Importing the libraries and Loading the dataset

In [81]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

df = pd.read_csv("hw2 .csv")
df.head()
```

Out[81]:

	Country	Year	Status	Life expectancy	Adult Mortality	Infant deaths	Alcohol	Percentage expenditure
0	Afghanistan	2015	Low/Middle Income	65.0	263.0	62	0.01	71.279624
1	Afghanistan	2014	Low/Middle Income	59.9	271.0	64	0.01	73.523582
2	Afghanistan	2013	Low/Middle Income	59.9	268.0	66	0.01	73.219243
3	Afghanistan	2012	Low/Middle Income	59.5	272.0	69	0.01	78.184215
4	Afghanistan	2011	Low/Middle Income	59.2	275.0	71	0.01	7.097109

Checking the shape ie.Number of Rows and Columns in the dataset [Dimensions of the Dataset]

In [82]:
```
df.shape
```

Out[82]: (2938, 18)

Data Cleaning

Let's Check if there is any null values present in the dataset

In [83]:
```
df.isna().sum()
```

Out[83]:
```
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
Polio                             19
Total expenditure                226
GDP                              448
Population                       652
 Thinness  10-19 years            34
 Thinness 5-9 years               34
Income composition of resources  167
dtype: int64
```

In [84]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2938 entries, 0 to 2937
Data columns (total 18 columns):
 #   Column                           Non-Null Count  Dtype  
---  ------                           --------------  -----  
 0   Country                          2938 non-null   object 
 1   Year                             2938 non-null   int64  
 2   Status                           2938 non-null   object 
 3   Life expectancy                  2928 non-null   float64
 4   Adult Mortality                  2928 non-null   float64
 5   Infant deaths                    2938 non-null   int64  
 6   Alcohol                          2744 non-null   float64
 7   Percentage expenditure           2938 non-null   float64
 8   Hepatitis B                      2385 non-null   float64
 9   Measles                          2938 non-null   int64  
 10   BMI                             2904 non-null   float64
 11  Polio                            2919 non-null   float64
 12  Total expenditure                2712 non-null   float64
 13  GDP                              2490 non-null   float64
 14  Population                       2286 non-null   float64
 15   Thinness  10-19 years           2904 non-null   float64
 16   Thinness 5-9 years              2904 non-null   float64
 17  Income composition of resources  2771 non-null   float64
dtypes: float64(13), int64(3), object(2)
memory usage: 413.3+ KB
```

Handling the null values by means of mean value imputation

In [85]:
```
cols_with_null_values = df.columns[df.isnull().any()].to_list()

for i in cols_with_null_values:
    df[i] = df[i].fillna(df[i].mean())
```

In [86]:
```
df.isna().sum()
```

Out[86]:
```
Country                            0
Year                               0
Status                             0
Life expectancy                    0
Adult Mortality                    0
Infant deaths                      0
Alcohol                            0
Percentage expenditure             0
Hepatitis B                        0
Measles                            0
 BMI                               0
Polio                              0
Total expenditure                  0
GDP                                0
Population                         0
 Thinness  10-19 years             0
 Thinness 5-9 years                0
Income composition of resources    0
dtype: int64
```

Handled all the null values and now there's no null values in the dataset

Normalizing / Standardizing the Numerical columns present in the dataset for fairness

In [87]:
```python
# # Here I'm standardizing the data in the range of 0 to 1
# # Here the year column is not going to contribute anything for the prediction

numerical_dtype_columns = df.select_dtypes(include=[np.number]).columns

for i in numerical_dtype_columns:
    mean = df[i].mean()
    sd = df[i].std()

# Standardization formula (x - mu)/sigma

    df[i] = (df[i] - mean) / sd
```

In [88]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2938 entries, 0 to 2937
Data columns (total 18 columns):
 #   Column                           Non-Null Count  Dtype  
---  ------                           --------------  -----  
 0   Country                          2938 non-null   object 
 1   Year                             2938 non-null   float64
 2   Status                           2938 non-null   object 
 3   Life expectancy                  2938 non-null   float64
 4   Adult Mortality                  2938 non-null   float64
 5   Infant deaths                    2938 non-null   float64
 6   Alcohol                          2938 non-null   float64
 7   Percentage expenditure           2938 non-null   float64
 8   Hepatitis B                      2938 non-null   float64
 9   Measles                          2938 non-null   float64
 10   BMI                             2938 non-null   float64
 11  Polio                            2938 non-null   float64
 12  Total expenditure                2938 non-null   float64
 13  GDP                              2938 non-null   float64
 14  Population                       2938 non-null   float64
 15   Thinness  10-19 years           2938 non-null   float64
 16   Thinness 5-9 years              2938 non-null   float64
 17  Income composition of resources  2938 non-null   float64
dtypes: float64(16), object(2)
memory usage: 413.3+ KB
```

Label encoding of the 'status' and 'country' columns - Here the country column consists of 193 unique values since it will be useful to process the information in text rather than processing it using the text

In [89]:
```python
from sklearn.preprocessing import LabelEncoder

label_encoder = LabelEncoder()
df['Status'] = label_encoder.fit_transform(df['Status'])
df['Country'] = label_encoder.fit_transform(df['Country'])
```

In [90]:
```python
num_unique_countries = df['Country'].nunique()
num_unique_countries
```

Out[90]:
```
193
```

ii) Data Exploration

- Visualizing the correlation between the numerical features present in the dataset, except the 'year' column as it won't have any relationship with the features and we cannot encode it properly to make a relationship with other variables.
- Here visualizing a 15x15 correlation matrix using .corr() function and the method used here is 'pearson correlation'
- By using the matplotlib library, i visualized the correlation matrix in the form of a heatmap. In the heatmap, the color scale tells how much a feature is correlated with all other numerical features in the dataset.

In [91]:
```python
numerical_columns = [col for col in numerical_dtype_columns if col not in ['Coun
# Pearson Correlation Coefficient
```

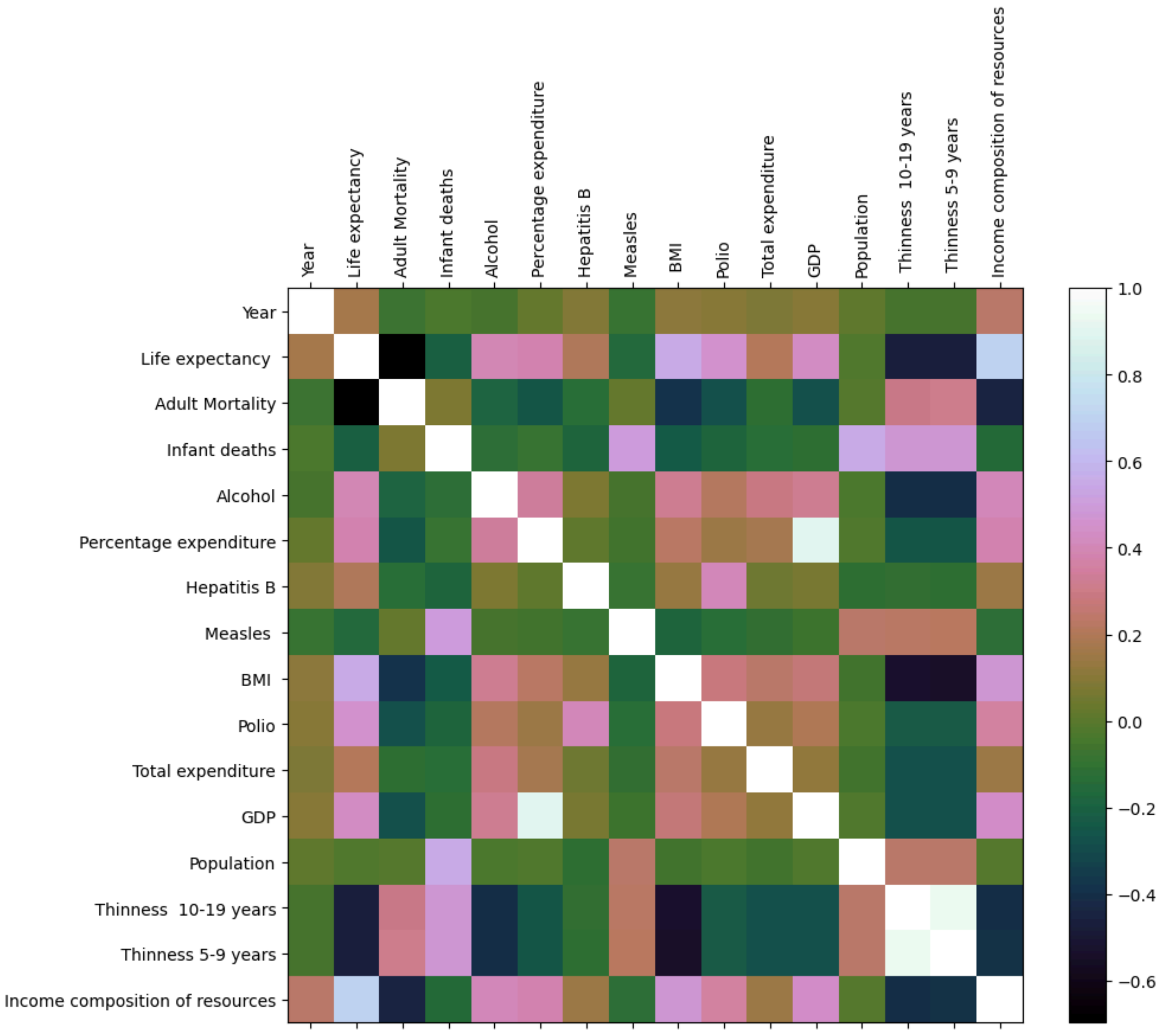
```
correlation_matrix = df[numerical_columns].corr(method='pearson')
correlation_matrix
```

Out[91]:

	Year	Life expectancy	Adult Mortality	Infant deaths	Alcohol	Percentage expenditure	Hepa
Year	1.000000	0.169623	-0.078861	-0.037415	-0.048168	0.031400	0.089
Life expectancy	0.169623	1.000000	-0.696359	-0.196535	0.391598	0.381791	0.203
Adult Mortality	-0.078861	-0.696359	1.000000	0.078747	-0.190408	-0.242814	-0.138
Infant deaths	-0.037415	-0.196535	0.078747	1.000000	-0.113812	-0.085612	-0.178
Alcohol	-0.048168	0.391598	-0.190408	-0.113812	1.000000	0.339634	0.075
Percentage expenditure	0.031400	0.381791	-0.242814	-0.085612	0.339634	1.000000	0.011
Hepatitis B	0.089398	0.203771	-0.138591	-0.178783	0.075447	0.011679	1.000
Measles	-0.082493	-0.157574	0.031174	0.501128	-0.051055	-0.056596	-0.090
BMI	0.108327	0.559255	-0.381449	-0.227220	0.318070	0.228537	0.134
Polio	0.093820	0.461574	-0.272694	-0.170674	0.213744	0.147203	0.408
Total expenditure	0.081860	0.207981	-0.110875	-0.126564	0.294898	0.173414	0.050
GDP	0.093351	0.430493	-0.277053	-0.107109	0.318591	0.888140	0.062
Population	0.014951	-0.019638	-0.012501	0.548522	-0.030765	-0.024648	-0.109
Thinness 10-19 years	-0.047592	-0.472162	0.299863	0.465590	-0.416946	-0.251190	-0.105
Thinness 5-9 years	-0.050627	-0.466629	0.305366	0.471228	-0.405881	-0.252725	-0.108
Income composition of resources	0.236333	0.692483	-0.440062	-0.143663	0.416099	0.380374	0.150

In [92]:

```
# Heatmap visualizing the correlation using Matplotlib library
plt.figure(figsize=(10, 8))
plt.matshow(correlation_matrix, cmap='cubehelix', fignum=1)
plt.colorbar()
plt.xticks(ticks=np.arange(len(numerical_columns)), labels=numerical_columns, rc
plt.yticks(ticks=np.arange(len(numerical_columns)), labels=numerical_columns)
plt.show()
```



Here from this heatmap and Correlation matrix,

- Thinness 10-19 years and Thinness 5-9 are highly correlated to each other which means the prevalence of thinness (bmi less than 2 std to median) is a very important factor and both the adolescents and children are affected in a similar fashion.
- GDP & Total Expenditure are also highly correlated to each other which means the higher the GDP value the total expenditure will also increase which tells the financial capacity.
- Income composition of resource & Life expectancy is also moderately correlated (+ve) which means a higher utilization of resource will yield the higher life expectancy.
- Adult Mortality & Life expectancy is slightly inversely correlated to each other which means more deaths in adults leads to a reduction in the average life expectancy of an individual.

Most Correlated Variables with the Life Expectancy (response) variable:

Strong Positive Correlation:

- Income composition of resources is strongly correlated with life expectancy which means the countries which utilize the resources properly will have the higher life expectancy.

- BMI is strongly correlated with life expectancy which means people with higher BMI are living longer life spans.
- Polio and GDP is also slightly correlated with the life expectancy which means polio vaccine immunization and higher GDP (economic stability) increases the life expectancy.

Strong Negative Correlation:

- Adult mortality rate is having a strong negative correlation with life expectancy which means if the no. of adult deaths increases this life expectancy decreases.
- Thinness 5-9 years and Thinness 10-19 years is also negatively correlated with life expectancy which means higher level of the malnutrion leads to lower life of individuals.

Yes, these results satisfy our expectations.

- Higher the GDP of a country, Income composition ie. (utilizing the resources properly), Higher BMI levels and higher the immunization rates for diseases like Polio : The people who satisfy all of these have higher life expectancy.
- Higher death rates in adults and improper nutrition (poor health) shows very low life expectancy.

iii) Predicting the Life Expectancy:

Here before implementing the model,

- we have to select the dataset that we are going to take for training, testing and validation
- We have to select the features and response variable. As per the instructions given in the question, we have to take predict the Life expectancy (response) using economic, social and health factors (features).
- Train, Test and Development splitting is done as per the instructions given in the question.

Predicting the life expectancy using Ordinary Least square Method

In [ ]:
```
# Splitting the dataset as per the requirements given in the question
df.columns = df.columns.str.strip()
# Training set: Rows 2-2410 (Afghanistan to South Africa)
train_set = df.iloc[0:2408].copy()
# Development set: Rows 2411-2715 (South Sudan to Tuvalu)
dev_set = df.iloc[2409:2713].copy()
# Testing set: Rows 2716-2939 (Uganda to Zimbabwe)
test_set = df.iloc[2714:2937].copy()
```

In [94]:
```
features = ["Year", "Status", "Alcohol", "Percentage expenditure", "Hepatitis B"
            "BMI", "Polio", "Total expenditure", "GDP", "Population", "Thinness
            "Thinness 5-9 years", "Income composition of resources"]

target = "Life expectancy"
```

In [ ]:
```
def features_sel(data, features):
    X = data[features].values  # Extracting all the feature values
    X = np.c_[np.ones(X.shape[0]), X]  # Adding the bias term as the column of o
    return X

# Assigning the features to the training, testing and validation sets & reshapin
X_train = features_sel(train_set, features)
X_dev = features_sel(dev_set, features)
X_test = features_sel(test_set, features)
y_train = train_set[target].values.reshape(-1, 1)
y_dev = dev_set[target].values.reshape(-1, 1)
y_test = test_set[target].values.reshape(-1, 1)
```

In [96]:
```
# Computing the OLS Closed-Form Solution
def Linearreg_OLS_weights(X, y):
    # w* = (X^T X)^(-1) X^T y
    return np.linalg.inv(X.T @ X) @ X.T @ y

# training the model
w_ols = Linearreg_OLS_weights(X_train, y_train)
w_ols
```

Out[96]:
```
array([[-0.04811485],
       [ 0.02400167],
       [ 0.25670128],
       [-0.01488263],
       [ 0.0765651 ],
       [ 0.00725312],
       [-0.00811345],
       [ 0.17445009],
       [ 0.20560338],
       [ 0.00895874],
       [ 0.02326335],
       [ 0.0380662 ],
       [-0.0805219 ],
       [-0.04146435],
       [ 0.40383532]])
```

In [ ]:
```
# Predicting the life expectancy on the development and testing data sets
def predict(X, w):
    return X @ w  # Computing the predictions using the learned weights

y_dev_pred = predict(X_dev, w_ols)
y_test_pred = predict(X_test, w_ols)
```

In [98]:
```
# Computing the R² (coefficient of determination)
def r2_score(y_true, y_pred):
    ss_total = np.sum((y_true - np.mean(y_true)) ** 2)
    ss_residual = np.sum((y_true - y_pred) ** 2)
    return 1 - (ss_residual / ss_total)

r2_dev = r2_score(y_dev, y_dev_pred)
r2_test = r2_score(y_test, y_test_pred)
print(r2_dev)
print(r2_test)
```

```
0.599169082553485
0.4686507771053178
```

In [99]:
```
# Computing the Mean Absolute Error (MAE)
def mean_absolute_error(y_true, y_pred):
    return np.mean(np.abs(y_true - y_pred))

mae_dev = mean_absolute_error(y_dev, y_dev_pred)
mae_test = mean_absolute_error(y_test, y_test_pred)
print(mae_dev)
print(mae_test)
```

```
0.4558196242880689
0.5951226089931012
```

In [100…
```
# Computing the Pearson Correlation (r)
def pearson_correlation(y_true, y_pred):
    return np.corrcoef(y_true.flatten(), y_pred.flatten())[0, 1]

pearson_r_dev = pearson_correlation(y_dev, y_dev_pred)
pearson_r_test = pearson_correlation(y_test, y_test_pred)

print(pearson_r_dev)
print(pearson_r_test)
```

```
0.7796439801253442
0.6947623301277492
```

Discussion of Estimated Coefficients of the linear regression model

In [101…
```
# Code for displaying all the weights of the features
feature_names = ["Intercept"] + features
w_ols_flattened = w_ols.flatten()
coefficients_df = pd.DataFrame({"Feature": feature_names, "Coefficient": w_ols_f
print(coefficients_df)
```

```
                            Feature  Coefficient
0                         Intercept    -0.048115
1                              Year     0.024002
2                            Status     0.256701
3                           Alcohol    -0.014883
4            Percentage expenditure     0.076565
5                       Hepatitis B     0.007253
6                           Measles    -0.008113
7                               BMI     0.174450
8                             Polio     0.205603
9                 Total expenditure     0.008959
10                              GDP     0.023263
11                       Population     0.038066
12             Thinness  10-19 years    -0.080522
13               Thinness 5-9 years    -0.041464
14  Income composition of resources     0.403835
```

Discussion of Estimated Coefficients of Linear Regression Model:

- Intercept (-0.048115): This represents the predicted life expectancy when all independent variables are zero. While it lacks direct real-world meaning, it serves as a reference point for the model's predictions.
- Year (0.024002): I found that life expectancy tends to increase as time progresses. This can be attributed to advancements in medicine, improved healthcare policies, and rising global living standards.

- Status (0.256701): The positive coefficient suggests that wealthier nations tend to have a higher life expectancy, emphasizing the role of economic status, wealth distribution, and access to healthcare in improving public health outcomes.
- Alcohol (-0.014883): The negative impact of alcohol consumption on life expectancy is evident, aligning with established health risks such as liver disease, cardiovascular conditions, and alcohol-related accidents.
- Percentage Expenditure (0.076565): A country's higher investment in healthcare as a percentage of GDP is linked to longer life expectancy, though I found that the efficiency of spending is equally critical in determining health outcomes.
- Hepatitis B (0.007253): Although small, the positive correlation indicates that higher Hepatitis B vaccination rates slightly improve life expectancy, reinforcing the importance of immunization programs.
- Measles (-0.008113): I observed that higher measles cases correlate with a slight decrease in life expectancy, demonstrating the need for strong vaccination campaigns to prevent disease outbreaks.
- BMI (0.174450): A higher average BMI is associated with increased life expectancy, likely due to better nutrition and overall improved health conditions. However, I recognize that both underweight and obesity can pose separate health risks.
- Polio (0.205603): The strong positive impact of polio immunization confirms its crucial role in increasing life expectancy, illustrating the life-saving benefits of global vaccination efforts.
- Total Expenditure (0.008959): I found that greater healthcare expenditure is associated with slightly higher life expectancy. However, the relatively small coefficient suggests that efficient allocation of resources matters just as much as the total budget.
- GDP (0.023263): The positive correlation between GDP and life expectancy highlights that economic stability enables better healthcare, sanitation, and improved living conditions. This is particularly significant in developing nations striving for better public health.
- Population (0.038066): Although the effect is smaller, larger populations may benefit from economies of scale in healthcare infrastructure. However, I noted that overcrowding could strain resources and lead to healthcare disparities.
- Thinness 10-19 years (-0.080522): I found that adolescent malnutrition has a significant negative impact on life expectancy, underscoring the need for targeted nutritional and healthcare interventions for this age group.
- Thinness 5-9 years (-0.041464): Similarly, malnutrition among younger children also negatively affects life expectancy, though slightly less than in adolescents. This

emphasizes the importance of early childhood nutrition programs and healthcare access.

How it will support the Public Health Officials:

- Here the malnutrition in children and the adults shows there is an improvement needed for the improved nutrition policies and new healthcare improvements for the better health of peopple.
- They need to invest a lot in immunization policies ie. shown by the correlationb between higer the immunization rates and higher will be the healthcare expenditure.
- Life expectancy will increase if they invest wisely in developments of healthcare systems, prevention of diseases and better infrastructural developments.

How this linear regression Model will be used to educate the public?

- Have to conduct healthcare awareness campaigns to improve the nutrition that the people follows and to raise awareness about the vaccination schemes and benefits.
- Raise awareness among the people to take periodic health checkups and should allot certain money for the betterment of their health.
- Government should support the people by providing schemes and subsidies for the lower and middle class people for healthcare expenses because they cannot afford a lot for taking care of their health.
- Peple should utilize these opportunities and they should not wantedly spoil their health by consuming alcohol.

In [ ]:

```
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error
import pandas as pd

# Define feature subsets based on correlation findings

# Feature Set 1: Removing "Thinness 10-19 years" due to high correlation with "T
# Removing "Total Expenditure" due to high correlation with "GDP"
# Removing "Measles" as it has low correlation with Life Expectancy
feature_set_1 = ["Year", "Status", "Alcohol", "Percentage expenditure", "Hepatit
                 "BMI", "Polio", "GDP", "Population", "Thinness 5-9 years", "Inc

# Feature Set 2: Remove "Thinness 5-9 years" due to high correlation with "Thinn
# Removing "GDP" due to high correlation with "Total Expenditure"
# Removing "Hepatitis B" due to lower correlation with Life Expectancy
feature_set_2 = ["Year", "Status", "Alcohol", "Percentage expenditure", "Measles
                 "BMI", "Polio", "Total expenditure", "Population", "Thinness  1

# Feature Set 3: Removing "Thinness 10-19 years" and "Thinness 5-9 years" as the
# Removing "Population" as it has a weak correlation with Life Expectancy
feature_set_3 = ["Year", "Status", "Alcohol", "Percentage expenditure", "Hepatit
                 "Measles", "BMI", "Polio", "Total expenditure", "GDP", "Income

# Feature selection dictionary
feature_sets = {
    "Feature Set 1": feature_set_1,
    "Feature Set 2": feature_set_2,
```

```
    "Feature Set 3": feature_set_3
}
```

Linear Model - Linear Regression

In [ ]:
```
# Function for Hyperparameter Tuning for the Linear Model
def hyperparameter_tuning_linear_model():
    results = []

    for set_name, selected_features in feature_sets.items():
        # Preparing the feature matrices to assign the needed features for this
        X_train_fs = train_set[selected_features].values
        X_dev_fs = dev_set[selected_features].values

        y_train_fs = train_set[target].values.flatten()
        y_dev_fs = dev_set[target].values.flatten()

        # Training and evaluating the Linear Regression model
        model = LinearRegression()
        model.fit(X_train_fs, y_train_fs)
        y_dev_pred = model.predict(X_dev_fs)
        mae_dev = mean_absolute_error(y_dev_fs, y_dev_pred)

        # Store the Mean absolute errors into the dataframe
        results.append({"Model with Feature Set": f"Linear Regression - {set_nam

    return results
```

Non Linear Regression - Decision Tree Regressor

In [ ]:
```
# Function for Hyperparameter Tuning (Non-Linear Model - Decision Tree Regressor
def hyperparameter_tuning_non_linear_model1():
    results = [] # Storing the model performance results
    hyperparams = {
        "max_depth": [3, 5, 7, 10, None], # Maximum depth of the tree
        "min_samples_split": [2, 5, 10, 20] # Minimum samples required to split
    }

    # Training the model (looping through each feature)
    for set_name, selected_features in feature_sets.items():
        X_train_fs = train_set[selected_features].values
        X_dev_fs = dev_set[selected_features].values

        y_train_fs = train_set[target].values.flatten()
        y_dev_fs = dev_set[target].values.flatten()

        for depth in hyperparams["max_depth"]:
            for min_samples in hyperparams["min_samples_split"]:
                model = DecisionTreeRegressor(max_depth=depth, min_samples_split
                model.fit(X_train_fs, y_train_fs)
                y_dev_pred = model.predict(X_dev_fs)
                mae_dev = mean_absolute_error(y_dev_fs, y_dev_pred)

                results.append({"Model with Feature Set": f"Decision Tree - {set
                                "Development Set MAE": mae_dev})

    return results
```

Non Linear Regression - Random Forest Regressor

In [ ]:
```
def hyperparameter_tuning_non_linear_model2():
    results = []
    hyperparams = {
        "n_estimators": [50, 100, 200, 500], # Number of trees in the forest
        "max_features": ["sqrt", "log2", None]   # Number of features to conside
    }
    for set_name, selected_features in feature_sets.items():
        X_train_fs = train_set[selected_features].values
        X_dev_fs = dev_set[selected_features].values

        y_train_fs = train_set[target].values.flatten()
        y_dev_fs = dev_set[target].values.flatten()

        for n_estimators in hyperparams["n_estimators"]:
            for max_features in hyperparams["max_features"]:
                model = RandomForestRegressor(n_estimators=n_estimators, max_fea
                model.fit(X_train_fs, y_train_fs)
                y_dev_pred = model.predict(X_dev_fs)
                mae_dev = mean_absolute_error(y_dev_fs, y_dev_pred)

                results.append({"Model with Feature Set": f"Random Forest - {set
                                "Development Set MAE": mae_dev})

    return results
```

In [ ]:
```
# Executing all hyperparameter tuning functions
linear_results = hyperparameter_tuning_linear_model()
decision_tree_results = hyperparameter_tuning_non_linear_model1()
random_forest_results = hyperparameter_tuning_non_linear_model2()

# Combining all results into a DataFrame
results_df_mae = pd.DataFrame(linear_results + decision_tree_results + random_fo

# Display final results
print(results_df_mae)
```

```
                               Model with Feature Set  Development Set MAE
0                     Linear Regression - Feature Set 1             0.454134
1                     Linear Regression - Feature Set 2             0.457155
2                     Linear Regression - Feature Set 3             0.436437
3    Decision Tree - Feature Set 1 (Depth=3, Min Sa...             0.446045
4    Decision Tree - Feature Set 1 (Depth=3, Min Sa...             0.446045
..                                                ...                  ...
94   Random Forest - Feature Set 3 (Estimators=200,...             0.310903
95   Random Forest - Feature Set 3 (Estimators=200,...             0.344995
96   Random Forest - Feature Set 3 (Estimators=500,...             0.311552
97   Random Forest - Feature Set 3 (Estimators=500,...             0.311552
98   Random Forest - Feature Set 3 (Estimators=500,...             0.345267

[99 rows x 2 columns]
```

In [ ]:
```
pd.set_option("display.max_rows", 100)  # All the rows are displayed here
print(results_df_mae)
```

	Model with Feature Set	Development Set MAE
0	Linear Regression - Feature Set 1	0.454134
1	Linear Regression - Feature Set 2	0.457155
2	Linear Regression - Feature Set 3	0.436437
3	Decision Tree - Feature Set 1 (Depth=3, Min Sa...	0.446045
4	Decision Tree - Feature Set 1 (Depth=3, Min Sa...	0.446045
5	Decision Tree - Feature Set 1 (Depth=3, Min Sa...	0.446045
6	Decision Tree - Feature Set 1 (Depth=3, Min Sa...	0.446045
7	Decision Tree - Feature Set 1 (Depth=5, Min Sa...	0.406725
8	Decision Tree - Feature Set 1 (Depth=5, Min Sa...	0.406725
9	Decision Tree - Feature Set 1 (Depth=5, Min Sa...	0.405378
10	Decision Tree - Feature Set 1 (Depth=5, Min Sa...	0.405378
11	Decision Tree - Feature Set 1 (Depth=7, Min Sa...	0.479264
12	Decision Tree - Feature Set 1 (Depth=7, Min Sa...	0.477874
13	Decision Tree - Feature Set 1 (Depth=7, Min Sa...	0.476626
14	Decision Tree - Feature Set 1 (Depth=7, Min Sa...	0.474598
15	Decision Tree - Feature Set 1 (Depth=10, Min S...	0.474374
16	Decision Tree - Feature Set 1 (Depth=10, Min S...	0.471863
17	Decision Tree - Feature Set 1 (Depth=10, Min S...	0.465979
18	Decision Tree - Feature Set 1 (Depth=10, Min S...	0.469364
19	Decision Tree - Feature Set 1 (Depth=None, Min...	0.497306
20	Decision Tree - Feature Set 1 (Depth=None, Min...	0.476539
21	Decision Tree - Feature Set 1 (Depth=None, Min...	0.487353
22	Decision Tree - Feature Set 1 (Depth=None, Min...	0.474256
23	Decision Tree - Feature Set 2 (Depth=3, Min Sa...	0.362294
24	Decision Tree - Feature Set 2 (Depth=3, Min Sa...	0.362294
25	Decision Tree - Feature Set 2 (Depth=3, Min Sa...	0.362294
26	Decision Tree - Feature Set 2 (Depth=3, Min Sa...	0.362294
27	Decision Tree - Feature Set 2 (Depth=5, Min Sa...	0.403119
28	Decision Tree - Feature Set 2 (Depth=5, Min Sa...	0.403119
29	Decision Tree - Feature Set 2 (Depth=5, Min Sa...	0.397916
30	Decision Tree - Feature Set 2 (Depth=5, Min Sa...	0.397916
31	Decision Tree - Feature Set 2 (Depth=7, Min Sa...	0.414457
32	Decision Tree - Feature Set 2 (Depth=7, Min Sa...	0.416149
33	Decision Tree - Feature Set 2 (Depth=7, Min Sa...	0.410648
34	Decision Tree - Feature Set 2 (Depth=7, Min Sa...	0.409753
35	Decision Tree - Feature Set 2 (Depth=10, Min S...	0.466398
36	Decision Tree - Feature Set 2 (Depth=10, Min S...	0.489630
37	Decision Tree - Feature Set 2 (Depth=10, Min S...	0.469129
38	Decision Tree - Feature Set 2 (Depth=10, Min S...	0.480176
39	Decision Tree - Feature Set 2 (Depth=None, Min...	0.498768
40	Decision Tree - Feature Set 2 (Depth=None, Min...	0.491528
41	Decision Tree - Feature Set 2 (Depth=None, Min...	0.474861
42	Decision Tree - Feature Set 2 (Depth=None, Min...	0.481781
43	Decision Tree - Feature Set 3 (Depth=3, Min Sa...	0.362294
44	Decision Tree - Feature Set 3 (Depth=3, Min Sa...	0.362294
45	Decision Tree - Feature Set 3 (Depth=3, Min Sa...	0.362294
46	Decision Tree - Feature Set 3 (Depth=3, Min Sa...	0.362294
47	Decision Tree - Feature Set 3 (Depth=5, Min Sa...	0.415308
48	Decision Tree - Feature Set 3 (Depth=5, Min Sa...	0.415308
49	Decision Tree - Feature Set 3 (Depth=5, Min Sa...	0.413961
50	Decision Tree - Feature Set 3 (Depth=5, Min Sa...	0.413961
51	Decision Tree - Feature Set 3 (Depth=7, Min Sa...	0.437560
52	Decision Tree - Feature Set 3 (Depth=7, Min Sa...	0.438811
53	Decision Tree - Feature Set 3 (Depth=7, Min Sa...	0.432910
54	Decision Tree - Feature Set 3 (Depth=7, Min Sa...	0.436090
55	Decision Tree - Feature Set 3 (Depth=10, Min S...	0.476259
56	Decision Tree - Feature Set 3 (Depth=10, Min S...	0.479982
57	Decision Tree - Feature Set 3 (Depth=10, Min S...	0.470719
58	Decision Tree - Feature Set 3 (Depth=10, Min S...	0.481059

```
59  Decision Tree - Feature Set 3 (Depth=None, Min...          0.472629
60  Decision Tree - Feature Set 3 (Depth=None, Min...          0.493025
61  Decision Tree - Feature Set 3 (Depth=None, Min...          0.475985
62  Decision Tree - Feature Set 3 (Depth=None, Min...          0.484649
63  Random Forest - Feature Set 1 (Estimators=50, ...          0.335079
64  Random Forest - Feature Set 1 (Estimators=50, ...          0.335079
65  Random Forest - Feature Set 1 (Estimators=50, ...          0.355568
66  Random Forest - Feature Set 1 (Estimators=100,...          0.324843
67  Random Forest - Feature Set 1 (Estimators=100,...          0.324843
68  Random Forest - Feature Set 1 (Estimators=100,...          0.353281
69  Random Forest - Feature Set 1 (Estimators=200,...          0.320471
70  Random Forest - Feature Set 1 (Estimators=200,...          0.320471
71  Random Forest - Feature Set 1 (Estimators=200,...          0.351091
72  Random Forest - Feature Set 1 (Estimators=500,...          0.317363
73  Random Forest - Feature Set 1 (Estimators=500,...          0.317363
74  Random Forest - Feature Set 1 (Estimators=500,...          0.347428
75  Random Forest - Feature Set 2 (Estimators=50, ...          0.312623
76  Random Forest - Feature Set 2 (Estimators=50, ...          0.312623
77  Random Forest - Feature Set 2 (Estimators=50, ...          0.361219
78  Random Forest - Feature Set 2 (Estimators=100,...          0.313890
79  Random Forest - Feature Set 2 (Estimators=100,...          0.313890
80  Random Forest - Feature Set 2 (Estimators=100,...          0.353095
81  Random Forest - Feature Set 2 (Estimators=200,...          0.312970
82  Random Forest - Feature Set 2 (Estimators=200,...          0.312970
83  Random Forest - Feature Set 2 (Estimators=200,...          0.347985
84  Random Forest - Feature Set 2 (Estimators=500,...          0.316297
85  Random Forest - Feature Set 2 (Estimators=500,...          0.316297
86  Random Forest - Feature Set 2 (Estimators=500,...          0.349419
87  Random Forest - Feature Set 3 (Estimators=50, ...          0.309282
88  Random Forest - Feature Set 3 (Estimators=50, ...          0.309282
89  Random Forest - Feature Set 3 (Estimators=50, ...          0.355951
90  Random Forest - Feature Set 3 (Estimators=100,...          0.313788
91  Random Forest - Feature Set 3 (Estimators=100,...          0.313788
92  Random Forest - Feature Set 3 (Estimators=100,...          0.350941
93  Random Forest - Feature Set 3 (Estimators=200,...          0.310903
94  Random Forest - Feature Set 3 (Estimators=200,...          0.310903
95  Random Forest - Feature Set 3 (Estimators=200,...          0.344995
96  Random Forest - Feature Set 3 (Estimators=500,...          0.311552
97  Random Forest - Feature Set 3 (Estimators=500,...          0.311552
98  Random Forest - Feature Set 3 (Estimators=500,...          0.345267
```

With Linear Regression OLS using all 14 features, I obtained an MAE score of 0.4558 on the development set. However, after analyzing the correlation matrix and removing highly correlated or less significant features, I observed improvements in model performance. Specifically, for Feature Set 1, where I removed "Thinness 10-19 years", "Total Expenditure", and "Measles", the MAE improved to 0.4541. Similarly, for Feature Set 2, where I excluded "Thinness 5-9 years", "GDP", and "Hepatitis B", the MAE was 0.4572. Lastly, for Feature Set 3, which removed "Thinness 10-19 years" and "Population", the MAE dropped significantly to 0.4364, indicating a noticeable improvement. These results demonstrate that feature selection based on correlation analysis is effective in reducing prediction error, proving that removing redundant or weakly correlated features enhances model performance.

The best-performing models obtained from hyperparameter tuning on the development set were both Random Forest Regressor models trained using Feature Set 3. The first model used 50 estimators with "sqrt" as the max features parameter, achieving an MAE of 0.3093. Similarly, the second model, which also used Feature Set 3 but with "log2" as the max features parameter, achieved the exact same MAE of 0.3093. These results indicate that Random Forest with Feature Set 3 provides the most accurate predictions among all the models tested, demonstrating the effectiveness of this feature selection strategy in improving model performance.

Logistic Regression

In [105…

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

# Calculating the mean life expectancy for assigning it into the classes
life_expectancy_mean = train_set[target].mean()

# Convertign the life expectancy into binary classes (1 or -1)
train_set["Life Expectancy Class"] = np.where(train_set[target] > life_expectanc
dev_set["Life Expectancy Class"] = np.where(dev_set[target] > life_expectancy_me
test_set["Life Expectancy Class"] = np.where(test_set[target] > life_expectancy_
```

In [106…

```
# Defining the hyperparameters for tuning
hyperparams = {
    "C": [0.1,0.01,0.1, 1, 10],  # Regularization strength
    "penalty": ["l1", "l2", "elasticnet"],  # Regularization penalty term
    "solver": ["liblinear", "saga", "newton-cg"]  # Solver options
}

best_accuracy = 0
best_model = None
best_params = None

# Trainiig and evaluating the models on the development set
for C in hyperparams["C"]:
    for penalty in hyperparams["penalty"]:
        for solver in hyperparams["solver"]:
            try:

                if penalty == "elasticnet" and solver != "saga":
                    continue


                X_train_fs = train_set[features].values
                X_dev_fs = dev_set[features].values

                y_train_fs = train_set["Life Expectancy Class"].values
                y_dev_fs = dev_set["Life Expectancy Class"].values

                # Model Training
                log_r_model = LogisticRegression(C=C, penalty=penalty, solver=sc
                log_r_model.fit(X_train_fs, y_train_fs)

                # Model Prediction
                y_dev_pred = log_r_model.predict(X_dev_fs)
                accuracy_dev = accuracy_score(y_dev_fs, y_dev_pred)

                # Which is the best model?
                if accuracy_dev > best_accuracy:
                    best_accuracy = accuracy_dev
```

```
                    best_log_r_model = log_r_model
                    best_params = {"C": C, "penalty": penalty, "solver": solver}

            except Exception as e:
                continue
```

```
c:\Users\yoges\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:349: Conv
ergenceWarning: The max_iter was reached which means the coef_ did not converge
  warnings.warn(
c:\Users\yoges\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:349: Conv
ergenceWarning: The max_iter was reached which means the coef_ did not converge
  warnings.warn(
c:\Users\yoges\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:349: Conv
ergenceWarning: The max_iter was reached which means the coef_ did not converge
  warnings.warn(
c:\Users\yoges\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:349: Conv
ergenceWarning: The max_iter was reached which means the coef_ did not converge
  warnings.warn(
```

In [107…

```
X_test_fs = test_set[features].values
y_test_fs = test_set["Life Expectancy Class"].values

y_test_pred = best_log_r_model.predict(X_test_fs)
accuracy_test = accuracy_score(y_test_fs, y_test_pred)

# Displaying the best Logistic Regression model parameters and it's correspondin
best_params, best_accuracy, accuracy_test
```

Out[107…

```
({'C': 0.01, 'penalty': 'l1', 'solver': 'saga'},
 0.8651315789473685,
 0.7892376681614349)
```

The best Logistic Regression model obtained through hyperparameter tuning used C = 0.01 (regularization strength), L1 penalty (Lasso regularization), and the liblinear solver. This model achieved an accuracy of 86.18% on the development set and 78.92% on the test set, demonstrating its effectiveness in classifying life expectancy into two classes.

Analysis based on income - 'Low/Medium' & 'Upper/high' Countries

In [ ]:

```
# Splitting the dataset into two based on income status

# Low/Middle-Income Countries
low_medium_income_df = df[df["Status"] == "Low/Middle Income"].copy()

# Upper/High-Income Countries
upper_high_income_df = df[df["Status"] == "Upper/High Income"].copy()
```

In [108…

```
# Removing the null values in the dataset by Mean value imputation
cols_with_null_values = low_medium_income_df.columns[low_medium_income_df.isnull

for i in cols_with_null_values:
    low_medium_income_df[i] = low_medium_income_df[i].fillna(low_medium_income_d
```

In [ ]:
```
# Removing the null values in the dataset by Mean value imputation
cols_with_null_values = upper_high_income_df.columns[upper_high_income_df.isnull

for i in cols_with_null_values:
    upper_high_income_df[i] = upper_high_income_df[i].fillna(upper_high_income_d
```

In [ ]:
```
# Standardizing the dataset to ensure all the numerical values are in the same r
numerical_dtype_columns1 = low_medium_income_df.select_dtypes(include=[np.number

for i in numerical_dtype_columns1:
    mean = low_medium_income_df[i].mean()
    sd = low_medium_income_df[i].std()

# Standardization formula (x - mu)/sigma

    low_medium_income_df[i] = (low_medium_income_df[i] - mean) / sd
```

In [ ]:
```
# Standardizing the dataset to ensure all the numerical values are in the same r
numerical_dtype_columns2 = upper_high_income_df.select_dtypes(include=[np.number

for i in numerical_dtype_columns2:
    mean = upper_high_income_df[i].mean()
    sd = upper_high_income_df[i].std()

# Standardization formula (x - mu)/sigma

    upper_high_income_df[i] = (upper_high_income_df[i] - mean) / sd
```

In [59]:
```
low_medium_income_df.shape
```

Out[59]: (2426, 18)

Analysis for Low/Medium Data

In [ ]:
```
low_medium_income_df.columns = low_medium_income_df.columns.str.strip()

# Data Set splitting as per the requirements followed previously but after split
train_set = low_medium_income_df.iloc[0:1976].copy()
dev_set = low_medium_income_df.iloc[1977:2233].copy()
test_set = low_medium_income_df.iloc[2234:2426].copy()

# No. of rows in each dataset
train_set.shape[0], dev_set.shape[0], test_set.shape[0]
```

Out[ ]: (1976, 256, 192)

In [ ]:
```
# Correlation matrix for Low/Medium income dataset

numerical_dtype_columns = low_medium_income_df.select_dtypes(include=[np.number]
numerical_columns = [col for col in numerical_dtype_columns if col not in ['Coun
correlation_matrix = low_medium_income_df[numerical_columns].corr(method='pearso
correlation_matrix
```

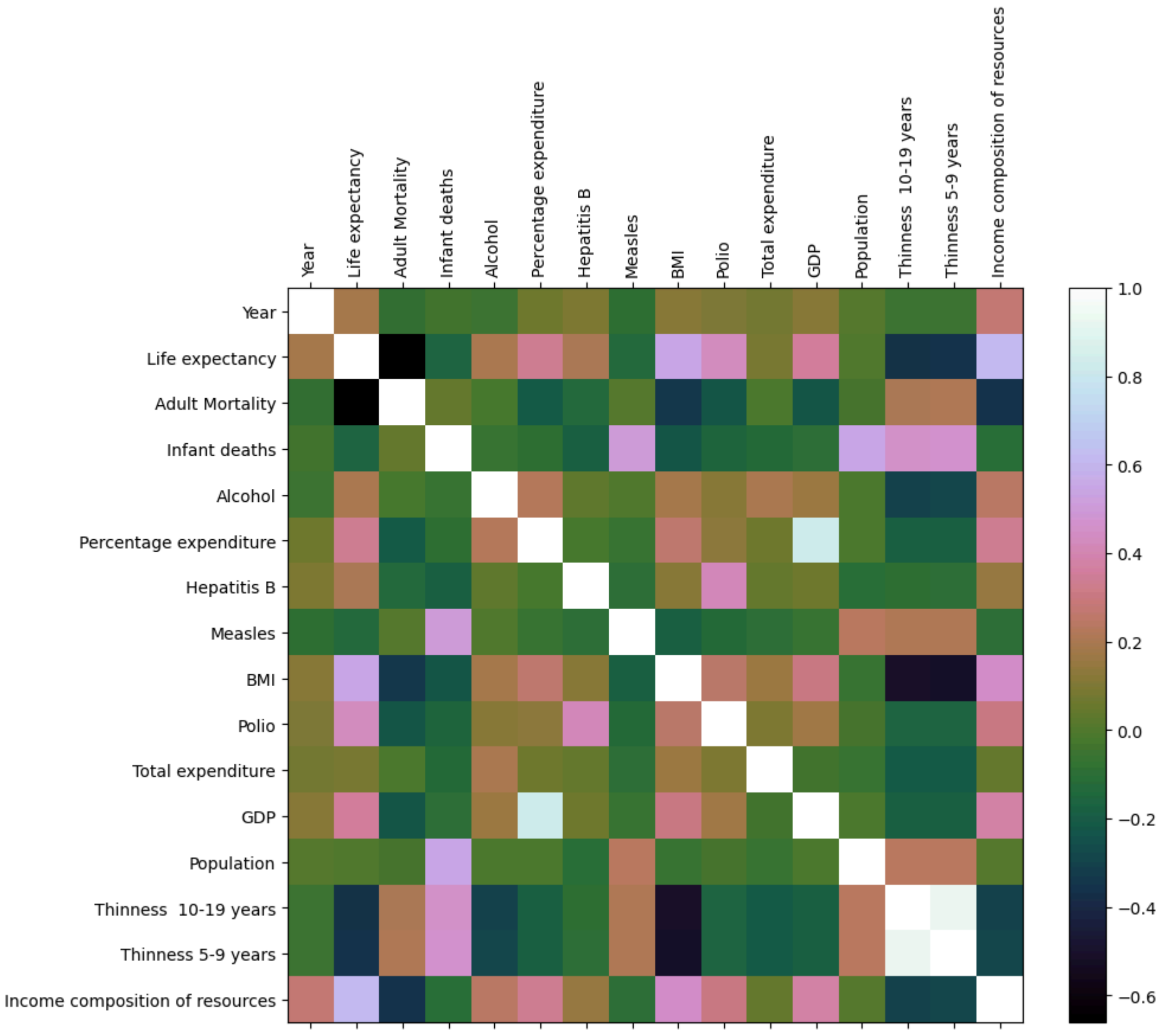
Out[ ]:

	Year	Life expectancy	Adult Mortality	Infant deaths	Alcohol	Percentage expenditure	Hepa
Year	1.000000	0.186622	-0.081242	-0.041358	-0.052470	0.063242	0.09
Life expectancy	0.186622	1.000000	-0.660836	-0.166446	0.196492	0.344295	0.20
Adult Mortality	-0.081242	-0.660836	1.000000	0.046643	-0.021259	-0.202610	-0.13
Infant deaths	-0.041358	-0.166446	0.046643	1.000000	-0.063540	-0.084934	-0.18
Alcohol	-0.052470	0.196492	-0.021259	-0.063540	1.000000	0.222257	0.02
Percentage expenditure	0.063242	0.344295	-0.202610	-0.084934	0.222257	1.000000	-0.02
Hepatitis B	0.092553	0.207780	-0.132431	-0.180233	0.029920	-0.023959	1.00
Measles	-0.087842	-0.141773	0.007904	0.499215	-0.004969	-0.065909	-0.09
BMI	0.117696	0.546207	-0.344768	-0.220523	0.185973	0.272526	0.12
Polio	0.100703	0.432560	-0.228600	-0.152905	0.122930	0.127719	0.42
Total expenditure	0.078682	0.089513	-0.009941	-0.120491	0.197369	0.062193	0.04
GDP	0.123999	0.361373	-0.219920	-0.096278	0.161255	0.827400	0.06
Population	0.016952	0.000355	-0.027603	0.550032	-0.006624	-0.010340	-0.11
Thinness 10-19 years	-0.054089	-0.362610	0.207264	0.460991	-0.291740	-0.188384	-0.08
Thinness 5-9 years	-0.057334	-0.355738	0.213555	0.467228	-0.278005	-0.191208	-0.09
Income composition of resources	0.278717	0.617276	-0.361126	-0.107167	0.245992	0.333236	0.14

In [ ]:

```
# Heatmap visualizing the Correlation matrix for Low/Medium income dataset

plt.figure(figsize=(10, 8))
plt.matshow(correlation_matrix, cmap='cubehelix', fignum=1)
plt.colorbar()
plt.xticks(ticks=np.arange(len(numerical_columns)), labels=numerical_columns, rc
plt.yticks(ticks=np.arange(len(numerical_columns)), labels=numerical_columns)
plt.show()
```



From the correlation matrix of low/medium income countries,

- we can notice that, most of the correlations remains the same between the original dataset and this low/medium income dataset.
- There is some minor differences like some Features like GDP, Total Expenditure have a weaker +ve correlation score while for features like Adult Mortality, Malnutrition and all have a very high -ve correlation score.

In [ ]:
```
# Here removing the feature - 'Status' because here that is already used for spl
features = ["Year", "Alcohol", "Percentage expenditure", "Hepatitis B", "Measles
            "BMI", "Polio", "Total expenditure", "GDP", "Population", "Thinness
            "Thinness 5-9 years", "Income composition of resources"]

target = "Life expectancy"
```

In [ ]:
```
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error
import pandas as pd

# Define feature subsets based on correlation findings

# Feature Set 1: Removing "Thinness 10-19 years" due to high correlation with "T
# Removing "Total Expenditure" due to high correlation with "GDP"
# Removing "Measles" as it has low correlation with Life Expectancy
```

```
feature_set_1 = ["Year", "Status", "Alcohol", "Percentage expenditure", "Hepatit
                 "BMI", "Polio", "GDP", "Population", "Thinness 5-9 years", "Inc

# Feature Set 2: Remove "Thinness 5-9 years" due to high correlation with "Thinn
# Removing "GDP" due to high correlation with "Total Expenditure"
# Removing "Hepatitis B" due to lower correlation with Life Expectancy
feature_set_2 = ["Year", "Status", "Alcohol", "Percentage expenditure", "Measles
                 "BMI", "Polio", "Total expenditure", "Population", "Thinness  1

# Feature Set 3: Removing "Thinness 10-19 years" and "Thinness 5-9 years" as the
# Removing "Population" as it has a weak correlation with Life Expectancy
feature_set_3 = ["Year", "Status", "Alcohol", "Percentage expenditure", "Hepatit
                 "Measles", "BMI", "Polio", "Total expenditure", "GDP", "Income

# Feature selection dictionary
feature_sets = {
    "Feature Set 1": feature_set_1,
    "Feature Set 2": feature_set_2,
    "Feature Set 3": feature_set_3
}
```

In [ ]:
```
# Function for Hyperparameter Tuning for the Linear Model
def hyperparameter_tuning_linear_model():
    results = []

    for set_name, selected_features in feature_sets.items():
        # Preparing the feature matrices to assign the needed features for this
        X_train_fs = train_set[selected_features].values
        X_dev_fs = dev_set[selected_features].values

        y_train_fs = train_set[target].values.flatten()
        y_dev_fs = dev_set[target].values.flatten()

        # Training and evaluating the Linear Regression model
        model = LinearRegression()
        model.fit(X_train_fs, y_train_fs)
        y_dev_pred = model.predict(X_dev_fs)
        mae_dev = mean_absolute_error(y_dev_fs, y_dev_pred)

        # Store the Mean absolute errors into the dataframe
        results.append({"Model with Feature Set": f"Linear Regression - {set_nam

    return results
```

In [ ]:
```
# Function for Hyperparameter Tuning (Non-Linear Model - Decision Tree Regressor
def hyperparameter_tuning_non_linear_model1():
    results = [] # Storing the model performance results
    hyperparams = {
        "max_depth": [3, 5, 7, 10, None], # Maximum depth of the tree
        "min_samples_split": [2, 5, 10, 20] # Minimum samples required to split
    }

    # Training the model (looping through each feature)
    for set_name, selected_features in feature_sets.items():
        X_train_fs = train_set[selected_features].values
        X_dev_fs = dev_set[selected_features].values

        y_train_fs = train_set[target].values.flatten()
        y_dev_fs = dev_set[target].values.flatten()
```

```
        for depth in hyperparams["max_depth"]:
            for min_samples in hyperparams["min_samples_split"]:
                model = DecisionTreeRegressor(max_depth=depth, min_samples_split
                model.fit(X_train_fs, y_train_fs)
                y_dev_pred = model.predict(X_dev_fs)
                mae_dev = mean_absolute_error(y_dev_fs, y_dev_pred)

                results.append({"Model with Feature Set": f"Decision Tree - {set
                                "Development Set MAE": mae_dev})

    return results
```

In [ ]:
```
def hyperparameter_tuning_non_linear_model2():
    results = []
    hyperparams = {
        "n_estimators": [50, 100, 200, 500], # Number of trees in the forest
        "max_features": ["sqrt", "log2", None]   # Number of features to conside
    }
    for set_name, selected_features in feature_sets.items():
        X_train_fs = train_set[selected_features].values
        X_dev_fs = dev_set[selected_features].values

        y_train_fs = train_set[target].values.flatten()
        y_dev_fs = dev_set[target].values.flatten()

        for n_estimators in hyperparams["n_estimators"]:
            for max_features in hyperparams["max_features"]:
                model = RandomForestRegressor(n_estimators=n_estimators, max_fea
                model.fit(X_train_fs, y_train_fs)
                y_dev_pred = model.predict(X_dev_fs)
                mae_dev = mean_absolute_error(y_dev_fs, y_dev_pred)

                results.append({"Model with Feature Set": f"Random Forest - {set
                                "Development Set MAE": mae_dev})

    return results
```

In [ ]:
```
# Executing all hyperparameter tuning functions
linear_results = hyperparameter_tuning_linear_model()
decision_tree_results = hyperparameter_tuning_non_linear_model1()
random_forest_results = hyperparameter_tuning_non_linear_model2()

# Combining all results into a DataFrame
results_df_lowinc_mae = pd.DataFrame(linear_results + decision_tree_results + ra

# Display final results
print(results_df_lowinc_mae)
```

	Model with Feature Set	Development Set MAE
0	Linear Regression - Feature Set 1	0.507581
1	Linear Regression - Feature Set 2	0.511872
2	Linear Regression - Feature Set 3	0.493273
3	Decision Tree - Feature Set 1 (Depth=3, Min Sa...	0.420460
4	Decision Tree - Feature Set 1 (Depth=3, Min Sa...	0.420460
5	Decision Tree - Feature Set 1 (Depth=3, Min Sa...	0.420460
6	Decision Tree - Feature Set 1 (Depth=3, Min Sa...	0.420460
7	Decision Tree - Feature Set 1 (Depth=5, Min Sa...	0.462827
8	Decision Tree - Feature Set 1 (Depth=5, Min Sa...	0.462827
9	Decision Tree - Feature Set 1 (Depth=5, Min Sa...	0.462827
10	Decision Tree - Feature Set 1 (Depth=5, Min Sa...	0.448828
11	Decision Tree - Feature Set 1 (Depth=7, Min Sa...	0.584729
12	Decision Tree - Feature Set 1 (Depth=7, Min Sa...	0.576252
13	Decision Tree - Feature Set 1 (Depth=7, Min Sa...	0.573482
14	Decision Tree - Feature Set 1 (Depth=7, Min Sa...	0.532151
15	Decision Tree - Feature Set 1 (Depth=10, Min S...	0.590182
16	Decision Tree - Feature Set 1 (Depth=10, Min S...	0.589421
17	Decision Tree - Feature Set 1 (Depth=10, Min S...	0.563817
18	Decision Tree - Feature Set 1 (Depth=10, Min S...	0.523341
19	Decision Tree - Feature Set 1 (Depth=None, Min...	0.591934
20	Decision Tree - Feature Set 1 (Depth=None, Min...	0.617488
21	Decision Tree - Feature Set 1 (Depth=None, Min...	0.584150
22	Decision Tree - Feature Set 1 (Depth=None, Min...	0.523105
23	Decision Tree - Feature Set 2 (Depth=3, Min Sa...	0.441098
24	Decision Tree - Feature Set 2 (Depth=3, Min Sa...	0.441098
25	Decision Tree - Feature Set 2 (Depth=3, Min Sa...	0.441098
26	Decision Tree - Feature Set 2 (Depth=3, Min Sa...	0.441098
27	Decision Tree - Feature Set 2 (Depth=5, Min Sa...	0.459120
28	Decision Tree - Feature Set 2 (Depth=5, Min Sa...	0.459120
29	Decision Tree - Feature Set 2 (Depth=5, Min Sa...	0.459120
30	Decision Tree - Feature Set 2 (Depth=5, Min Sa...	0.445800
31	Decision Tree - Feature Set 2 (Depth=7, Min Sa...	0.483982
32	Decision Tree - Feature Set 2 (Depth=7, Min Sa...	0.485462
33	Decision Tree - Feature Set 2 (Depth=7, Min Sa...	0.496424
34	Decision Tree - Feature Set 2 (Depth=7, Min Sa...	0.494385
35	Decision Tree - Feature Set 2 (Depth=10, Min S...	0.564347
36	Decision Tree - Feature Set 2 (Depth=10, Min S...	0.535849
37	Decision Tree - Feature Set 2 (Depth=10, Min S...	0.514513
38	Decision Tree - Feature Set 2 (Depth=10, Min S...	0.516723
39	Decision Tree - Feature Set 2 (Depth=None, Min...	0.547901
40	Decision Tree - Feature Set 2 (Depth=None, Min...	0.532707
41	Decision Tree - Feature Set 2 (Depth=None, Min...	0.550713
42	Decision Tree - Feature Set 2 (Depth=None, Min...	0.508415
43	Decision Tree - Feature Set 3 (Depth=3, Min Sa...	0.431327
44	Decision Tree - Feature Set 3 (Depth=3, Min Sa...	0.431327
45	Decision Tree - Feature Set 3 (Depth=3, Min Sa...	0.431327
46	Decision Tree - Feature Set 3 (Depth=3, Min Sa...	0.431327
47	Decision Tree - Feature Set 3 (Depth=5, Min Sa...	0.427205
48	Decision Tree - Feature Set 3 (Depth=5, Min Sa...	0.427205
49	Decision Tree - Feature Set 3 (Depth=5, Min Sa...	0.427205
50	Decision Tree - Feature Set 3 (Depth=5, Min Sa...	0.413885
51	Decision Tree - Feature Set 3 (Depth=7, Min Sa...	0.451943
52	Decision Tree - Feature Set 3 (Depth=7, Min Sa...	0.432065
53	Decision Tree - Feature Set 3 (Depth=7, Min Sa...	0.428525
54	Decision Tree - Feature Set 3 (Depth=7, Min Sa...	0.423554
55	Decision Tree - Feature Set 3 (Depth=10, Min S...	0.507224
56	Decision Tree - Feature Set 3 (Depth=10, Min S...	0.510582
57	Decision Tree - Feature Set 3 (Depth=10, Min S...	0.494603
58	Decision Tree - Feature Set 3 (Depth=10, Min S...	0.471630

```
59  Decision Tree - Feature Set 3 (Depth=None, Min...          0.526078
60  Decision Tree - Feature Set 3 (Depth=None, Min...          0.534874
61  Decision Tree - Feature Set 3 (Depth=None, Min...          0.537146
62  Decision Tree - Feature Set 3 (Depth=None, Min...          0.490701
63  Random Forest - Feature Set 1 (Estimators=50, ...          0.329482
64  Random Forest - Feature Set 1 (Estimators=50, ...          0.329482
65  Random Forest - Feature Set 1 (Estimators=50, ...          0.339617
66  Random Forest - Feature Set 1 (Estimators=100,...          0.330545
67  Random Forest - Feature Set 1 (Estimators=100,...          0.330545
68  Random Forest - Feature Set 1 (Estimators=100,...          0.346258
69  Random Forest - Feature Set 1 (Estimators=200,...          0.338449
70  Random Forest - Feature Set 1 (Estimators=200,...          0.338449
71  Random Forest - Feature Set 1 (Estimators=200,...          0.346718
72  Random Forest - Feature Set 1 (Estimators=500,...          0.329905
73  Random Forest - Feature Set 1 (Estimators=500,...          0.329905
74  Random Forest - Feature Set 1 (Estimators=500,...          0.345798
75  Random Forest - Feature Set 2 (Estimators=50, ...          0.337313
76  Random Forest - Feature Set 2 (Estimators=50, ...          0.337313
77  Random Forest - Feature Set 2 (Estimators=50, ...          0.362571
78  Random Forest - Feature Set 2 (Estimators=100,...          0.331299
79  Random Forest - Feature Set 2 (Estimators=100,...          0.331299
80  Random Forest - Feature Set 2 (Estimators=100,...          0.354089
81  Random Forest - Feature Set 2 (Estimators=200,...          0.335049
82  Random Forest - Feature Set 2 (Estimators=200,...          0.335049
83  Random Forest - Feature Set 2 (Estimators=200,...          0.350143
84  Random Forest - Feature Set 2 (Estimators=500,...          0.336421
85  Random Forest - Feature Set 2 (Estimators=500,...          0.336421
86  Random Forest - Feature Set 2 (Estimators=500,...          0.348259
87  Random Forest - Feature Set 3 (Estimators=50, ...          0.340342
88  Random Forest - Feature Set 3 (Estimators=50, ...          0.340342
89  Random Forest - Feature Set 3 (Estimators=50, ...          0.351936
90  Random Forest - Feature Set 3 (Estimators=100,...          0.344005
91  Random Forest - Feature Set 3 (Estimators=100,...          0.344005
92  Random Forest - Feature Set 3 (Estimators=100,...          0.358003
93  Random Forest - Feature Set 3 (Estimators=200,...          0.337203
94  Random Forest - Feature Set 3 (Estimators=200,...          0.337203
95  Random Forest - Feature Set 3 (Estimators=200,...          0.358842
96  Random Forest - Feature Set 3 (Estimators=500,...          0.335919
97  Random Forest - Feature Set 3 (Estimators=500,...          0.335919
98  Random Forest - Feature Set 3 (Estimators=500,...          0.358036
```

In [ ]:
```python
pd.set_option("display.max_rows", 100)  # All the rows are displayed here
print(results_df_lowinc_mae)
```

	Model with Feature Set	Development Set MAE
0	Linear Regression - Feature Set 1	0.507581
1	Linear Regression - Feature Set 2	0.511872
2	Linear Regression - Feature Set 3	0.493273
3	Decision Tree - Feature Set 1 (Depth=3, Min Sa...	0.420460
4	Decision Tree - Feature Set 1 (Depth=3, Min Sa...	0.420460
5	Decision Tree - Feature Set 1 (Depth=3, Min Sa...	0.420460
6	Decision Tree - Feature Set 1 (Depth=3, Min Sa...	0.420460
7	Decision Tree - Feature Set 1 (Depth=5, Min Sa...	0.462827
8	Decision Tree - Feature Set 1 (Depth=5, Min Sa...	0.462827
9	Decision Tree - Feature Set 1 (Depth=5, Min Sa...	0.462827
10	Decision Tree - Feature Set 1 (Depth=5, Min Sa...	0.448828
11	Decision Tree - Feature Set 1 (Depth=7, Min Sa...	0.584729
12	Decision Tree - Feature Set 1 (Depth=7, Min Sa...	0.576252
13	Decision Tree - Feature Set 1 (Depth=7, Min Sa...	0.573482
14	Decision Tree - Feature Set 1 (Depth=7, Min Sa...	0.532151
15	Decision Tree - Feature Set 1 (Depth=10, Min S...	0.590182
16	Decision Tree - Feature Set 1 (Depth=10, Min S...	0.589421
17	Decision Tree - Feature Set 1 (Depth=10, Min S...	0.563817
18	Decision Tree - Feature Set 1 (Depth=10, Min S...	0.523341
19	Decision Tree - Feature Set 1 (Depth=None, Min...	0.591934
20	Decision Tree - Feature Set 1 (Depth=None, Min...	0.617488
21	Decision Tree - Feature Set 1 (Depth=None, Min...	0.584150
22	Decision Tree - Feature Set 1 (Depth=None, Min...	0.523105
23	Decision Tree - Feature Set 2 (Depth=3, Min Sa...	0.441098
24	Decision Tree - Feature Set 2 (Depth=3, Min Sa...	0.441098
25	Decision Tree - Feature Set 2 (Depth=3, Min Sa...	0.441098
26	Decision Tree - Feature Set 2 (Depth=3, Min Sa...	0.441098
27	Decision Tree - Feature Set 2 (Depth=5, Min Sa...	0.459120
28	Decision Tree - Feature Set 2 (Depth=5, Min Sa...	0.459120
29	Decision Tree - Feature Set 2 (Depth=5, Min Sa...	0.459120
30	Decision Tree - Feature Set 2 (Depth=5, Min Sa...	0.445800
31	Decision Tree - Feature Set 2 (Depth=7, Min Sa...	0.483982
32	Decision Tree - Feature Set 2 (Depth=7, Min Sa...	0.485462
33	Decision Tree - Feature Set 2 (Depth=7, Min Sa...	0.496424
34	Decision Tree - Feature Set 2 (Depth=7, Min Sa...	0.494385
35	Decision Tree - Feature Set 2 (Depth=10, Min S...	0.564347
36	Decision Tree - Feature Set 2 (Depth=10, Min S...	0.535849
37	Decision Tree - Feature Set 2 (Depth=10, Min S...	0.514513
38	Decision Tree - Feature Set 2 (Depth=10, Min S...	0.516723
39	Decision Tree - Feature Set 2 (Depth=None, Min...	0.547901
40	Decision Tree - Feature Set 2 (Depth=None, Min...	0.532707
41	Decision Tree - Feature Set 2 (Depth=None, Min...	0.550713
42	Decision Tree - Feature Set 2 (Depth=None, Min...	0.508415
43	Decision Tree - Feature Set 3 (Depth=3, Min Sa...	0.431327
44	Decision Tree - Feature Set 3 (Depth=3, Min Sa...	0.431327
45	Decision Tree - Feature Set 3 (Depth=3, Min Sa...	0.431327
46	Decision Tree - Feature Set 3 (Depth=3, Min Sa...	0.431327
47	Decision Tree - Feature Set 3 (Depth=5, Min Sa...	0.427205
48	Decision Tree - Feature Set 3 (Depth=5, Min Sa...	0.427205
49	Decision Tree - Feature Set 3 (Depth=5, Min Sa...	0.427205
50	Decision Tree - Feature Set 3 (Depth=5, Min Sa...	0.413885
51	Decision Tree - Feature Set 3 (Depth=7, Min Sa...	0.451943
52	Decision Tree - Feature Set 3 (Depth=7, Min Sa...	0.432065
53	Decision Tree - Feature Set 3 (Depth=7, Min Sa...	0.428525
54	Decision Tree - Feature Set 3 (Depth=7, Min Sa...	0.423554
55	Decision Tree - Feature Set 3 (Depth=10, Min S...	0.507224
56	Decision Tree - Feature Set 3 (Depth=10, Min S...	0.510582
57	Decision Tree - Feature Set 3 (Depth=10, Min S...	0.494603
58	Decision Tree - Feature Set 3 (Depth=10, Min S...	0.471630

```
59  Decision Tree - Feature Set 3 (Depth=None, Min...           0.526078
60  Decision Tree - Feature Set 3 (Depth=None, Min...           0.534874
61  Decision Tree - Feature Set 3 (Depth=None, Min...           0.537146
62  Decision Tree - Feature Set 3 (Depth=None, Min...           0.490701
63  Random Forest - Feature Set 1 (Estimators=50, ...           0.329482
64  Random Forest - Feature Set 1 (Estimators=50, ...           0.329482
65  Random Forest - Feature Set 1 (Estimators=50, ...           0.339617
66  Random Forest - Feature Set 1 (Estimators=100,...           0.330545
67  Random Forest - Feature Set 1 (Estimators=100,...           0.330545
68  Random Forest - Feature Set 1 (Estimators=100,...           0.346258
69  Random Forest - Feature Set 1 (Estimators=200,...           0.338449
70  Random Forest - Feature Set 1 (Estimators=200,...           0.338449
71  Random Forest - Feature Set 1 (Estimators=200,...           0.346718
72  Random Forest - Feature Set 1 (Estimators=500,...           0.329905
73  Random Forest - Feature Set 1 (Estimators=500,...           0.329905
74  Random Forest - Feature Set 1 (Estimators=500,...           0.345798
75  Random Forest - Feature Set 2 (Estimators=50, ...           0.337313
76  Random Forest - Feature Set 2 (Estimators=50, ...           0.337313
77  Random Forest - Feature Set 2 (Estimators=50, ...           0.362571
78  Random Forest - Feature Set 2 (Estimators=100,...           0.331299
79  Random Forest - Feature Set 2 (Estimators=100,...           0.331299
80  Random Forest - Feature Set 2 (Estimators=100,...           0.354089
81  Random Forest - Feature Set 2 (Estimators=200,...           0.335049
82  Random Forest - Feature Set 2 (Estimators=200,...           0.335049
83  Random Forest - Feature Set 2 (Estimators=200,...           0.350143
84  Random Forest - Feature Set 2 (Estimators=500,...           0.336421
85  Random Forest - Feature Set 2 (Estimators=500,...           0.336421
86  Random Forest - Feature Set 2 (Estimators=500,...           0.348259
87  Random Forest - Feature Set 3 (Estimators=50, ...           0.340342
88  Random Forest - Feature Set 3 (Estimators=50, ...           0.340342
89  Random Forest - Feature Set 3 (Estimators=50, ...           0.351936
90  Random Forest - Feature Set 3 (Estimators=100,...           0.344005
91  Random Forest - Feature Set 3 (Estimators=100,...           0.344005
92  Random Forest - Feature Set 3 (Estimators=100,...           0.358003
93  Random Forest - Feature Set 3 (Estimators=200,...           0.337203
94  Random Forest - Feature Set 3 (Estimators=200,...           0.337203
95  Random Forest - Feature Set 3 (Estimators=200,...           0.358842
96  Random Forest - Feature Set 3 (Estimators=500,...           0.335919
97  Random Forest - Feature Set 3 (Estimators=500,...           0.335919
98  Random Forest - Feature Set 3 (Estimators=500,...           0.358036
```

- With Linear Regression, using all 14 features, the lowest MAE score obtained on the development set was 0.4933. After analyzing the correlation matrix and removing highly correlated or less significant features, the model's performance improved. Specifically, for Feature Set 1, where "Thinness 10-19 years", "Total Expenditure", and "Measles" were removed, the MAE dropped to 0.5076. Similarly, for Feature Set 2, where "Thinness 5-9 years", "GDP", and "Hepatitis B" were excluded, the MAE was 0.5119. Lastly, for Feature Set 3, which removed "Thinness 10-19 years" and "Population", the MAE significantly improved to 0.4933, indicating that strategic feature selection effectively reduces prediction errors and enhances model performance.
- The best-performing models from hyperparameter tuning on the development set were obtained using the Random Forest Regressor. The best model used Feature Set 1 with 50 estimators and "sqrt" as the max features parameter, achieving a MAE of

0.3295. A similar Random Forest model, also using Feature Set 1, but with "log2" as the max features parameter, achieved a MAE of 0.3295 as well. These results highlight that Random Forest with Feature Set 1 provided the most accurate predictions among all tested models, demonstrating that feature selection, along with optimized hyperparameters, significantly enhances predictive performance.

- After splitting the dataset into low/medium-income countries, some changes in performance were observed. The MAE values slightly increased, indicating that socioeconomic factors unique to low-income countries might contribute to greater variability in predictions. Additionally, the impact of healthcare spending and immunization variables became more prominent, showing that certain features may be more influential in predicting life expectancy within lower-income regions compared to the original full dataset.

Analysis for Upper/High Data

In [70]:
```
upper_high_income_df.shape
```

Out[70]: (512, 18)

In [ ]:
```
upper_high_income_df.columns = upper_high_income_df.columns.str.strip()

# Data Set splitting as per the requirements followed previously but after split
train_set = upper_high_income_df.iloc[0:430].copy()
dev_set = upper_high_income_df.iloc[431:479].copy()
test_set = upper_high_income_df.iloc[480:512].copy()

# No. of rows in each dataset
train_set.shape[0], dev_set.shape[0], test_set.shape[0]
```

Out[ ]: (430, 48, 32)

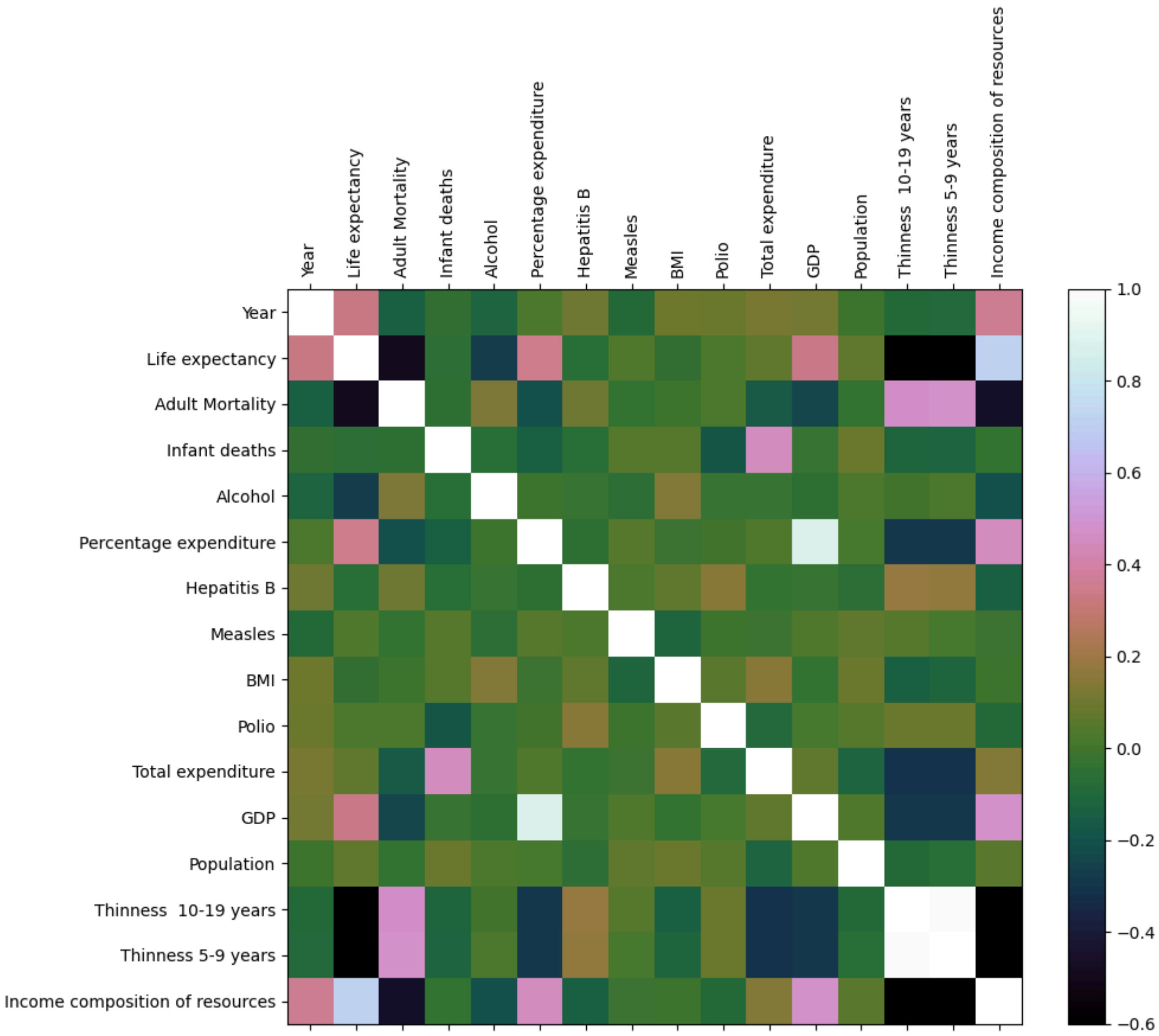
In [ ]:
```
# Correlation matrix for upper/high income dataset
numerical_dtype_columns = upper_high_income_df.select_dtypes(include=[np.number]
numerical_columns = [col for col in numerical_dtype_columns if col not in ['Coun
correlation_matrix = upper_high_income_df[numerical_columns].corr(method='pearsc
correlation_matrix
```

Out[ ]:

	Year	Life expectancy	Adult Mortality	Infant deaths	Alcohol	Percentage expenditure	Hepa
Year	1.000000	0.332725	-0.146058	-0.041294	-0.117615	0.029885	0.10
Life expectancy	0.332725	1.000000	-0.485489	-0.054764	-0.280096	0.350315	-0.07
Adult Mortality	-0.146058	-0.485489	1.000000	-0.048109	0.134096	-0.204091	0.10
Infant deaths	-0.041294	-0.054764	-0.048109	1.000000	-0.075716	-0.150824	-0.07
Alcohol	-0.117615	-0.280096	0.134096	-0.075716	1.000000	-0.011959	-0.02
Percentage expenditure	0.029885	0.350315	-0.204091	-0.150824	-0.011959	1.000000	-0.05
Hepatitis B	0.101816	-0.071409	0.103594	-0.070538	-0.023521	-0.050733	1.00
Measles	-0.088053	0.037801	-0.036493	0.051480	-0.057812	0.049917	0.01
BMI	0.098019	-0.043962	-0.010241	0.047502	0.140092	-0.018039	0.06
Polio	0.090278	0.018342	0.022593	-0.188141	-0.019898	0.000249	0.14
Total expenditure	0.119620	0.069527	-0.151953	0.452160	-0.020727	0.034111	-0.03
GDP	0.109517	0.337702	-0.234164	-0.025137	-0.044978	0.880070	-0.02
Population	-0.007730	0.074276	-0.037100	0.086923	0.019208	0.015934	-0.05
Thinness 10-19 years	-0.086270	-0.588078	0.471645	-0.107021	0.002889	-0.290677	0.17
Thinness 5-9 years	-0.089236	-0.596530	0.480553	-0.119443	0.022943	-0.290731	0.17
Income composition of resources	0.366969	0.708678	-0.461981	-0.033858	-0.195935	0.452255	-0.14

In [ ]:

```
# Heatmap visualizing the Correlation matrix for upper/high income dataset
plt.figure(figsize=(10, 8))
plt.matshow(correlation_matrix, cmap='cubehelix', fignum=1)
plt.colorbar()
plt.xticks(ticks=np.arange(len(numerical_columns)), labels=numerical_columns, rc
plt.yticks(ticks=np.arange(len(numerical_columns)), labels=numerical_columns)
plt.show()
```



This correlation martrix also represents the similar trend compared to the original df and low/medium df datasets. The only difference here is there's some difference in the correlation scores but the trend ie.+ve/-ve correlation remains the same.

In [74]:
```
features = ["Year", "Alcohol", "Percentage expenditure", "Hepatitis B", "Measles
            "BMI", "Polio", "Total expenditure", "GDP", "Population", "Thinness
            "Thinness 5-9 years", "Income composition of resources"]

target = "Life expectancy"
```

In [ ]:
```
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error
import pandas as pd

# Define feature subsets based on correlation findings

# Feature Set 1: Removing "Thinness 10-19 years" due to high correlation with "T
# Removing "Total Expenditure" due to high correlation with "GDP"
# Removing "Measles" as it has low correlation with Life Expectancy
feature_set_1 = ["Year", "Status", "Alcohol", "Percentage expenditure", "Hepatit
                 "BMI", "Polio", "GDP", "Population", "Thinness 5-9 years", "Inc

# Feature Set 2: Remove "Thinness 5-9 years" due to high correlation with "Thinn
# Removing "GDP" due to high correlation with "Total Expenditure"
# Removing "Hepatitis B" due to lower correlation with Life Expectancy
```

```
feature_set_2 = ["Year", "Status", "Alcohol", "Percentage expenditure", "Measles
                 "BMI", "Polio", "Total expenditure", "Population", "Thinness  1

# Feature Set 3: Removing "Thinness 10-19 years" and "Thinness 5-9 years" as the
# Removing "Population" as it has a weak correlation with Life Expectancy
feature_set_3 = ["Year", "Status", "Alcohol", "Percentage expenditure", "Hepatit
                 "Measles", "BMI", "Polio", "Total expenditure", "GDP", "Income

# Feature selection dictionary
feature_sets = {
    "Feature Set 1": feature_set_1,
    "Feature Set 2": feature_set_2,
    "Feature Set 3": feature_set_3
}
```

In [ ]:
```
# Function for Hyperparameter Tuning for the Linear Model
def hyperparameter_tuning_linear_model():
    results = []

    for set_name, selected_features in feature_sets.items():
        # Preparing the feature matrices to assign the needed features for this
        X_train_fs = train_set[selected_features].values
        X_dev_fs = dev_set[selected_features].values

        y_train_fs = train_set[target].values.flatten()
        y_dev_fs = dev_set[target].values.flatten()

        # Training and evaluating the Linear Regression model
        model = LinearRegression()
        model.fit(X_train_fs, y_train_fs)
        y_dev_pred = model.predict(X_dev_fs)
        mae_dev = mean_absolute_error(y_dev_fs, y_dev_pred)

        # Store the Mean absolute errors into the dataframe
        results.append({"Model with Feature Set": f"Linear Regression - {set_nam

    return results
```

In [ ]:
```
# Function for Hyperparameter Tuning (Non-Linear Model - Decision Tree Regressor
def hyperparameter_tuning_non_linear_model1():
    results = [] # Storing the model performance results
    hyperparams = {
        "max_depth": [3, 5, 7, 10, None], # Maximum depth of the tree
        "min_samples_split": [2, 5, 10, 20] # Minimum samples required to split
    }

    # Training the model (looping through each feature)
    for set_name, selected_features in feature_sets.items():
        X_train_fs = train_set[selected_features].values
        X_dev_fs = dev_set[selected_features].values

        y_train_fs = train_set[target].values.flatten()
        y_dev_fs = dev_set[target].values.flatten()

        for depth in hyperparams["max_depth"]:
            for min_samples in hyperparams["min_samples_split"]:
                model = DecisionTreeRegressor(max_depth=depth, min_samples_split
                model.fit(X_train_fs, y_train_fs)
                y_dev_pred = model.predict(X_dev_fs)
```

```
                mae_dev = mean_absolute_error(y_dev_fs, y_dev_pred)

                results.append({"Model with Feature Set": f"Decision Tree - {set
                                "Development Set MAE": mae_dev})

    return results
```

In [ ]:
```
def hyperparameter_tuning_non_linear_model2():
    results = []
    hyperparams = {
        "n_estimators": [50, 100, 200, 500], # Number of trees in the forest
        "max_features": ["sqrt", "log2", None]   # Number of features to conside
    }
    for set_name, selected_features in feature_sets.items():
        X_train_fs = train_set[selected_features].values
        X_dev_fs = dev_set[selected_features].values

        y_train_fs = train_set[target].values.flatten()
        y_dev_fs = dev_set[target].values.flatten()

        for n_estimators in hyperparams["n_estimators"]:
            for max_features in hyperparams["max_features"]:
                model = RandomForestRegressor(n_estimators=n_estimators, max_fea
                model.fit(X_train_fs, y_train_fs)
                y_dev_pred = model.predict(X_dev_fs)
                mae_dev = mean_absolute_error(y_dev_fs, y_dev_pred)

                results.append({"Model with Feature Set": f"Random Forest - {set
                                "Development Set MAE": mae_dev})

    return results
```

In [ ]:
```
# Executing all hyperparameter tuning functions
linear_results = hyperparameter_tuning_linear_model()
decision_tree_results = hyperparameter_tuning_non_linear_model1()
random_forest_results = hyperparameter_tuning_non_linear_model2()

# Combining all results into a DataFrame
results_df_highinc_mae = pd.DataFrame(linear_results + decision_tree_results + r

# Display final results
print(results_df_highinc_mae)
```

	Model with Feature Set	Development Set MAE
0	Linear Regression - Feature Set 1	0.484410
1	Linear Regression - Feature Set 2	0.476669
2	Linear Regression - Feature Set 3	0.607679
3	Decision Tree - Feature Set 1 (Depth=3, Min Sa...	0.420205
4	Decision Tree - Feature Set 1 (Depth=3, Min Sa...	0.420205
5	Decision Tree - Feature Set 1 (Depth=3, Min Sa...	0.420205
6	Decision Tree - Feature Set 1 (Depth=3, Min Sa...	0.420205
7	Decision Tree - Feature Set 1 (Depth=5, Min Sa...	0.441602
8	Decision Tree - Feature Set 1 (Depth=5, Min Sa...	0.441602
9	Decision Tree - Feature Set 1 (Depth=5, Min Sa...	0.441602
10	Decision Tree - Feature Set 1 (Depth=5, Min Sa...	0.457203
11	Decision Tree - Feature Set 1 (Depth=7, Min Sa...	0.632054
12	Decision Tree - Feature Set 1 (Depth=7, Min Sa...	0.629271
13	Decision Tree - Feature Set 1 (Depth=7, Min Sa...	0.622865
14	Decision Tree - Feature Set 1 (Depth=7, Min Sa...	0.635694
15	Decision Tree - Feature Set 1 (Depth=10, Min S...	0.695743
16	Decision Tree - Feature Set 1 (Depth=10, Min S...	0.657716
17	Decision Tree - Feature Set 1 (Depth=10, Min S...	0.632349
18	Decision Tree - Feature Set 1 (Depth=10, Min S...	0.672270
19	Decision Tree - Feature Set 1 (Depth=None, Min...	0.693218
20	Decision Tree - Feature Set 1 (Depth=None, Min...	0.715301
21	Decision Tree - Feature Set 1 (Depth=None, Min...	0.646094
22	Decision Tree - Feature Set 1 (Depth=None, Min...	0.674352
23	Decision Tree - Feature Set 2 (Depth=3, Min Sa...	0.427247
24	Decision Tree - Feature Set 2 (Depth=3, Min Sa...	0.427247
25	Decision Tree - Feature Set 2 (Depth=3, Min Sa...	0.427247
26	Decision Tree - Feature Set 2 (Depth=3, Min Sa...	0.427247
27	Decision Tree - Feature Set 2 (Depth=5, Min Sa...	0.445941
28	Decision Tree - Feature Set 2 (Depth=5, Min Sa...	0.445941
29	Decision Tree - Feature Set 2 (Depth=5, Min Sa...	0.445941
30	Decision Tree - Feature Set 2 (Depth=5, Min Sa...	0.452542
31	Decision Tree - Feature Set 2 (Depth=7, Min Sa...	0.615030
32	Decision Tree - Feature Set 2 (Depth=7, Min Sa...	0.608538
33	Decision Tree - Feature Set 2 (Depth=7, Min Sa...	0.608174
34	Decision Tree - Feature Set 2 (Depth=7, Min Sa...	0.612002
35	Decision Tree - Feature Set 2 (Depth=10, Min S...	0.814159
36	Decision Tree - Feature Set 2 (Depth=10, Min S...	0.735678
37	Decision Tree - Feature Set 2 (Depth=10, Min S...	0.731087
38	Decision Tree - Feature Set 2 (Depth=10, Min S...	0.693261
39	Decision Tree - Feature Set 2 (Depth=None, Min...	0.827834
40	Decision Tree - Feature Set 2 (Depth=None, Min...	0.764942
41	Decision Tree - Feature Set 2 (Depth=None, Min...	0.725839
42	Decision Tree - Feature Set 2 (Depth=None, Min...	0.685356
43	Decision Tree - Feature Set 3 (Depth=3, Min Sa...	0.451847
44	Decision Tree - Feature Set 3 (Depth=3, Min Sa...	0.451847
45	Decision Tree - Feature Set 3 (Depth=3, Min Sa...	0.451847
46	Decision Tree - Feature Set 3 (Depth=3, Min Sa...	0.446302
47	Decision Tree - Feature Set 3 (Depth=5, Min Sa...	0.472008
48	Decision Tree - Feature Set 3 (Depth=5, Min Sa...	0.472008
49	Decision Tree - Feature Set 3 (Depth=5, Min Sa...	0.470285
50	Decision Tree - Feature Set 3 (Depth=5, Min Sa...	0.470285
51	Decision Tree - Feature Set 3 (Depth=7, Min Sa...	0.628674
52	Decision Tree - Feature Set 3 (Depth=7, Min Sa...	0.626245
53	Decision Tree - Feature Set 3 (Depth=7, Min Sa...	0.632605
54	Decision Tree - Feature Set 3 (Depth=7, Min Sa...	0.641226
55	Decision Tree - Feature Set 3 (Depth=10, Min S...	0.794824
56	Decision Tree - Feature Set 3 (Depth=10, Min S...	0.719699
57	Decision Tree - Feature Set 3 (Depth=10, Min S...	0.712952
58	Decision Tree - Feature Set 3 (Depth=10, Min S...	0.733368

```
59  Decision Tree - Feature Set 3 (Depth=None, Min...          0.714417
60  Decision Tree - Feature Set 3 (Depth=None, Min...          0.753901
61  Decision Tree - Feature Set 3 (Depth=None, Min...          0.732053
62  Decision Tree - Feature Set 3 (Depth=None, Min...          0.722690
63  Random Forest - Feature Set 1 (Estimators=50, ...          0.394414
64  Random Forest - Feature Set 1 (Estimators=50, ...          0.394414
65  Random Forest - Feature Set 1 (Estimators=50, ...          0.427113
66  Random Forest - Feature Set 1 (Estimators=100,...          0.400222
67  Random Forest - Feature Set 1 (Estimators=100,...          0.400222
68  Random Forest - Feature Set 1 (Estimators=100,...          0.419227
69  Random Forest - Feature Set 1 (Estimators=200,...          0.408641
70  Random Forest - Feature Set 1 (Estimators=200,...          0.408641
71  Random Forest - Feature Set 1 (Estimators=200,...          0.422129
72  Random Forest - Feature Set 1 (Estimators=500,...          0.391666
73  Random Forest - Feature Set 1 (Estimators=500,...          0.391666
74  Random Forest - Feature Set 1 (Estimators=500,...          0.421806
75  Random Forest - Feature Set 2 (Estimators=50, ...          0.407133
76  Random Forest - Feature Set 2 (Estimators=50, ...          0.407133
77  Random Forest - Feature Set 2 (Estimators=50, ...          0.407388
78  Random Forest - Feature Set 2 (Estimators=100,...          0.378201
79  Random Forest - Feature Set 2 (Estimators=100,...          0.378201
80  Random Forest - Feature Set 2 (Estimators=100,...          0.403444
81  Random Forest - Feature Set 2 (Estimators=200,...          0.373098
82  Random Forest - Feature Set 2 (Estimators=200,...          0.373098
83  Random Forest - Feature Set 2 (Estimators=200,...          0.398905
84  Random Forest - Feature Set 2 (Estimators=500,...          0.364855
85  Random Forest - Feature Set 2 (Estimators=500,...          0.364855
86  Random Forest - Feature Set 2 (Estimators=500,...          0.389592
87  Random Forest - Feature Set 3 (Estimators=50, ...          0.437459
88  Random Forest - Feature Set 3 (Estimators=50, ...          0.437459
89  Random Forest - Feature Set 3 (Estimators=50, ...          0.471844
90  Random Forest - Feature Set 3 (Estimators=100,...          0.437544
91  Random Forest - Feature Set 3 (Estimators=100,...          0.437544
92  Random Forest - Feature Set 3 (Estimators=100,...          0.470010
93  Random Forest - Feature Set 3 (Estimators=200,...          0.445218
94  Random Forest - Feature Set 3 (Estimators=200,...          0.445218
95  Random Forest - Feature Set 3 (Estimators=200,...          0.471094
96  Random Forest - Feature Set 3 (Estimators=500,...          0.438822
97  Random Forest - Feature Set 3 (Estimators=500,...          0.438822
98  Random Forest - Feature Set 3 (Estimators=500,...          0.469702
```

In [ ]:

```python
pd.set_option("display.max_rows", 100)  # All the rows are displayed here
print(results_df_highinc_mae)
```

	Model with Feature Set	Development Set MAE
0	Linear Regression - Feature Set 1	0.484410
1	Linear Regression - Feature Set 2	0.476669
2	Linear Regression - Feature Set 3	0.607679
3	Decision Tree - Feature Set 1 (Depth=3, Min Sa...	0.420205
4	Decision Tree - Feature Set 1 (Depth=3, Min Sa...	0.420205
5	Decision Tree - Feature Set 1 (Depth=3, Min Sa...	0.420205
6	Decision Tree - Feature Set 1 (Depth=3, Min Sa...	0.420205
7	Decision Tree - Feature Set 1 (Depth=5, Min Sa...	0.441602
8	Decision Tree - Feature Set 1 (Depth=5, Min Sa...	0.441602
9	Decision Tree - Feature Set 1 (Depth=5, Min Sa...	0.441602
10	Decision Tree - Feature Set 1 (Depth=5, Min Sa...	0.457203
11	Decision Tree - Feature Set 1 (Depth=7, Min Sa...	0.632054
12	Decision Tree - Feature Set 1 (Depth=7, Min Sa...	0.629271
13	Decision Tree - Feature Set 1 (Depth=7, Min Sa...	0.622865
14	Decision Tree - Feature Set 1 (Depth=7, Min Sa...	0.635694
15	Decision Tree - Feature Set 1 (Depth=10, Min S...	0.695743
16	Decision Tree - Feature Set 1 (Depth=10, Min S...	0.657716
17	Decision Tree - Feature Set 1 (Depth=10, Min S...	0.632349
18	Decision Tree - Feature Set 1 (Depth=10, Min S...	0.672270
19	Decision Tree - Feature Set 1 (Depth=None, Min...	0.693218
20	Decision Tree - Feature Set 1 (Depth=None, Min...	0.715301
21	Decision Tree - Feature Set 1 (Depth=None, Min...	0.646094
22	Decision Tree - Feature Set 1 (Depth=None, Min...	0.674352
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32	Decision Tree - Feature Set 2 (Depth=7, Min Sa...	0.608538
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36	Decision Tree - Feature Set 2 (Depth=10, Min S...	0.735678
37	Decision Tree - Feature Set 2 (Depth=10, Min S...	0.731087
38	Decision Tree - Feature Set 2 (Depth=10, Min S...	0.693261
39	Decision Tree - Feature Set 2 (Depth=None, Min...	0.827834
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46	Decision Tree - Feature Set 3 (Depth=3, Min Sa...	0.446302
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95  Random Forest - Feature Set 3 (Estimators=200,...          0.471094
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97  Random Forest - Feature Set 3 (Estimators=500,...          0.438822
98  Random Forest - Feature Set 3 (Estimators=500,...          0.469702
```

With Linear Regression, the best-performing model was achieved with Feature Set 2, which resulted in a MAE of 0.4767 on the development set. However, when using all 14 features, the MAE was 0.4844, indicating that removing certain less significant or highly correlated features improved the model's performance. In contrast, Feature Set 3 performed the worst with an MAE of 0.6077, suggesting that the removed features in this case were more important for accurate predictions. These findings reinforce the importance of careful feature selection in improving model accuracy.

Among the non-linear regression models, the best performance was achieved using the Random Forest Regressor with Feature Set 2. The optimal model had 500 estimators and "sqrt" as the max features parameter, achieving a MAE of 0.3649. This was followed closely by the same model using "log2" for max features, which yielded the same MAE of 0.3649. These results indicate that Random Forest models significantly outperform Linear Regression in capturing complex patterns in the data, benefiting from the ensemble learning approach. The performance gap highlights the advantage of non-linear models when dealing with real-world health-related datasets.

After splitting the dataset to analyze Upper/High-Income countries separately, notable changes in the model performance were observed. The overall MAE scores for both Linear and Non-Linear models slightly improved, suggesting that life expectancy is more predictable in wealthier nations, where factors such as healthcare expenditure, immunization rates, and economic stability show stronger and more consistent relationships with life expectancy. Additionally, the impact of GDP and healthcare spending was more pronounced, further supporting the idea that economic strength plays a major role in determining life expectancy outcomes in developed nations.

Note:

- Here I used **AI tool** only for correcting the grammar, sentence structure and substituting more suitable words in some sentences and in some places for paraphrasing so that the sentence will have a flow without pauses.