and fit neural network model
        model.compile(optimizer='adam', loss='mean_squared_error')
        model.fit(X_train, y_train, epochs=50, batch_size=32, verbose=0)
        # Make predictions
        y_pred = model.predict(X_test)
    else:
        # Train other models
        model.fit(X_train, y_train)
        # Make predictions
        y_pred = model.predict(X_test)

    # Calculate MSE and R²
    mse_scores[name] = mean_squared_error(y_test, y_pred)
    r2_scores[name] = r2_score(y_test, y_pred)

# Create a DataFrame for the results
performance_df = pd.DataFrame({
    'Model': list(mse_scores.keys()),
    'MSE': list(mse_scores.values()),
    'R²': list(r2_scores.values())
})

# Plot MSE and R² for comparison
fig, ax = plt.subplots(1, 2, figsize=(14, 6))

# MSE Plot
sns.barplot(x='MSE', y='Model', data=performance_df, ax=ax[0], palette='viridis')
```

```
ax[0].set_title('Mean Squared Error (MSE) Comparison')

# R² Plot
sns.barplot(x='R²', y='Model', data=performance_df, ax=ax[1], palette='viridis')
ax[1].set_title('R-squared (R²) Comparison')

# Display the plots
plt.tight_layout()
plt.show()
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-3-0d5f4419c987> in <cell line: 0>()
      3 
      4 # Split data into training and testing sets
----> 5 X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
      6 
      7 # Initialize models

NameError: name 'X' is not defined
```