CLUSTERING COUNTRIES

The following dataset has been provided by the 'HELP Orgainization'(an international humanitarian NGO) which contains all the Socio-Economic and Health Standards information of all the countries in the world.

'Country-data.csv' has features like country , exports , imports , health , gdpp, life expectancy and many more. 'data-dictionary.csv' files contains the description of the dataset.

MAIN OBJECTIVE : Our primary goal is to develop a model that helps in clustering of countries so as to easily classify countries with respect to their development and which countries need help.

The overview of the steps to perform:
1) Data Visualization
2) Data Cleaning A) Eliminate NA/Null Data Records B) Feature Engineering .
3) Tranforming and Scaling of Data
4) Run Unsupervised Models
5) Optimize the best model
6) Predict Results and Best Model
7) Conclusions

IMPORT LIBRARIES

In [1]:

```
import pandas as pd
import numpy as np
import os , seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
# sns.set_palette(palette)

#  WARNINGS
import warnings
warnings.filterwarnings("ignore" , category=RuntimeWarning)
warnings.filterwarnings("ignore" , category=UserWarning)
```

DATA

In [143]:

```
# Description
desc_path = 'data-dictionary.csv'
desc = pd.read_csv(desc_path)

#  Dataset
filepath = 'Country-data.csv'
data = pd.read_csv(filepath)
```

In [3]:

```
desc
```

Out[3]:

	Column Name	Description
0	country	Name of the country
1	child_mort	Death of children under 5 years of age per 100...
2	exports	Exports of goods and services per capita. Give...
3	health	Total health spending per capita. Given as %ag...
4	imports	Imports of goods and services per capita. Give...
5	Income	Net income per person
6	Inflation	The measurement of the annual growth rate of t...
7	life_expec	The average number of years a new born child w...
8	total_fer	The number of children that would be born to e...
9	gdpp	The GDP per capita. Calculated as the Total GD...

In [22]:

```
data
```

Out[22]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
0	Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	553
1	Albania	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	4090
2	Algeria	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	4460
3	Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	3530
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	12200
...	...	...	...	...	...	...	...	...	...	...
162	Vanuatu	29.2	46.6	5.25	52.7	2950	2.62	63.0	3.50	2970
163	Venezuela	17.1	28.5	4.91	17.6	16500	45.90	75.4	2.47	13500
164	Vietnam	23.3	72.0	6.84	80.2	4490	12.10	73.1	1.95	1310
165	Yemen	56.3	30.0	5.18	34.4	4480	23.60	67.5	4.67	1310
166	Zambia	83.1	37.0	5.89	30.9	3280	14.00	52.0	5.40	1460

167 rows × 10 columns

In [5]:

```
data.shape
```

Out[5]:

```
(167, 10)
```

The dataset has 10 features and 167 data records(countries).

In [6]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 167 entries, 0 to 166
Data columns (total 10 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   country     167 non-null    object 
 1   child_mort  167 non-null    float64
 2   exports     167 non-null    float64
 3   health      167 non-null    float64
 4   imports     167 non-null    float64
 5   income      167 non-null    int64  
 6   inflation   167 non-null    float64
 7   life_expec  167 non-null    float64
 8   total_fer   167 non-null    float64
 9   gdpp        167 non-null    int64  
dtypes: float64(7), int64(2), object(1)
memory usage: 13.2+ KB
```

In [7]:

```
print('No. of Float Data types   : ' ,(data.dtypes == 'float64').sum())
print('No. of Object Data types  : ' ,(data.dtypes == 'object').sum())
print('No. of Integer Data types : ' ,(data.dtypes == 'int64').sum())
```

```
No. of Float Data types   :  7
No. of Object Data types  :  1
No. of Integer Data types :  2
```

In [8]:

```
# DATA INFO and DISTRIBUTION

data.describe()
```

Out[8]:

	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
count	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000
mean	38.270060	41.108976	6.815689	46.890215	17144.688623	7.781832	70.555689	2.947964	12964.155689
std	40.328931	27.412010	2.746837	24.209589	19278.067698	10.570704	8.893172	1.513848	18328.704809
min	2.600000	0.109000	1.810000	0.065900	609.000000	-4.210000	32.100000	1.150000	231.000000
25%	8.250000	23.800000	4.920000	30.200000	3355.000000	1.810000	65.300000	1.795000	1330.000000
50%	19.300000	35.000000	6.320000	43.300000	9960.000000	5.390000	73.100000	2.410000	4660.000000
75%	62.100000	51.350000	8.600000	58.750000	22800.000000	10.750000	76.800000	3.880000	14050.000000
max	208.000000	200.000000	17.900000	174.000000	125000.000000	104.000000	82.800000	7.490000	105000.000000

Since the avg mean of the features have very large difference thus we need to scale the data. Also, features like 'child_mort', 'imports' , 'exports' , 'income' , 'gdpp' and 'inflation' have a significant rise in value after 75% percentile and max that signifies that these are right skewed. We need to transform these features first. 'country' is a Categorical Feature and needs to be encoded.

CHECK NULL VALUE

In [9]:

```
data.isnull().sum()
```

Out[9]:

```
country       0
child_mort    0
exports       0
health        0
imports       0
income        0
inflation     0
life_expec    0
total_fer     0
gdpp          0
dtype: int64
```

In [10]:

```
data.isna().sum()
```

Out[10]:

```
country       0
child_mort    0
exports       0
health        0
imports       0
income        0
inflation     0
life_expec    0
total_fer     0
gdpp          0
dtype: int64
```

There's no Null values in the dataset. So we can move forward to Data Visualization.

DATA VISUALIZATION

In [144]:

```
# colors = ['#DB1C18','#DBDB3B','#51A2DB']
# sns.set(palette=colors, font='Serif', style='white', rc={'axes.facecolor':'whitesmoke',
'figure.facecolor':'whitesmoke'})
country = data.country
numerical_cols = data.select_dtypes(exclude='object').columns
data2 = data[numerical_cols]
data2
```

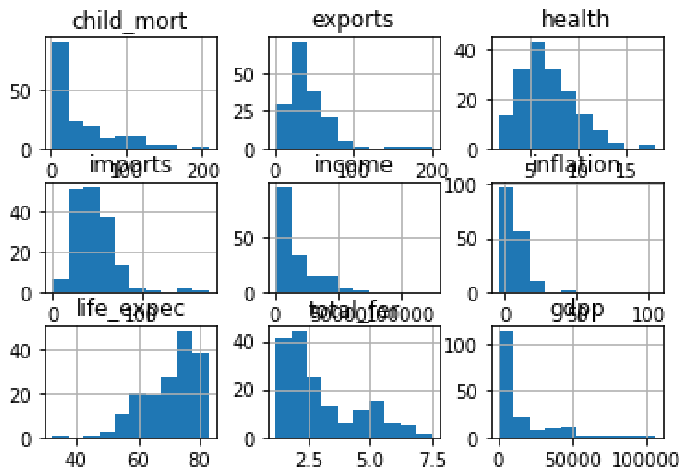
Out[144]:

	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
0	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	553
1	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	4090
2	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	4460
3	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	3530
4	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	12200
...	...	...	...	...	...	...	...	...	...
162	29.2	46.6	5.25	52.7	2950	2.62	63.0	3.50	2970
163	17.1	28.5	4.91	17.6	16500	45.90	75.4	2.47	13500
164	23.3	72.0	6.84	80.2	4490	12.10	73.1	1.95	1310
165	56.3	30.0	5.18	34.4	4480	23.60	67.5	4.67	1310
166	83.1	37.0	5.89	30.9	3280	14.00	52.0	5.40	1460

167 rows × 9 columns

In [12]:

```
# DATA DISTRIBUTION - HISTOGRAM
data2.hist()
plt.show()
```



As infered earlier features like 'child_mort', 'imports' , 'exports' , 'income' , 'gdpp' and 'inflation' heavily right skewed and need to be transformed.

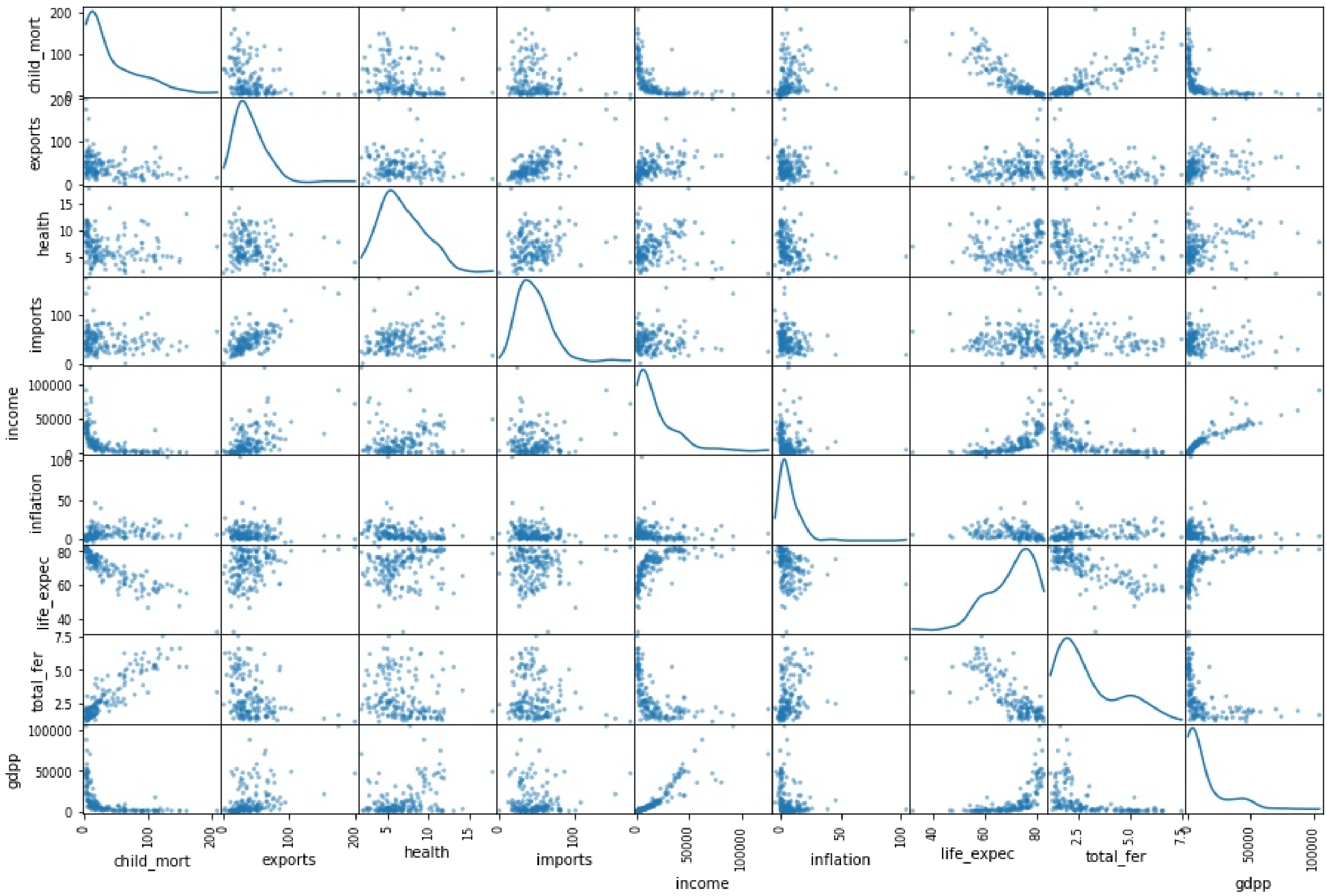
In [13]:

```
# SCATTER PLOT

# sns.pairplot(data, corner =True  )
# plt.show()
```

In [14]:

```
from pandas.plotting import scatter_matrix
scatter_matrix(data ,diagonal='kde' ,figsize=(15,10) )
plt.show()
```



In [15]:

```
#  BOXPLOT
# fig = plt.figure()
# fig.suptitle('Classifier Comparison')
# ax = fig.add_subplot(111)
# plt.boxplot(data2)
# # ax.set_xticklabels(country)
# plt.show()
```

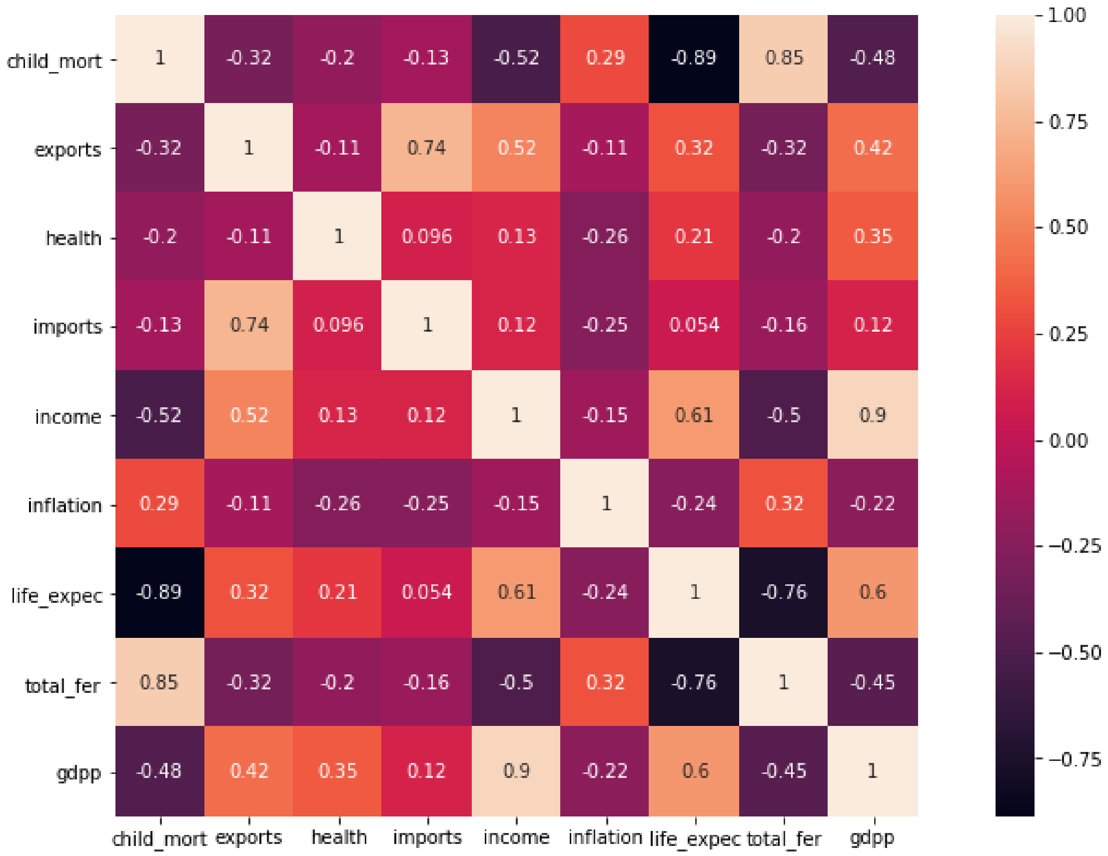
From the graph it is visible there are two cluster formation.
Some observation : 1) Child_mort, total_fer have negative correlation with gdpp.
2) Income has positive correlation with gdpp.
3) Child_mort and total_fer have a clear positive correlation.

In [16]:

```
# HEATMAP
fig=plt.figure(figsize=(15,8))
sns.heatmap(data.corr(), annot=True, square=True )
```

Out[16]:

```
<AxesSubplot:>
```



DATA TRANSFORM

In [145]:

```
# Transform features
for col in data2.columns:
    data2[col] = np.log(data2[[col]])

# MinMaxScaler
from sklearn.preprocessing import StandardScaler
# mm = StandardScaler()
# for col in data2.columns:
#     data2[col] = mm.fit_transform(data2[[col]])
df_scaled = StandardScaler().fit_transform(data.drop(['country'], axis=1))
```

```
<ipython-input-145-07b3fee602ce>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  data2[col] = np.log(data2[[col]])
```

In [146]:

```
pd.DataFrame(df_scaled , columns=numerical_cols)
```

Out[146]:

	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
0	1.291532	-1.138280	0.279088	-0.082455	-0.808245	0.157336	-1.619092	1.902882	-0.679180
1	-0.538949	-0.479658	-0.097016	0.070837	-0.375369	-0.312347	0.647866	-0.859973	-0.485623
2	-0.272833	-0.099122	-0.966073	-0.641762	-0.220844	0.789274	0.670423	-0.038404	-0.465376
3	2.007808	0.775381	-1.448071	-0.165315	-0.585043	1.387054	-1.179234	2.128151	-0.516268
4	-0.695634	0.160668	-0.286894	0.497568	0.101732	-0.601749	0.704258	-0.541946	-0.041817
...	...	...	...	...	...	...	...	...	...
162	-0.225578	0.200917	-0.571711	0.240700	-0.738527	-0.489784	-0.852161	0.365754	-0.546913
163	-0.526514	-0.461363	-0.695862	-1.213499	-0.033542	3.616865	0.546361	-0.316678	0.029323
164	-0.372315	1.130305	0.008877	1.380030	-0.658404	0.409732	0.286958	-0.661206	-0.637754
165	0.448417	-0.406478	-0.597272	-0.517472	-0.658924	1.500916	-0.344633	1.140944	-0.637754
166	1.114951	-0.150348	-0.338015	-0.662477	-0.721358	0.590015	-2.092785	1.624609	-0.629546

167 rows × 9 columns

DATA MODELING

Using PCA dimensional analysis lets see the cluster formation.

In [147]:

```
#  PCA

from sklearn.decomposition import PCA
# pca_list

PCA_model = PCA(svd_solver='auto')
PCA_model.fit(df_scaled)
```

Out[147]:

```
PCA()
```

In [148]:

```
#  EXPALINED VARIANCE RATIO OF AXIS
exp_variance = np.cumsum(np.round(PCA_model.explained_variance_ratio_ , 2))
print('\nThe EXPALINED VARIANC RATIO OF AXIS : \n',exp_variance)
```

```
The EXPALINED VARIANC RATIO OF AXIS :
 [0.46 0.63 0.76 0.87 0.94 0.96 0.97 0.98 0.99]
```

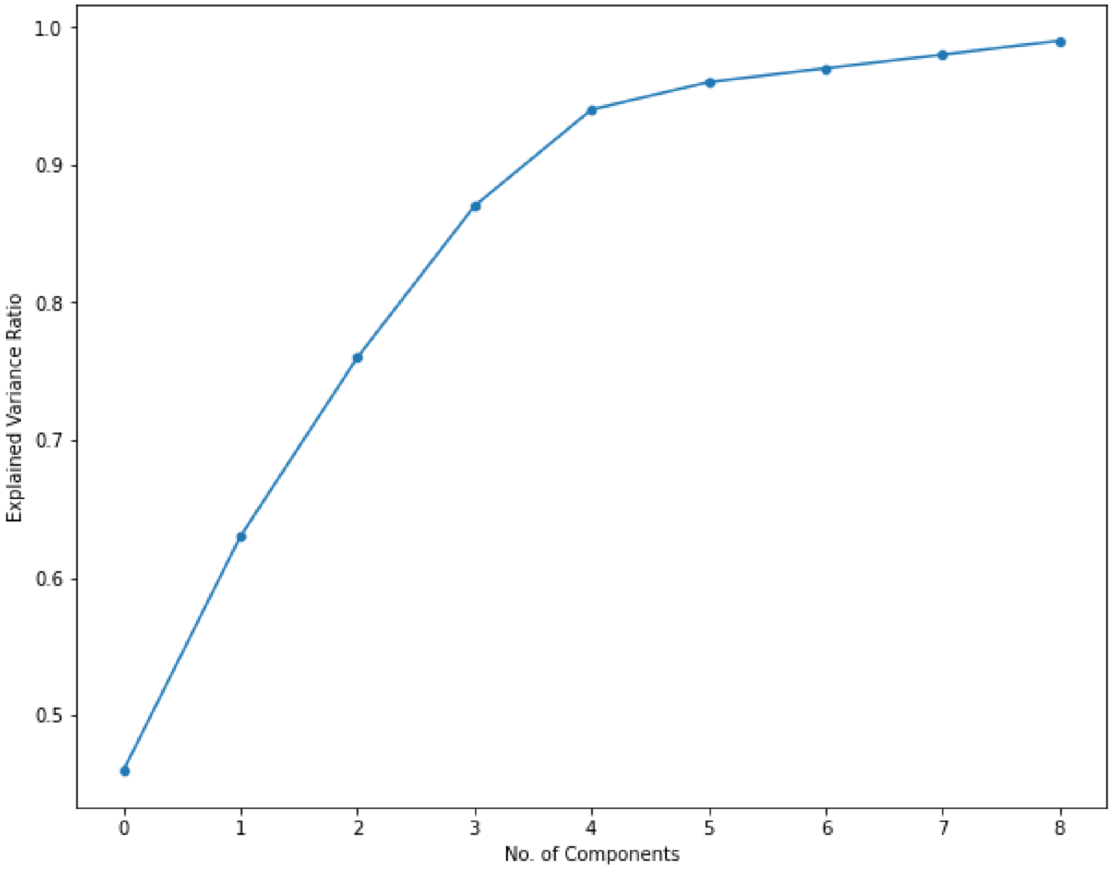
In [72]:

```
# PLOT

fig = plt.figure(figsize=(10,8))
ax = sns.lineplot(y=exp_variance , x=np.arange(0, len(exp_variance)))
ax = sns.scatterplot(y=exp_variance , x=np.arange(0, len(exp_variance)))
ax.set_xlabel('No. of Components')
ax.set_ylabel('Explained Variance Ratio')
```

Out[72]:

```
Text(0, 0.5, 'Explained Variance Ratio')
```

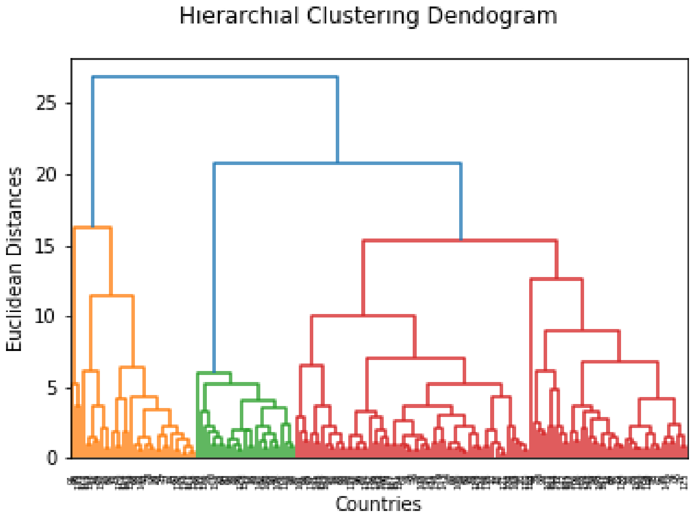


So, from the graph it is pretty evident that the Explained Variance deviation is not much between 3 to 5 and negligible after 5. Thus, we would be considering clusters of 3,4 and 5 in our model and check for the best results.

1) HIERARCHIAL CLUSTER

In [73]:

```
from scipy.cluster import hierarchy
Z= hierarchy.linkage(df_scaled , method='ward')
dendogram = hierarchy.dendrogram(Z)
plt.suptitle('Hierarchial Clustering Dendogram')
plt.xlabel('Countries')
plt.ylabel('Euclidean Distances')
plt.show()
```



For Hierarchial Clustering we can clearly see 3 distant cluster.

2) K MEANS

Running K Means in a loop for different K values from 1 to 10

In [77]:

```
from sklearn.cluster import KMeans
# Store the Inertia and model object for each K
km_list = list()

for k in range(1,10):
    km = KMeans(n_clusters= k , random_state=7)
    km.fit(df_scaled)

    km_list.append(pd.Series({
        'clusters' : k,
        'inertia' : km.inertia_,
        'model' : km
    }))
```

In [79]:

```
pd.DataFrame(km_list)
```

Out[79]:

	clusters	inertia	model
0	1	1503.000000	KMeans(n_clusters=1, random_state=7)
1	2	1050.214558	KMeans(n_clusters=2, random_state=7)
2	3	831.424435	KMeans(n_clusters=3, random_state=7)
3	4	700.322999	KMeans(n_clusters=4, random_state=7)
4	5	619.937115	KMeans(n_clusters=5, random_state=7)
5	6	550.712602	KMeans(n_clusters=6, random_state=7)
6	7	497.745863	KMeans(n_clusters=7, random_state=7)
7	8	468.982215	KMeans(random_state=7)
8	9	431.711094	KMeans(n_clusters=9, random_state=7)

PLOT Distortion Elbow Curve

In [92]:

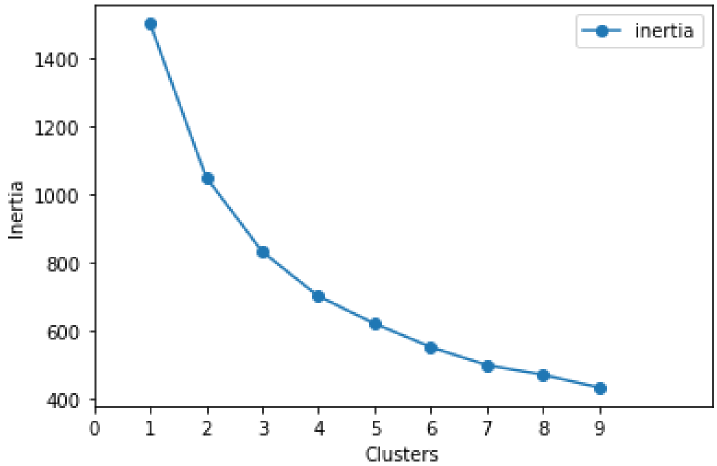
```
# Plot Inertia vs No.of Clusters

plot_data = (pd.concat(km_list, axis=1)
             .T[['clusters' , 'inertia']]
             .set_index('clusters') )

ax = plot_data.plot(marker = 'o' , ls='-')
ax.set_xticks(range(0 , 10 , 1))
ax.set_xlim(0 ,11)
ax.set(xlabel = 'Clusters' , ylabel='Inertia' )
```

Out[92]:

```
[Text(0.5, 0, 'Clusters'), Text(0, 0.5, 'Inertia')]
```



Even the Elbow Method for the KMeans clearly supports K=3 as a good choice for the our KMeans model for classification of models with relatively good distortion score(700.33).

KMeans K=3

In [149]:

```
#  Final Model

model  = KMeans(n_clusters=3 , random_state=1)
model.fit(df_scaled)

#  Store the Cluster Index into the DataFrame
data['KMeans_cluster'] = model.labels_
```

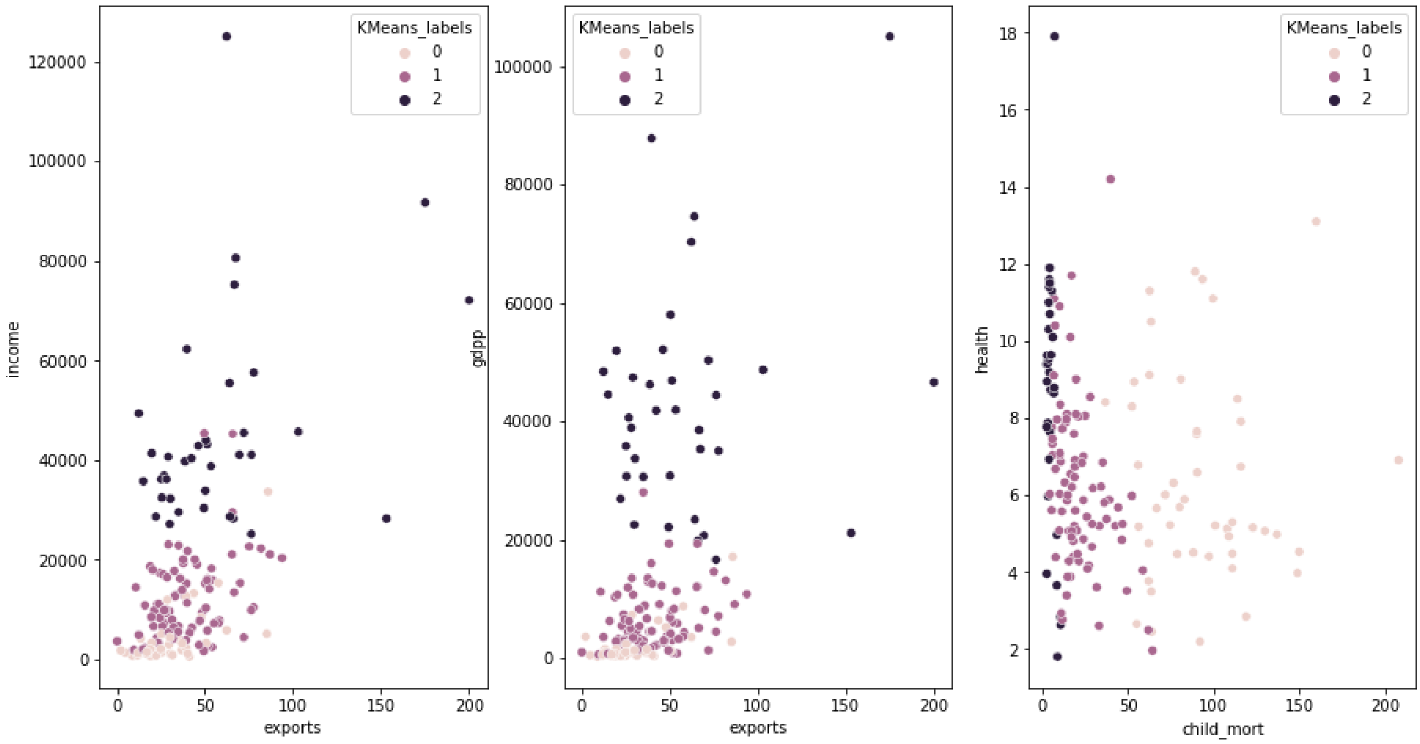
Clustering of our Countries

In [120]:

```
fig,ax=plt.subplots(nrows=1,ncols=3,figsize=(15,8))
sns.scatterplot(data=data, x='exports', y='income',hue='KMeans_cluster', ax=ax[0])
sns.scatterplot(data=data, x='exports', y='gdpp',hue='KMeans_cluster', ax=ax[1])
sns.scatterplot(data=data, x='child_mort', y='health', hue='KMeans_cluster', ax=ax[2])
```

Out[120]:

```
<AxesSubplot:xlabel='child_mort', ylabel='health'>
```



Analyze the Clusters

Need to decide the labels for the cluster well suitung the clusters so any country can easily be understood as developed or not or needs help or not.

In [127]:

```
data.groupby('KMeans_cluster').mean()
```

Out[127]:

	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
KMeans_labels									
0	92.961702	29.151277	6.388511	42.323404	3942.404255	12.019681	59.187234	5.008085	1922.382979
1	21.927381	40.243917	6.200952	47.473404	12305.595238	7.600905	72.814286	2.307500	6486.452381
2	5.000000	58.738889	8.807778	51.491667	45672.222222	2.671250	80.127778	1.752778	42494.444444

In [134]:

```
data.groupby(['KMeans_cluster' , 'country']).mean()
```

Out[134]:

		child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
KMeans_labels	**country**									
0	**Afghanistan**	90.2	10.0	7.58	44.9	1610	9.440	56.2	5.82	553
	Angola	119.0	62.3	2.85	42.9	5900	22.400	60.1	6.16	3530
	Benin	111.0	23.8	4.10	37.2	1820	0.885	61.8	5.36	758
	Botswana	52.5	43.6	8.30	51.3	13300	8.920	57.1	2.88	6350
	Burkina Faso	116.0	19.2	6.74	29.6	1430	6.810	57.9	5.87	575
...	**...**	...	...	...	...	...	...	...	...	...
2	**Sweden**	3.0	46.2	9.63	40.7	42900	0.991	81.5	1.98	52100
	Switzerland	4.5	64.0	11.50	53.3	55500	0.317	82.2	1.52	74600
	United Arab Emirates	8.6	77.7	3.66	63.6	57600	12.500	76.5	1.87	35000
	United Kingdom	5.2	28.2	9.64	30.8	36200	1.570	80.3	1.92	38900
	United States	7.3	12.4	17.90	15.8	49400	1.220	78.7	1.93	48400

167 rows × 9 columns

After analyzing the above tables I have decided the labels for each cluster in our dataset as:
0 : Need Help / Underdeveloped
1 : Might Need Help / Developing
2 : Donot Need Help / Developed

In [150]:

```
label = {0 : 'Need Help',
         1 : 'Might Need Help',
         2 : 'Donot Need Help'
        }

data['KMeans_labels'] = data['KMeans_cluster'].map(label)

# Number of Countries in each Cluster
data['KMeans_labels'].value_counts()
```

Out[150]:

```
Might Need Help    84
Need Help          47
Donot Need Help    36
Name: KMeans_labels, dtype: int64
```

There are 47 countries that need help , 84 countires that might need help and 36 countries that doesnit need help.

In [136]:

```
from sklearn.metrics import silhouette_score
silhouette_score(df_scaled,labels=model.labels_)
```

Out[136]:

```
0.28329575683463126
```

PREDICTIONS

The data has been successfully classified into 3 groups: 'Need Help' , 'Might Need Help' and 'Donot Need Help'.

Example listing all the countries need help:

In [138]:

```
data[data['KMeans_labels'] == 'Need Help']['country']
```

Out[138]:

```
0                   Afghanistan
3                        Angola
17                        Benin
21                     Botswana
25                 Burkina Faso
26                      Burundi
28                     Cameroon
31     Central African Republic
32                         Chad
36                      Comoros
37             Congo, Dem. Rep.
38                  Congo, Rep.
40                Cote d'Ivoire
49            Equatorial Guinea
50                      Eritrea
55                        Gabon
56                       Gambia
59                        Ghana
63                       Guinea
64                Guinea-Bissau
66                        Haiti
72                         Iraq
80                        Kenya
81                     Kiribati
84                          Lao
87                      Lesotho
88                      Liberia
93                   Madagascar
94                       Malawi
97                         Mali
99                   Mauritania
106                  Mozambique
108                     Namibia
112                       Niger
113                     Nigeria
116                    Pakistan
126                      Rwanda
129                     Senegal
132                Sierra Leone
137                South Africa
142                       Sudan
147                    Tanzania
149                 Timor-Leste
150                        Togo
155                      Uganda
165                       Yemen
166                      Zambia
Name: country, dtype: object
```

CONCLUSION

I have successfully classified all the countries into **'Need Help'** , **'Might Need Help'** and **'Donot Need Help'**.

1. Most of the American and European Countries may not need help.
2. Most of the African countries and Middle Eastern countries like Iraq, Yemen , Afghanisthan , Pakisthan requires help.
3. Most of the remaining Asian Countries Might require help, lying in between the two classes.

Thus, this completes my analysis with a KMeans Model of K=3 having distortion score(700.33) for classifying our Country.csv dataset.

IMPROVEMENTS :

Here I haven't considered other Unsupervised Models like Mean Shift and DBSCAN. Also only have been considered PCA for Dimensional Reduction could have improved by Kernel PCA or MDS. Also, for data transformation haven't tried other methods like boxcox for normalizing the skewed features.