

Life Expectancy Prediction Project

1.Loading Libraries And Data Sets

```
In [1]: import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
plt.style.use('ggplot')
import plotly.express as px
import plotly.graph_objects as go
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, LabelEncoder
import warnings
warnings.filterwarnings('ignore')
```

```
In [2]: df = pd.read_csv("E:\DATA ANALST Project Work\Life Expectancy Data.csv")
```

```
In [3]: df.head()
```

```
Out[3]:
```

	Country	Year	Status	Life expectancy	Adult Mortality	infant deaths	Alcohol	percentage expenditure	Hepatitis B
0	Afghanistan	2015	Developing	65.0	263.0	62	0.01	71.279624	65.0
1	Afghanistan	2014	Developing	59.9	271.0	64	0.01	73.523582	62.0
2	Afghanistan	2013	Developing	59.9	268.0	66	0.01	73.219243	64.0
3	Afghanistan	2012	Developing	59.5	272.0	69	0.01	78.184215	67.0
4	Afghanistan	2011	Developing	59.2	275.0	71	0.01	7.097109	68.0

5 rows × 22 columns

2. Data Cleaning

```
In [4]: print("missing values after imputation:")
print(df.isnull().sum())
```

missing values after imputation:

Country	0
Year	0
Status	0
Life expectancy	10
Adult Mortality	10
infant deaths	0
Alcohol	194
percentage expenditure	0
Hepatitis B	553
Measles	0
BMI	34
under-five deaths	0
Polio	19
Total expenditure	226
Diphtheria	19
HIV/AIDS	0
GDP	448
Population	652
thinness 1-19 years	34
thinness 5-9 years	34
Income composition of resources	167
Schooling	163

dtype: int64

```
In [5]: Imputer = SimpleImputer(missing_values = np.nan, strategy = 'mean')
        for col in df.columns:
            if df[col].isnull().sum() > 0:
                df[col] = Imputer.fit_transform(df[[col]])
```

```
In [6]: total_missing = df.isnull().sum().sum()
        print(f"Total missing values in the dataset: {total_missing}")

        Total missing values in the dataset: 0
```

```
In [7]: print(df.describe())
```

	Year	Life expectancy	Adult Mortality	infant deaths	\
count	2938.000000	2938.000000	2938.000000	2938.000000	
mean	2007.518720	69.224932	164.796448	30.303948	
std	4.613841	9.507640	124.080302	117.926501	
min	2000.000000	36.300000	1.000000	0.000000	
25%	2004.000000	63.200000	74.000000	0.000000	
50%	2008.000000	72.000000	144.000000	3.000000	
75%	2012.000000	75.600000	227.000000	22.000000	
max	2015.000000	89.000000	723.000000	1800.000000	

	Alcohol percentage	expenditure	Hepatitis B	Measles	\
count	2938.000000	2938.000000	2938.000000	2938.000000	
mean	4.602861	738.251295	80.940461	2419.592240	
std	3.916288	1987.914858	22.586855	11467.272489	
min	0.010000	0.000000	1.000000	0.000000	
25%	1.092500	4.685343	80.940461	0.000000	
50%	4.160000	64.912906	87.000000	17.000000	
75%	7.390000	441.534144	96.000000	360.250000	
max	17.870000	19479.911610	99.000000	212183.000000	

	BMI	under-five deaths	Polio	Total expenditure	\
count	2938.000000	2938.000000	2938.000000	2938.000000	
mean	38.321247	42.035739	82.550188	5.938190	
std	19.927677	160.445548	23.352143	2.400274	
min	1.000000	0.000000	3.000000	0.370000	
25%	19.400000	0.000000	78.000000	4.370000	
50%	43.000000	4.000000	93.000000	5.938190	
75%	56.100000	28.000000	97.000000	7.330000	
max	87.300000	2500.000000	99.000000	17.600000	

	Diphtheria	HIV/AIDS	GDP	Population	\
count	2938.000000	2938.000000	2938.000000	2.938000e+03	
mean	82.324084	1.742103	7483.158469	1.275338e+07	
std	23.640073	5.077785	13136.800417	5.381546e+07	
min	2.000000	0.100000	1.681350	3.400000e+01	
25%	78.000000	0.100000	580.486996	4.189172e+05	
50%	93.000000	0.100000	3116.561755	3.675929e+06	
75%	97.000000	0.800000	7483.158469	1.275338e+07	
max	99.000000	50.600000	119172.741800	1.293859e+09	

	thinness 1-19 years	thinness 5-9 years	\
count	2938.000000	2938.000000	
mean	4.839704	4.870317	
std	4.394535	4.482708	
min	0.100000	0.100000	
25%	1.600000	1.600000	
50%	3.400000	3.400000	
75%	7.100000	7.200000	
max	27.700000	28.600000	

	Income composition of resources	Schooling
count	2938.000000	2938.000000
mean	0.627551	11.992793
std	0.204820	3.264381
min	0.000000	0.000000
25%	0.504250	10.300000
50%	0.662000	12.100000
75%	0.772000	14.100000
max	0.948000	20.700000

3. Outlier Handling(IQR Method)

```
In [9]: # Select numerical columns
numerical_cols = df.select_dtypes(include=['float64', 'int64']).columns

# Create subplots (4 rows x 5 columns = 20 plots)
fig, axes = plt.subplots(4, 5, figsize=(20, 16))
fig.suptitle('Boxplots of Numerical Columns', fontsize=16)

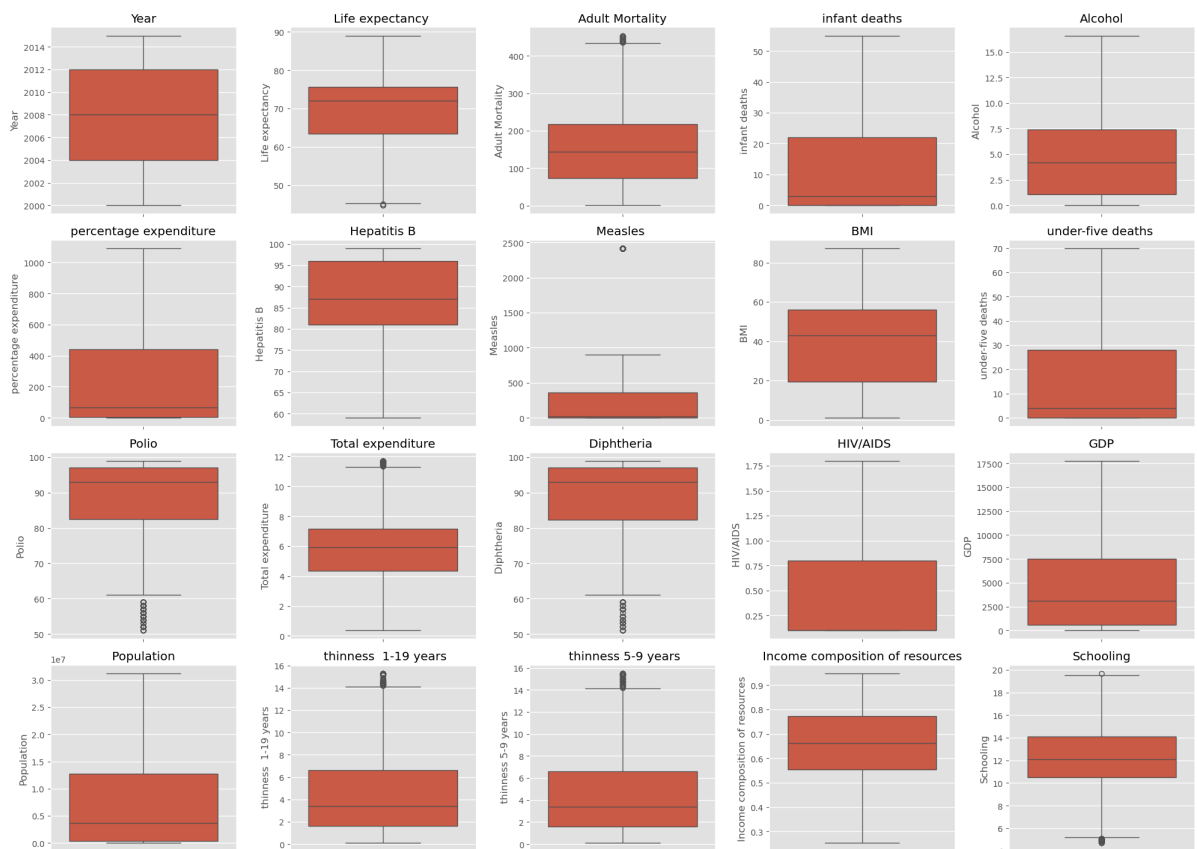
# Flatten the 2D axes array for easy indexing
axes = axes.flatten()

# Plot boxplots for each numerical column
for i, col in enumerate(numerical_cols):
    sns.boxplot(y=df[col], ax=axes[i])
    axes[i].set_title(col)

# Remove any unused subplots (if you have less than 20 columns)
for j in range(len(numerical_cols), len(axes)):
    fig.delaxes(axes[j])

# Apply layout and show the final figure (outside the loop!)
plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```

Boxplots of Numerical Columns



```
In [10]: #specify the list of columns you want to handle outliers for
outlier_cols = ['Adult Mortality', 'infant deaths', 'Alcohol', 'percentage expenditure',
                'BMI', 'under-five deaths', 'Polio', 'Total expenditure', 'Diphtheria',
                'Population', 'thinness 1-19 years', 'thinness 5-9 years', 'Income co
```

```
In [12]: df.columns = df.columns.str.strip() # remove spaces

# Keep only columns that exist
outlier_cols = [col for col in outlier_cols if col in df.columns]

for col_name in outlier_cols:
```

```
q1 = df[col_name].quantile(0.25)
q3 = df[col_name].quantile(0.75)
iqr = q3 - q1
lower_bound = q1 - 1.5 * iqr
upper_bound = q3 + 1.5 * iqr

df[col_name] = np.where(
    (df[col_name] > upper_bound) | (df[col_name] < lower_bound),
    df[col_name].mean(),
    df[col_name]
)
```

In [13]: `df.shape`

Out[13]: (2938, 22)

```
In [ ]: # Select only numerical columns (no .columns here!)
numerical_cols = df.select_dtypes(include=['float64', 'int64']).columns

# Create subplots
fig, axes = plt.subplots(4, 5, figsize=(20, 16))
fig.suptitle('Boxplots of Numerical Columns', fontsize=16)

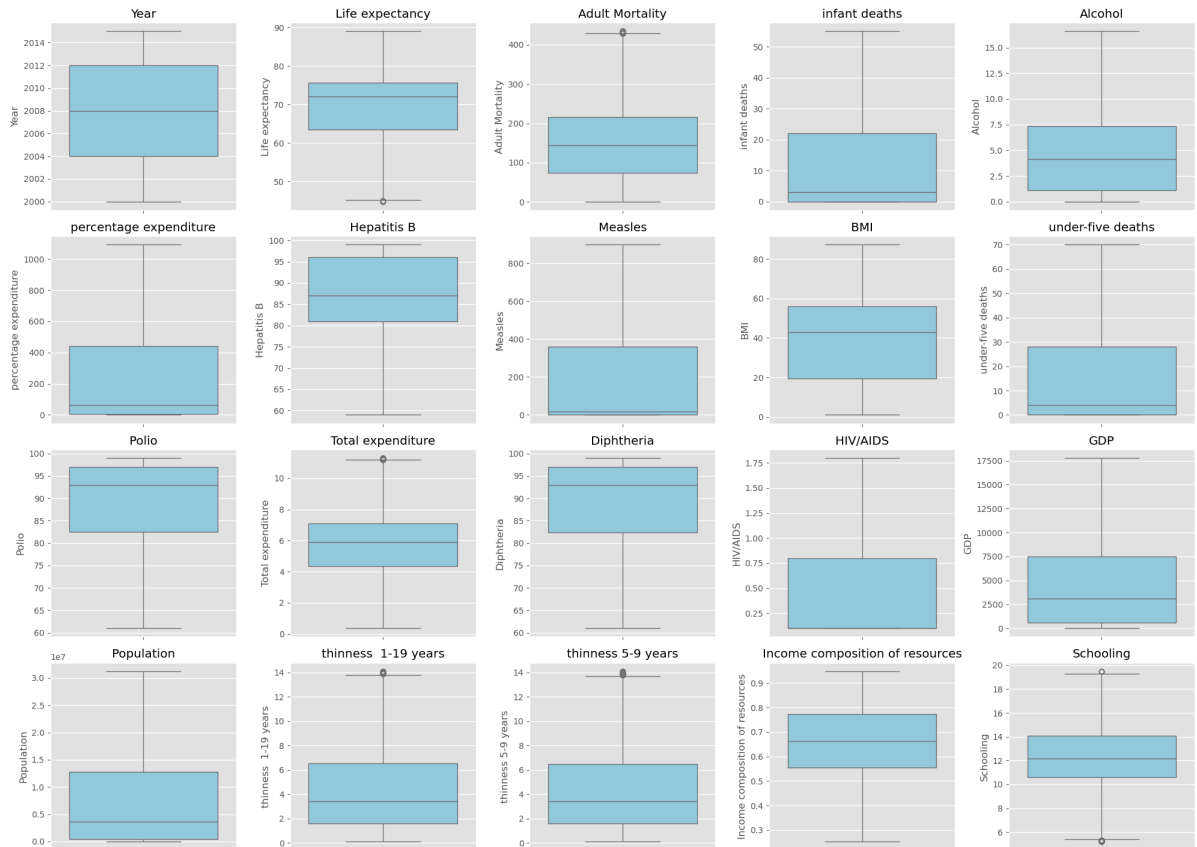
# Flatten axes for easy access
axes = axes.flatten()

# Plot boxplots
for i, col in enumerate(numerical_cols):
    sns.boxplot(y=df[col], ax=axes[i], color='skyblue')
    axes[i].set_title(col)

# Remove unused subplots
for j in range(len(numerical_cols), len(axes)):
    fig.delaxes(axes[j])

# Adjust layout and show
plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```

Boxplots of Numerical Columns



4. Exploratory Data Analysis

In [15]: `df.head()`

Out[15]:

	Country	Year	Status	Life expectancy	Adult Mortality	infant deaths	Alcohol	percentage expenditure	Hepati
0	Afghanistan	2015.0	Developing	65.0	263.0	30.303948	0.01	71.279624	6
1	Afghanistan	2014.0	Developing	59.9	271.0	30.303948	0.01	73.523582	6
2	Afghanistan	2013.0	Developing	59.9	268.0	30.303948	0.01	73.219243	6
3	Afghanistan	2012.0	Developing	59.5	272.0	30.303948	0.01	78.184215	6
4	Afghanistan	2011.0	Developing	59.2	275.0	30.303948	0.01	7.097109	6

5 rows × 22 columns

In [16]: `df.Country.value_counts()`

```
Out[16]: Country
Afghanistan      16
Peru              16
Nicaragua        16
Niger            16
Nigeria          16
..
Niue              1
San Marino        1
Nauru             1
Saint Kitts and Nevis 1
Dominica          1
Name: count, Length: 193, dtype: int64
```

Life Expectancy Vs Year

```
In [ ]: import plotly.express as px

# Strip column names to remove any trailing spaces
df.columns = df.columns.str.strip()

# Calculate the average life expectancy for each year
average_life_expectancy = df.groupby('Year')['Life expectancy'].mean().reset_index()

# Create the interactive line plot using Plotly
fig = px.line(
    average_life_expectancy,
    x='Year',
    y='Life expectancy',
    title='Average Life Expectancy over the Years',
    labels={'Year': 'Year', 'Life expectancy': 'Life Expectancy (years)'},
    template='plotly_dark'
)

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

Population vs Life Expectancy

```
In [ ]: import plotly.express as px

# Strip column names to avoid issues with trailing spaces
df.columns = df.columns.str.strip()

# Create the interactive animated scatter plot
fig = px.scatter(
    df,
    x='Population',
    y='Life expectancy',
    hover_name='Country',
    color='Status',
    animation_frame='Year',
    title='Population vs Life Expectancy Over the Years',
    labels={
        'Population': 'Population',
        'Life expectancy': 'Life Expectancy (years)'
    },
    template='plotly_dark',
    size_max=60
)
```

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

Country Status Count

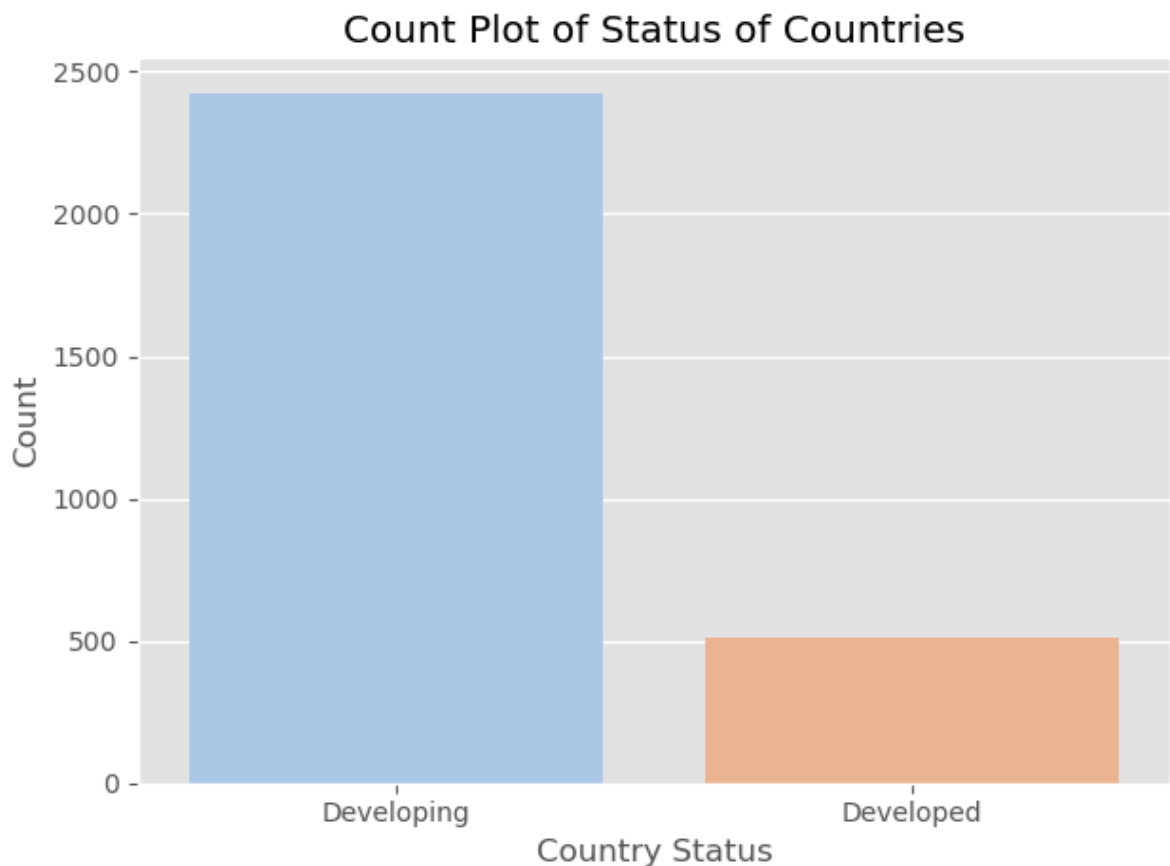
```
In [ ]: import seaborn as sns
import matplotlib.pyplot as plt

# Strip column names (important if 'Status' has extra spaces)
df.columns = df.columns.str.strip()

# Create a count plot for 'Status'
sns.countplot(x=df['Status'], palette='pastel')

# Add title and layout formatting
plt.title('Count Plot of Status of Countries')
plt.xlabel('Country Status')
plt.ylabel('Count')

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



Average Life Expectancy Vs Country Status

```
In [ ]: # Histogram of Average Life Expectancy by Country Status
import plotly.express as px

# Clean column names to remove trailing spaces
df.columns = df.columns.str.strip()
```



```
# Group by 'Status' and calculate mean Life expectancy
life_expect_status = df.groupby('Status')['Life expectancy'].mean().reset_index()

# Create histogram using Plotly
fig = px.histogram(
    life_expect_status,
    x='Status',
    y='Life expectancy',
    color='Status',
    text_auto=True
)

# Update layout and title
fig.update_layout(
    title=dict(
        text='<b>Average Life Expectancy for Country Status</b>',
        x=0.5,
        font=dict(size=18)
    ),
    yaxis_title='Life Expectancy (years)',
    xaxis_title='Country Status',
    template='plotly_dark'
)

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

Life Expectancy VS Alcohol Consumption

```
In [ ]: # Life Expectancy Vs Alcohol Consumption(Dual Y-axis)
import plotly.graph_objects as go

# Clean column names
df.columns = df.columns.str.strip()

# Calculate average Life expectancy and alcohol consumption per year
average_data = df.groupby('Year').agg({
    'Life expectancy': 'mean',
    'Alcohol': 'mean'
}).reset_index()

# Create a figure with dual Y-axes
fig = go.Figure()

# Life Expectancy trace (Left Y-axis)
fig.add_trace(go.Scatter(
    x=average_data['Year'],
    y=average_data['Life expectancy'],
    mode='lines+markers',
    name='Life Expectancy',
    yaxis='y1'
))

# Alcohol Consumption trace (right Y-axis)
fig.add_trace(go.Scatter(
    x=average_data['Year'],
    y=average_data['Alcohol'],
    mode='lines+markers',
    name='Alcohol Consumption',
    yaxis='y2'
))
```

```
# Update Layout to use dual Y-axes
fig.update_layout(
    title='Life Expectancy and Alcohol Consumption Over the Years',
    xaxis=dict(title='Year'),
    yaxis=dict(
        title='Life Expectancy (years)',
        side='left'
    ),
    yaxis2=dict(
        title='Alcohol Consumption (liters)',
        side='right',
        overlaying='y'
    ),
    template='plotly_dark'
)

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

Alcohol Consumption VS Country Status

```
In [ ]: # Average Alcohol Consumption by Country Status
import plotly.express as px

# Clean column names
df.columns = df.columns.str.strip()

# Group by 'Status' and calculate mean Alcohol consumption
alcohol_by_status = df.groupby('Status', as_index=False).agg({'Alcohol': 'mean'})

# Create bar chart using Plotly
fig = px.bar(
    alcohol_by_status,
    x='Status',
    y='Alcohol',
    title='Average Alcohol Consumption of Developing and Developed Countries',
    labels={
        'Alcohol': 'Alcohol Consumption (liters per capita)',
        'Status': 'Country Status'
    },
    template='plotly_dark',
    text_auto=True # Adds value labels on bars
)

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

Life Expectancy VS Year of Schooling

```
In [ ]: # Life Expectancy vs Years of schooling(interactive line plot)
import plotly.express as px

# Clean column names
df.columns = df.columns.str.strip()

# Group by 'Schooling' and calculate average Life expectancy
aggregated_data = df.groupby('Schooling')['Life expectancy'].mean().reset_index()
```

```

# Create interactive line plot
fig = px.line(
    aggregated_data,
    x='Schooling',
    y='Life expectancy',
    title='Average Life Expectancy vs. Years of Schooling',
    labels={
        'Schooling': 'Years of Schooling',
        'Life expectancy': 'Life Expectancy (years)'
    },
    template='plotly_dark',
    markers=True
)

# Show the plot
fig.show()

```

Correltion HeatMap

```

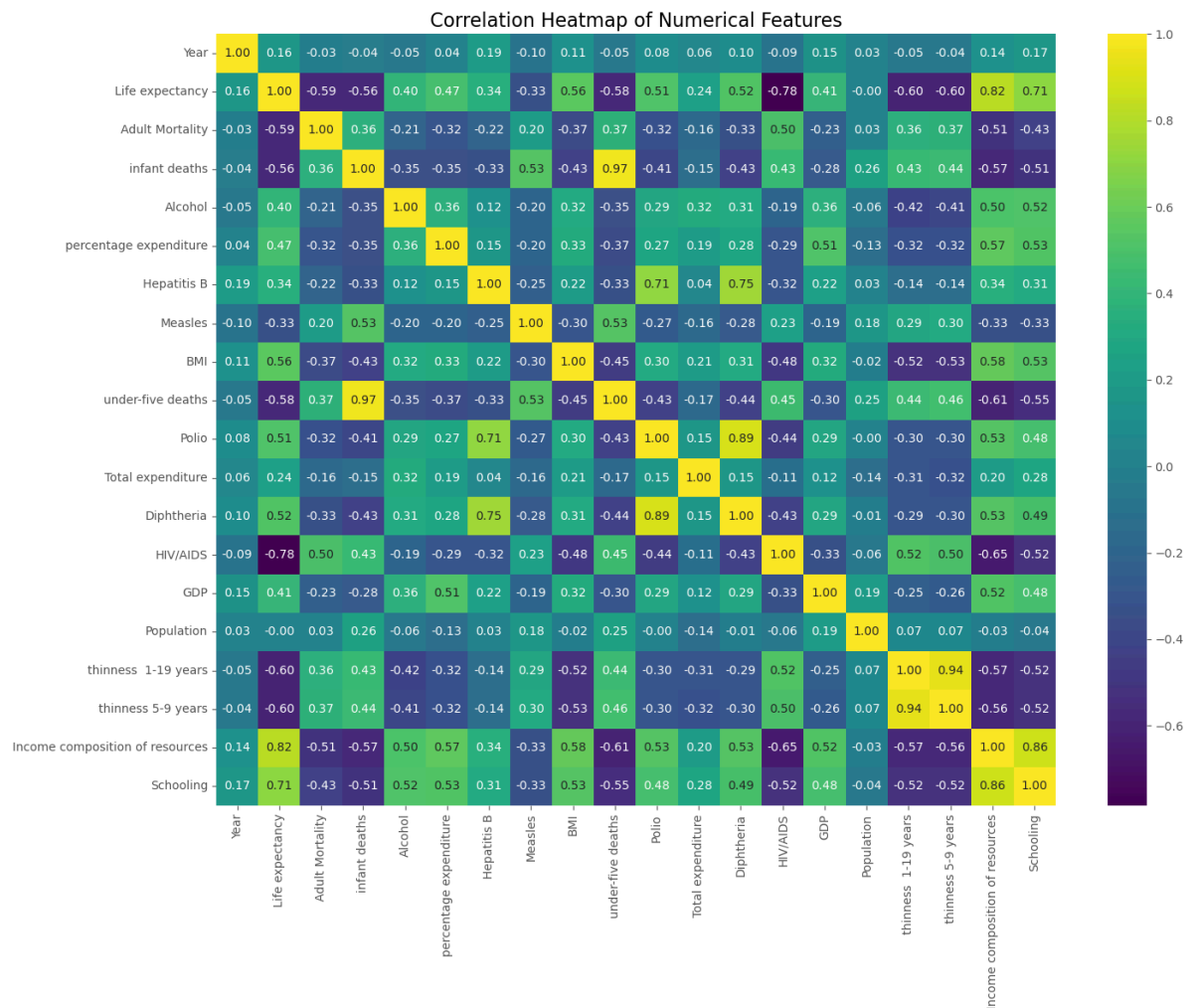
In [ ]: # Correlation Heatmap of Numerical Columns
import matplotlib.pyplot as plt
import seaborn as sns

# Clean column names
df.columns = df.columns.str.strip()

# Select numerical columns
numerical_cols = df.select_dtypes(include=['float64', 'int64']).columns

# Create correlation heatmap
plt.figure(figsize=(15, 12))
sns.heatmap(
    df[numerical_cols].corr(),
    cmap='viridis',
    annot=True,
    fmt=".2f"
)
plt.title('Correlation Heatmap of Numerical Features', fontsize=16)
plt.tight_layout()
plt.show()

```



5. Data Preprocessing

```
In [ ]: from sklearn.preprocessing import LabelEncoder

# Initialize the Label encoder
le = LabelEncoder()

# Identify categorical columns
cat_cols = df.select_dtypes(include='object').columns

# Apply label encoding to each categorical column
for col in cat_cols:
    df[col] = le.fit_transform(df[col])
```

```
In [26]: x= df.drop(columns='Life expectancy')
y=df['Life expectancy']
```

```
In [27]: scaler=StandardScaler()
cols_to_scale=x.drop(columns='Status').columns
# for cols in cols_to_scale:
x[cols_to_scale]=scaler.fit_transform(x[cols_to_scale])
```

```
In [28]: x.head()
```

Out[28]:

	Country	Year	Status	Adult Mortality	infant deaths	Alcohol	percentage expenditure	Hepatitis B	Measles	
0	-1.691042	1.621762	1	1.112066	1.351263	-1.176057	-0.553370	-2.391880	1.536427	-0.000000
1	-1.691042	1.404986	1	1.191723	1.351263	-1.176057	-0.545858	-2.717043	1.440436	-0.000000
2	-1.691042	1.188210	1	1.161852	1.351263	-1.176057	-0.546877	-2.500268	1.169468	-0.000000
3	-1.691042	0.971434	1	1.201680	1.351263	-1.176057	-0.530255	-2.175105	1.536427	-0.000000
4	-1.691042	0.754658	1	1.231551	1.351263	-1.176057	-0.768242	-2.066717	1.536427	-0.000000

5 rows × 21 columns

6. Model Building And Evaluation

```
In [29]: from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score, mean_squared_error
from sklearn.ensemble import RandomForestRegressor, ExtraTreesRegressor, GradientBoostingRegressor
from xgboost import XGBRegressor
from sklearn.metrics import r2_score, mean_squared_error
```

```
In [30]: x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=30)
```

```
In [31]: print(f"Shape of X_train is: {x_train.shape}")
print(f"Shape of Y_train is: {y_train.shape}\n")
print(f"Shape of X_test is: {x_test.shape}")
print(f"Shape of Y_test is: {y_test.shape}")
```

```
Shape of X_train is: (2350, 21)
Shape of Y_train is: (2350,)
```

```
Shape of X_test is: (588, 21)
Shape of Y_test is: (588,)
```

```
In [32]: models = {
    'Random Forest': RandomForestRegressor(random_state=42),
    'Extra Trees Regressor':
        ExtraTreesRegressor(random_state=42),
    'GradientBoost Regressor':
        GradientBoostingRegressor(random_state=42),
    'XGB Regressor': XGBRegressor()
}
```

```
In [33]: result = []
```

```
In [34]: # Loop through all models
for model_name, model in models.items():
    # Train
    model.fit(x_train, y_train)

    # Predict
    y_pred = model.predict(x_test)

    # Evaluate
    rmse = np.sqrt(mean_squared_error(y_test, y_pred))
    r2 = r2_score(y_test, y_pred)
```

```

# Store
result.append({'Model': model_name, 'RMSE': rmse, 'R2 Score': r2})

# Convert to DataFrame
results_df = pd.DataFrame(result)

# Display
print(results_df)

```

	Model	RMSE	R2 Score
0	Random Forest	2.376430	0.937948
1	Extra Trees Regressor	2.294144	0.942171
2	GradientBoost Regressor	2.925963	0.905932
3	XGB Regressor	2.359460	0.938831

```

In [35]: results_df=results_df.sort_values("R2 Score", ascending = False)
results_df

```

```

Out[35]:

```

	Model	RMSE	R2 Score
1	Extra Trees Regressor	2.294144	0.942171
3	XGB Regressor	2.359460	0.938831
0	Random Forest	2.376430	0.937948
2	GradientBoost Regressor	2.925963	0.905932

```

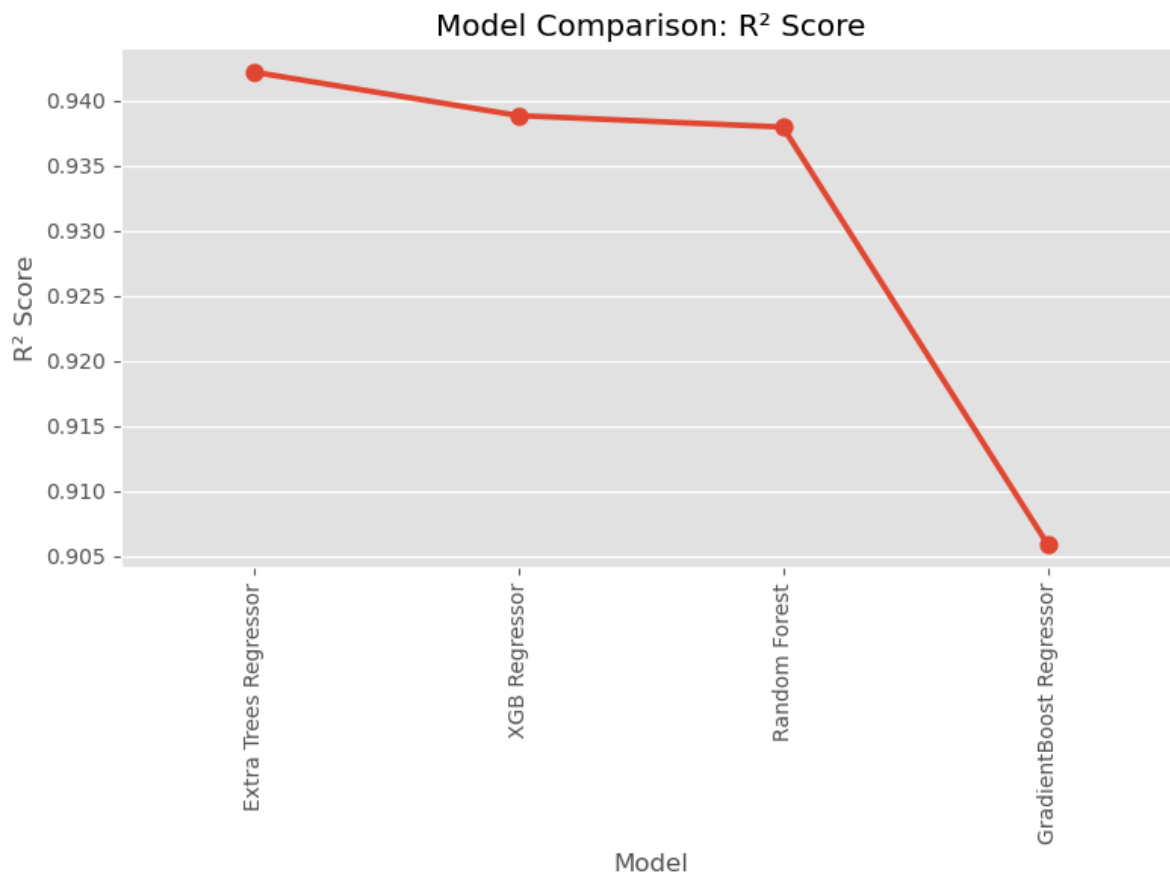
In [ ]: import matplotlib.pyplot as plt
import seaborn as sns

# Fix spacing in column name (if needed)
results_df.columns = results_df.columns.str.strip()

# Rename column if it has a space (optional)
# If your column is actually named 'R2 Score', rename it for consistency
results_df = results_df.rename(columns={'R2 Score': 'R2Score'})

# Create the point plot
plt.figure(figsize=(8, 6))
sns.pointplot(x='Model', y='R2Score', data=results_df)
plt.xticks(rotation=90)
plt.title('Model Comparison: R2 Score')
plt.ylabel('R2 Score')
plt.xlabel('Model')
plt.tight_layout()
plt.show()

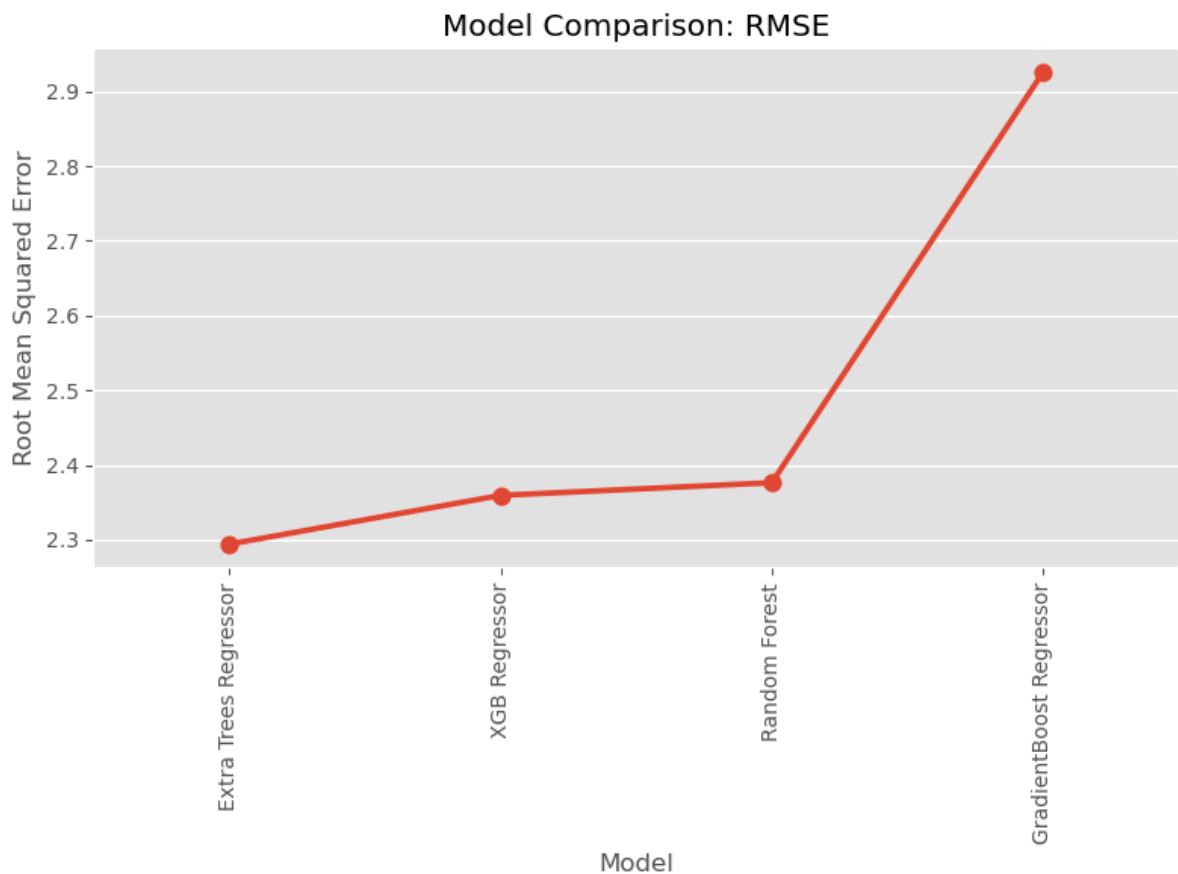
```



```
In [ ]: import matplotlib.pyplot as plt
import seaborn as sns

# Ensure clean column names
results_df.columns = results_df.columns.str.strip()

# Create the point plot for RMSE
plt.figure(figsize=(8, 6))
sns.pointplot(x='Model', y='RMSE', data=results_df)
plt.xticks(rotation=90)
plt.title('Model Comparison: RMSE')
plt.ylabel('Root Mean Squared Error')
plt.xlabel('Model')
plt.tight_layout()
plt.show()
```



7. Cross Validation Final Model

```
In [ ]: from sklearn.model_selection import cross_val_score, KFold
        from xgboost import XGBRegressor

        # Define model
        best_model = XGBRegressor()

        # Create 20-fold cross-validation setup
        kf = KFold(n_splits=20, shuffle=True, random_state=42)

        # Perform cross-validation
        cross_val_scores = cross_val_score(
            best_model,
            x,
            y,
            cv=kf,
            scoring='r2'
        )

        # Display results
        print("Cross-validation R2 scores:")
        print(cross_val_scores)
        print("\nAverage R2 score:", round(cross_val_scores.mean(), 4))
        print("Standard Deviation:", round(cross_val_scores.std(), 4))
```

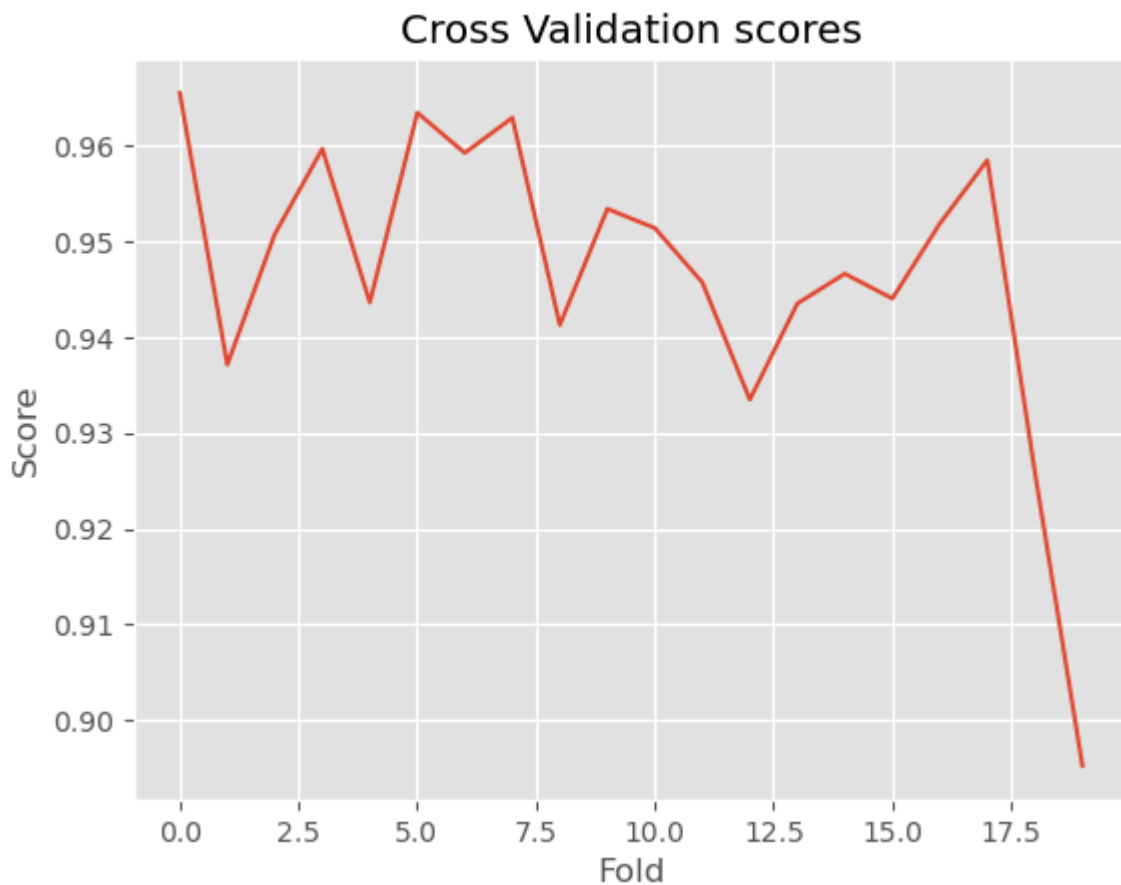
```
Cross-validation R2 scores:
[0.96551357 0.93711351 0.95077552 0.95967247 0.94363115 0.9634485
 0.95924749 0.96292845 0.94127479 0.95340885 0.95139463 0.94572323
 0.93347476 0.94351532 0.94662614 0.9440392 0.95187541 0.95849145
 0.92589777 0.8952312 ]
```

```
Average R2 score: 0.9467
Standard Deviation: 0.0156
```



```
In [39]: plt.plot(cross_val_scores)
plt.xlabel('Fold')
plt.ylabel('Score')
plt.title("Cross Validation scores")
```

```
Out[39]: Text(0.5, 1.0, 'Cross Validation scores')
```



```
In [40]: cross_val_scores.mean()
```

```
Out[40]: 0.9466641711313615
```

```
In [41]: cross_val_scores.std()
```

```
Out[41]: 0.015618282444082386
```

Objectives

Q. Do various predicting factors which have been chosen initially really affect the Life expectancy? What are the predicting variables actually affecting life expectancy?

Ans - Life expectancy is not random — it is strongly affected by education, income, healthcare access, disease prevalence, and lifestyle factors. Countries with low adult mortality, high schooling, higher GDP, good healthcare, and low infectious disease rates tend to have higher life expectancy.

Q. Should a country having a lower life expectancy value(<65) increase its healthcare expenditure in order to improve its average lifespan?

Ans - Yes, increasing healthcare expenditure can improve life expectancy in countries with low average lifespan, but it should be targeted and well-managed to address the main health issues in the country.

Q. How does Infant and Adult mortality rates affect life expectancy?

Ans - Both infant and adult mortality rates have a negative relationship with life expectancy. Higher mortality rates (more deaths) → lower life expectancy. Lower mortality rates (fewer deaths) → higher life expectancy.

Q. Does Life Expectancy has positive or negative correlation with eating habits,lifestyle, exercise, smoking, drinking alcohol etc.

Ans- Healthy lifestyle choices (good diet, regular exercise, avoiding smoking and excess drinking) are positively linked to life expectancy, while unhealthy habits have a negative effect and shorten lifespan.

Q. What is the impact of schooling on the lifespan of humans?

Ans - Schooling has a positive correlation with life expectancy. More education = more knowledge, better income, healthier lifestyle → people live longer.

Q. Does Life Expectancy have positive or negative relationship with drinking alcohol?

Ans - In many countries, very high alcohol consumption is linked to lower life expectancy. Countries with low to moderate alcohol use often have higher life expectancy, but that's also because they have better healthcare, education, and living conditions. Overall, life expectancy has a negative relationship with heavy alcohol consumption. The more people drink excessively, the shorter their average lifespan tends to be.

Q. Do densely populated countries tend to have lower life expectancy?

Ans - Densely populated countries can have lower life expectancy if resources and healthcare are poor. But in developed nations with strong infrastructure, high density does not always reduce lifespan.

Q. What is the impact of Immunization coverage on life Expectancy?

Ans - Immunization coverage has a positive relationship with life expectancy. The more people are vaccinated, the longer the population tends to live.