ML Project Country Clustering

Problem Statement

HELP International have been able to raise around $ 10 million. Now the CEO of the NGO needs to decide how to use this money strategically and effectively. So, CEO has to make decision to choose the countries that are in the direst need of aid. Hence, your Job as a Data scientist is to categorise the countries using some socio-economic and health factors that determine the overall development of the country.

Exploratory data analysis

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings as wn
wn.filterwarnings('ignore')
```

In [2]:
```
df = pd.read_csv('Country-data.csv')
dd = pd.read_csv('data-dictionary.csv')
```

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

Out[3]:

	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

In [4]:
```
pd.set_option('display.max_colwidth', -1)
dd.head(10)
```

Out[4]:

	Column Name	Description
0	country	Name of the country
1	child_mort	Death of children under 5 years of age per 1000 live births
2	exports	Exports of goods and services per capita. Given as %age of the GDP per capita
3	health	Total health spending per capita. Given as %age of GDP per capita
4	imports	Imports of goods and services per capita. Given as %age of the GDP per capita
5	Income	Net income per person
6	Inflation	The measurement of the annual growth rate of the Total GDP
7	life_expec	The average number of years a new born child would live if the current mortality patterns are to remain the same
8	total_fer	The number of children that would be born to each woman if the current age-fertility rates remain the same.
9	gdpp	The GDP per capita. Calculated as the Total GDP divided by the total population.

In [5]:
```
df.duplicated().sum()
```

Out[5]:
```
0
```

- **There are no Duplicated Values in the Dataset.**

In [6]:
```
df.isnull().sum()
```

Out[6]:
```
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 are No Null Values in the Dataset at all.

In [7]:
```
df.shape
```

Out[7]:
```
(167, 10)
```

In [8]:
```
df_cpy = df
```

In [9]:
```
df= df.drop(columns='country')
```

In [10]:
```
df.head()
```

Out[10]:

	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

In [11]:
```
df_cpy.sort_values('child_mort',ascending=False).head(10)
```

Out[11]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
66	Haiti	208.0	15.3	6.91	64.7	1500	5.45	32.1	3.33	662
132	Sierra Leone	160.0	16.8	13.10	34.5	1220	17.20	55.0	5.20	399
32	Chad	150.0	36.8	4.53	43.5	1930	6.39	56.5	6.59	897
31	Central African Republic	149.0	11.8	3.98	26.5	888	2.01	47.5	5.21	446
97	Mali	137.0	22.8	4.98	35.1	1870	4.37	59.5	6.55	708
113	Nigeria	130.0	25.3	5.07	17.4	5150	104.00	60.5	5.84	2330
112	Niger	123.0	22.2	5.16	49.1	814	2.55	58.8	7.49	348
3	Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	3530
25	Burkina Faso	116.0	19.2	6.74	29.6	1430	6.81	57.9	5.87	575
37	Congo, Dem. Rep.	116.0	41.1	7.91	49.6	609	20.80	57.5	6.54	334

- These Are the Top 10 Countries Having Very High Child Mortality Rate.Which Is Not Good for a Good Country.

In [12]:
```
df_cpy.sort_values('gdpp',ascending=True).head(10)
```

Out[12]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
26	Burundi	93.6	8.92	11.60	39.2	764	12.30	57.7	6.26	231
88	Liberia	89.3	19.10	11.80	92.6	700	5.47	60.8	5.02	327
37	Congo, Dem. Rep.	116.0	41.10	7.91	49.6	609	20.80	57.5	6.54	334
112	Niger	123.0	22.20	5.16	49.1	814	2.55	58.8	7.49	348
132	Sierra Leone	160.0	16.80	13.10	34.5	1220	17.20	55.0	5.20	399
93	Madagascar	62.2	25.00	3.77	43.0	1390	8.79	60.8	4.60	413
106	Mozambique	101.0	31.50	5.21	46.2	918	7.64	54.5	5.56	419
31	Central African Republic	149.0	11.80	3.98	26.5	888	2.01	47.5	5.21	446
94	Malawi	90.5	22.80	6.59	34.9	1030	12.10	53.1	5.31	459
50	Eritrea	55.2	4.79	2.66	23.3	1420	11.60	61.7	4.61	482

- These are 10 Countries Having lowest GDPP.

In [13]:
```
df_cpy.sort_values('inflation',ascending=False).head(10)
```

Out[13]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
113	Nigeria	130.0	25.3	5.07	17.4	5150	104.0	60.5	5.84	2330
163	Venezuela	17.1	28.5	4.91	17.6	16500	45.9	75.4	2.47	13500
103	Mongolia	26.1	46.7	5.44	56.7	7710	39.2	66.2	2.64	2650
149	Timor-Leste	62.6	2.2	9.12	27.8	1850	26.5	71.1	6.23	3600
49	Equatorial Guinea	111.0	85.8	4.48	58.9	33700	24.9	60.9	5.21	17100
165	Yemen	56.3	30.0	5.18	34.4	4480	23.6	67.5	4.67	1310
140	Sri Lanka	11.2	19.6	2.94	26.8	8560	22.8	74.4	2.20	2810
3	Angola	119.0	62.3	2.85	42.9	5900	22.4	60.1	6.16	3530
5	Argentina	14.5	18.9	8.10	16.0	18700	20.9	75.8	2.37	10300
37	Congo, Dem. Rep.	116.0	41.1	7.91	49.6	609	20.8	57.5	6.54	334

- **The List of 10 Countries Having High Inflation Rate.**

In [14]:
```
df_cpy.sort_values('health',ascending=True).head(5)
```

Out[14]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
123	Qatar	9.0	62.300	1.81	23.8000	125000	6.98	79.5	2.07	70300
107	Myanmar	64.4	0.109	1.97	0.0659	3720	7.04	66.8	2.41	988
116	Pakistan	92.1	13.500	2.20	19.4000	4280	10.90	65.3	3.85	1040
38	Congo, Rep.	63.9	85.100	2.46	54.7000	5190	20.70	60.4	4.95	2740
154	Turkmenistan	62.0	76.300	2.50	44.5000	9940	2.31	67.9	2.83	4440

- **Here we can see that health is given as percentage of gdpp so this sorting did not judge accurate health wise report so finding health expenditure in next cell.**

In [15]:
```
df_cpy.health = ((df_cpy.health*df_cpy.gdpp)/100)
```

In [16]:
```
df_cpy.sort_values('health',ascending=True).head(10)
```

Out[16]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
50	Eritrea	55.2	4.790	12.8212	23.3000	1420	11.60	61.7	4.61	482
93	Madagascar	62.2	25.000	15.5701	43.0000	1390	8.79	60.8	4.60	413
31	Central African Republic	149.0	11.800	17.7508	26.5000	888	2.01	47.5	5.21	446
112	Niger	123.0	22.200	17.9568	49.1000	814	2.55	58.8	7.49	348
107	Myanmar	64.4	0.109	19.4636	0.0659	3720	7.04	66.8	2.41	988
106	Mozambique	101.0	31.500	21.8299	46.2000	918	7.64	54.5	5.56	419
116	Pakistan	92.1	13.500	22.8800	19.4000	4280	10.90	65.3	3.85	1040
37	Congo, Dem. Rep.	116.0	41.100	26.4194	49.6000	609	20.80	57.5	6.54	334
12	Bangladesh	49.4	16.000	26.6816	21.8000	2440	7.14	70.4	2.33	758
26	Burundi	93.6	8.920	26.7960	39.2000	764	12.30	57.7	6.26	231

- **These are 10 Countries lacking in Health.**

In [17]:
```
df_cpy.exports = ((df_cpy.exports*df_cpy.gdpp)/100)
df_cpy.imports = ((df_cpy.imports*df_cpy.gdpp)/100)
```

In [18]:
```
List = df_cpy.imports>df_cpy.exports
Impgtexp=[]
Howgreater=[]
for i in range(0,167):
    if (List[i]):
        Impgtexp.append(df_cpy.country[i])
        Howgreater.append(df_cpy.imports[i]-df_cpy.exports[i])
D={'Country Name':Impgtexp,'HowMuchGreater':Howgreater}
IED = pd.DataFrame(data=D)
IED=IED.sort_values(by=['HowMuchGreater'],ascending=False)
pd.set_option('display.max_rows', 200)
IED.head(20)
```

Out[18]:

	Country Name	HowMuchGreater
5	Bahamas	2436.00
39	Greece	2313.40
28	Cyprus	2248.40
55	Lebanon	2161.84
91	St. Vincent and the Grenadines	1881.46
40	Grenada	1871.98
69	Montenegro	1716.76
96	Tonga	1700.45
79	Portugal	1687.50
102	United States	1645.60
66	Micronesia, Fed. Sts.	1644.50
2	Antigua and Barbuda	1634.80
85	Seychelles	1533.60
7	Barbados	1472.00
101	United Kingdom	1011.40
11	Bosnia and Herzegovina	995.76
51	Kiribati	992.34
20	Cape Verde	963.21
94	Timor-Leste	921.60
19	Canada	900.60

- **20 Countries Having Imports greater than Exports that leads to bad Country Economy.**

In [19]:
```
df_cpy.sort_values('imports',ascending=False).head(10)
```

Out[19]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
91	Luxembourg	2.8	183750.0	8158.50	149100.0	91700	3.620	81.3	1.63	105000
133	Singapore	2.8	93200.0	1845.36	81084.0	72100	-0.046	82.7	1.15	46600
73	Ireland	4.2	50161.0	4475.53	42125.5	45700	-3.220	80.4	2.05	48700
145	Switzerland	4.5	47744.0	8579.00	39761.8	55500	0.317	82.2	1.52	74600
15	Belgium	4.5	33921.6	4750.80	33166.8	41100	1.880	80.0	1.86	44400
98	Malta	6.8	32283.0	1825.15	32494.0	28300	3.830	80.3	1.36	21100
110	Netherlands	4.5	36216.0	5985.70	31990.8	45500	0.848	80.7	1.79	50300
44	Denmark	4.1	29290.0	6612.00	25288.0	44000	3.220	79.5	1.87	58000
114	Norway	3.2	34856.6	8323.44	25023.0	62300	5.950	81.0	1.95	87800
8	Austria	4.3	24059.7	5159.00	22418.2	43200	0.873	80.5	1.44	46900

- **10 Countries Having highest Exports.**

In [20]:
```
df_cpy.sort_values('exports',ascending=True).head(10)
```

Out[20]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
107	Myanmar	64.4	1.07692	19.4636	0.651092	3720	7.04	66.8	2.41	988
26	Burundi	93.6	20.60520	26.7960	90.552000	764	12.30	57.7	6.26	231
50	Eritrea	55.2	23.08780	12.8212	112.306000	1420	11.60	61.7	4.61	482
31	Central African Republic	149.0	52.62800	17.7508	118.190000	888	2.01	47.5	5.21	446
0	Afghanistan	90.2	55.30000	41.9174	248.297000	1610	9.44	56.2	5.82	553
109	Nepal	47.0	56.71360	31.0800	215.488000	1990	15.10	68.3	2.61	592
88	Liberia	89.3	62.45700	38.5860	302.802000	700	5.47	60.8	5.02	327
132	Sierra Leone	160.0	67.03200	52.2690	137.655000	1220	17.20	55.0	5.20	399
126	Rwanda	63.6	67.56000	59.1150	168.900000	1350	2.61	64.6	4.51	563
112	Niger	123.0	77.25600	17.9568	170.868000	814	2.55	58.8	7.49	348

- **10 Countries Having lowest exports.**

In [21]:
```
df_cpy.sort_values('life_expec',ascending=True).head(10)
```

Out[21]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
66	Haiti	208.0	101.286	45.7442	428.314	1500	5.45	32.1	3.33	662
87	Lesotho	99.7	460.980	129.8700	1181.700	2380	4.15	46.5	3.30	1170
31	Central African Republic	149.0	52.628	17.7508	118.190	888	2.01	47.5	5.21	446
166	Zambia	83.1	540.200	85.9940	451.140	3280	14.00	52.0	5.40	1460
94	Malawi	90.5	104.652	30.2481	160.191	1030	12.10	53.1	5.31	459
137	South Africa	53.7	2082.080	650.8320	1994.720	12000	6.35	54.3	2.59	7280
106	Mozambique	101.0	131.985	21.8299	193.578	918	7.64	54.5	5.56	419
132	Sierra Leone	160.0	67.032	52.2690	137.655	1220	17.20	55.0	5.20	399
64	Guinea-Bissau	114.0	81.503	46.4950	192.544	1390	2.97	55.6	5.05	547
0	Afghanistan	90.2	55.300	41.9174	248.297	1610	9.44	56.2	5.82	553

- 10 Countries In which Life Expectancy is Lowest

In [22]:
```
df_cpy.sort_values('total_fer',ascending=False).head(10)
```

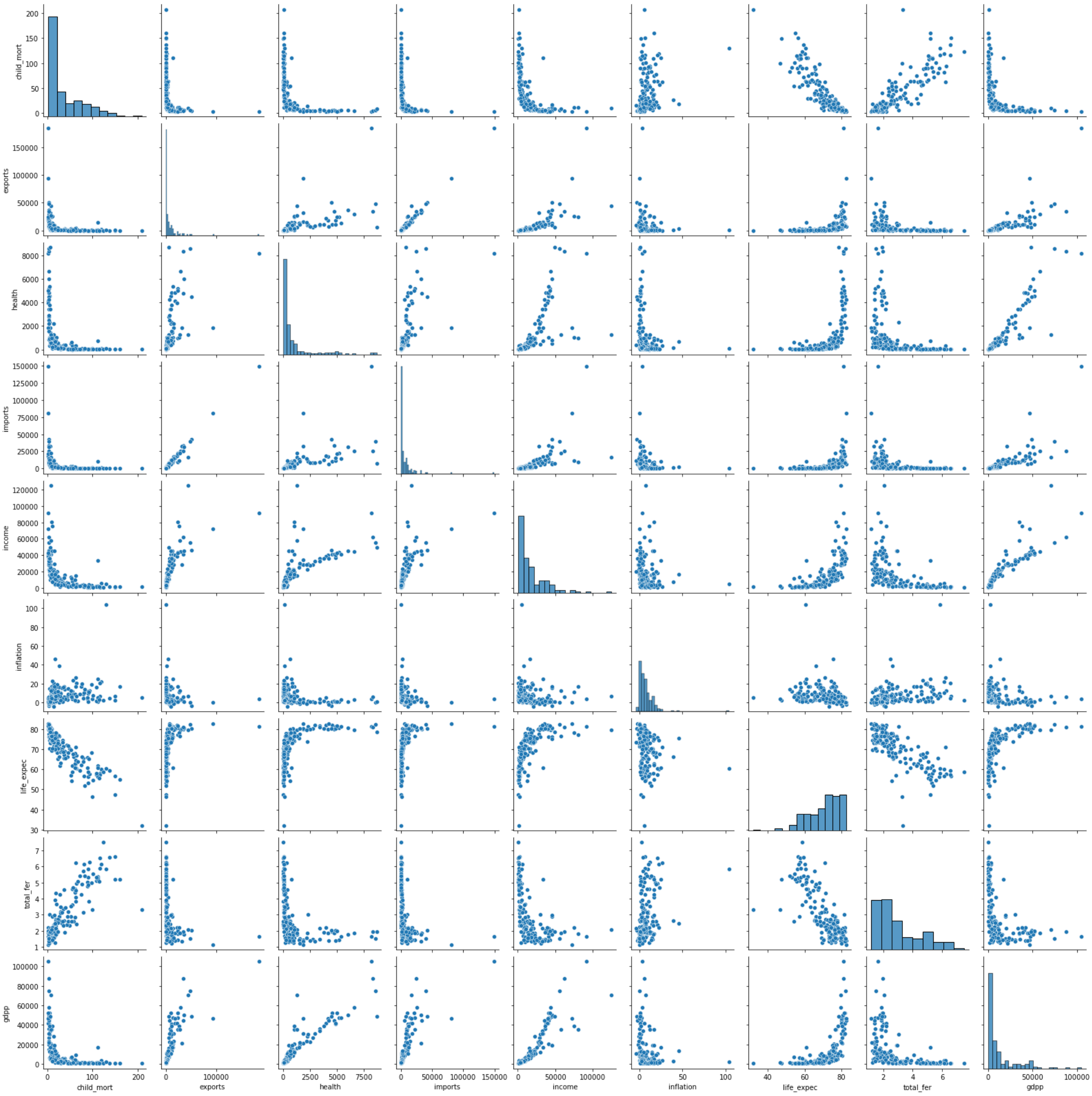
Out[22]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
112	Niger	123.0	77.2560	17.9568	170.868	814	2.55	58.8	7.49	348
32	Chad	150.0	330.0960	40.6341	390.195	1930	6.39	56.5	6.59	897
97	Mali	137.0	161.4240	35.2584	248.508	1870	4.37	59.5	6.55	708
37	Congo, Dem. Rep.	116.0	137.2740	26.4194	165.664	609	20.80	57.5	6.54	334
26	Burundi	93.6	20.6052	26.7960	90.552	764	12.30	57.7	6.26	231
149	Timor-Leste	62.6	79.2000	328.3200	1000.800	1850	26.50	71.1	6.23	3600
3	Angola	119.0	2199.1900	100.6050	1514.370	5900	22.40	60.1	6.16	3530
155	Uganda	81.0	101.7450	53.6095	170.170	1540	10.60	56.8	6.15	595
25	Burkina Faso	116.0	110.4000	38.7550	170.200	1430	6.81	57.9	5.87	575
113	Nigeria	130.0	589.4900	118.1310	405.420	5150	104.00	60.5	5.84	2330

- Top 10 Countries in which Total Fertility Rate is Highest.

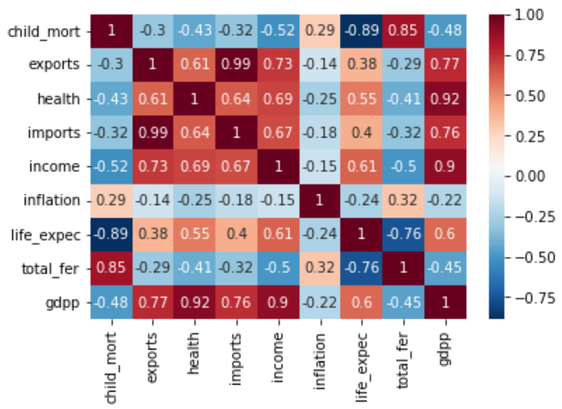
In [23]:
```
df = df_cpy.drop(columns='country')
```

In [24]:
```
sns.pairplot(data=df)
plt.show()
```



- **Checking Corelation**

In [25]:
```
sns.heatmap(data=df.corr(),cmap='RdBu_r', annot=True)
plt.show()
```



	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
child_mort	1	-0.3	-0.43	-0.32	-0.52	0.29	-0.89	0.85	-0.48
exports	-0.3	1	0.61	0.99	0.73	-0.14	0.38	-0.29	0.77
health	-0.43	0.61	1	0.64	0.69	-0.25	0.55	-0.41	0.92
imports	-0.32	0.99	0.64	1	0.67	-0.18	0.4	-0.32	0.76
income	-0.52	0.73	0.69	0.67	1	-0.15	0.61	-0.5	0.9
inflation	0.29	-0.14	-0.25	-0.18	-0.15	1	-0.24	0.32	-0.22
life_expec	-0.89	0.38	0.55	0.4	0.61	-0.24	1	-0.76	0.6
total_fer	0.85	-0.29	-0.41	-0.32	-0.5	0.32	-0.76	1	-0.45
gdpp	-0.48	0.77	0.92	0.76	0.9	-0.22	0.6	-0.45	1

There is Highest Correlation is betweeen

- health and gdpp which is 0.95
- income and gdpp which is 0.9
- child mortality and total Fertality Which is 0.85
- exports and gdpp Which is 0.77.

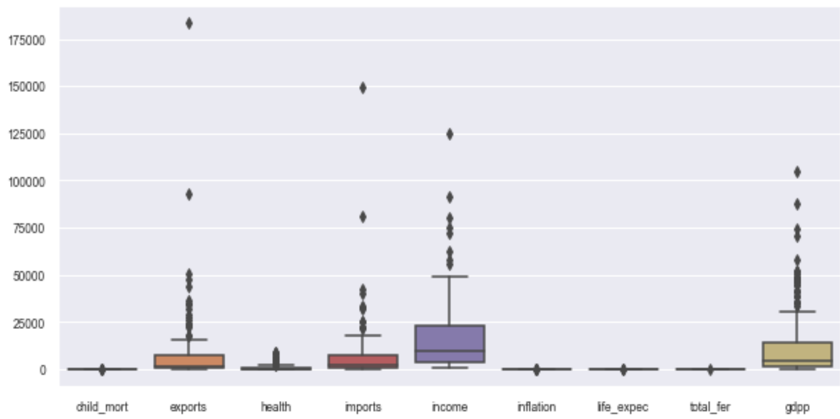
In [26]:
```
df.describe()
```

Out[26]:

	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	7420.618847	1056.733204	6588.352108	17144.688623	7.781832	70.555689	2.947964	12964.155689
std	40.328931	17973.885795	1801.408906	14710.810418	19278.067698	10.570704	8.893172	1.513848	18328.704809
min	2.600000	1.076920	12.821200	0.651092	609.000000	-4.210000	32.100000	1.150000	231.000000
25%	8.250000	447.140000	78.535500	640.215000	3355.000000	1.810000	65.300000	1.795000	1330.000000
50%	19.300000	1777.440000	321.886000	2045.580000	9960.000000	5.390000	73.100000	2.410000	4660.000000
75%	62.100000	7278.000000	976.940000	7719.600000	22800.000000	10.750000	76.800000	3.880000	14050.000000
max	208.000000	183750.000000	8663.600000	149100.000000	125000.000000	104.000000	82.800000	7.490000	105000.000000

- **There May be Outliers Present in Exports Imports Income and GDPP**

In [27]:
```
sns.set(rc={'figure.figsize':(10,5)}, font_scale=.75)
sns.boxplot(data=df,orient='v')
plt.show()
```



- **There are Outliers Present in Exports Gdpp and Income to large Extent. and in Health and Imports are there but very Less.**

Creating Model - K Means

In [28]:
```
from sklearn.preprocessing import MinMaxScaler
import warnings
warnings.filterwarnings('ignore')
```

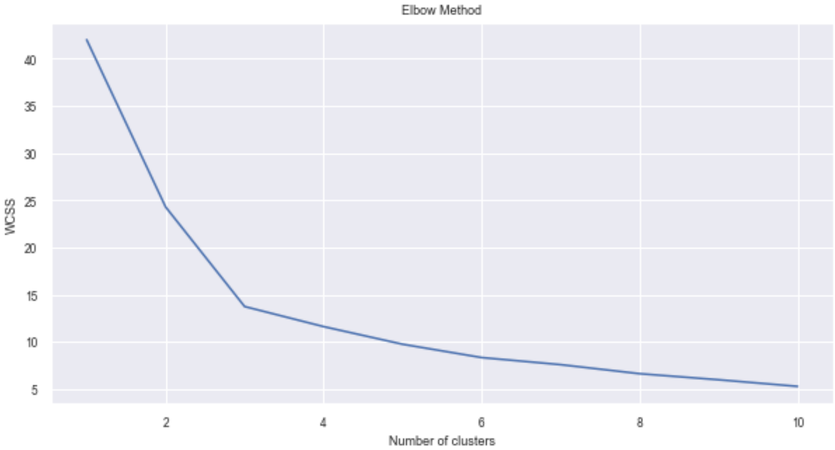
- **I Have Applied Standard Scaler also but that is giving Final Model Score less as compared to Min Max Scaler**

In [29]:
```
scaler = MinMaxScaler()
x = scaler.fit_transform(df)
```

In [30]:
```
# Saving Data for Hierchical Clustering
x2 = x
```

In [31]:
```
from sklearn.cluster import KMeans
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', random_state=42)
    kmeans.fit(x)
    wcss.append(kmeans.inertia_)

plt.plot(range(1, 11), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



- From The Elbow Curve Above We Choose the Number of cluster to be 3 In this Case

In [32]:
```
kmeans = KMeans(n_clusters=3, init='k-means++', random_state=42)
kmeans.fit(x)
clusters = kmeans.predict(x)
```

In [33]:
```
clusters
```

Out[33]:
```
array([1, 0, 0, 1, 0, 0, 0, 2, 2, 0, 0, 0, 0, 0, 0, 2, 0, 1, 0, 0, 0, 0,
       0, 2, 0, 1, 1, 0, 1, 2, 0, 1, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0,
       2, 0, 0, 0, 0, 1, 1, 0, 0, 2, 2, 1, 1, 0, 2, 1, 0, 0, 0, 1, 1, 0,
       1, 0, 2, 0, 0, 0, 1, 2, 0, 2, 0, 2, 0, 0, 1, 1, 2, 0, 1, 0, 0, 1,
       1, 0, 0, 2, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0,
       2, 2, 1, 1, 2, 0, 1, 0, 0, 0, 0, 0, 0, 2, 0, 0, 1, 0, 0, 1, 0, 0,
       1, 2, 0, 0, 1, 0, 0, 2, 0, 0, 1, 0, 2, 2, 0, 1, 0, 1, 1, 0, 0, 0,
       0, 1, 0, 2, 2, 2, 0, 0, 0, 0, 0, 1, 1])
```

- These are the clusters Assigned to all countries.Now we add This to our dataset.

In [34]:
```
df_cpy['cluster']=clusters
```

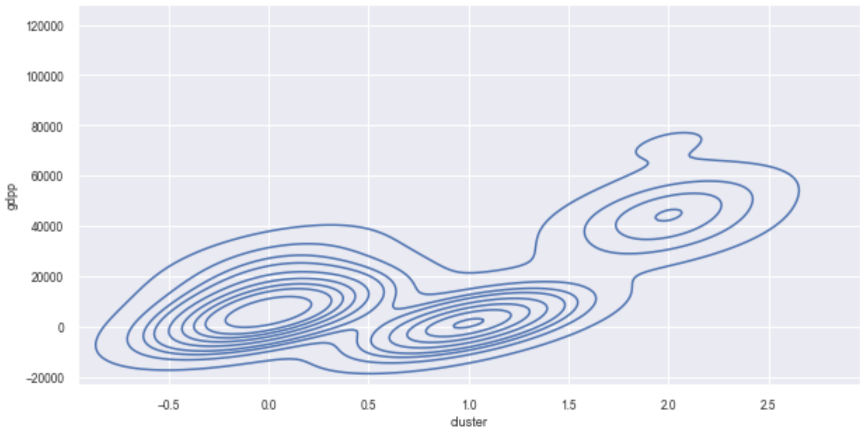
In [35]:
```
df_cpy.head(5)
```

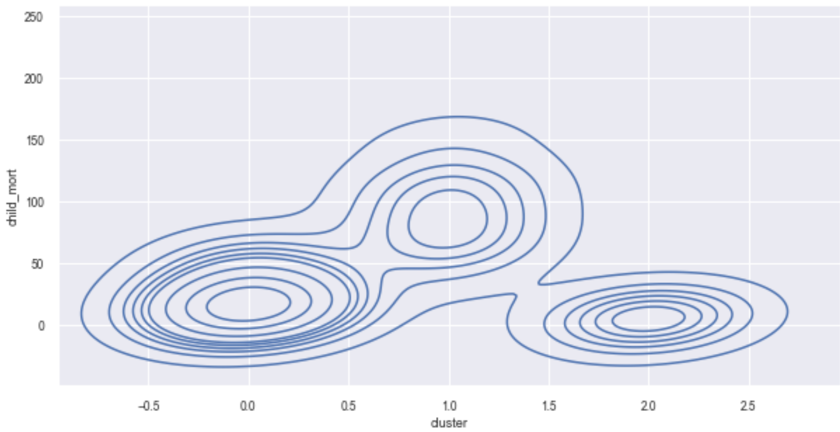
Out[35]:

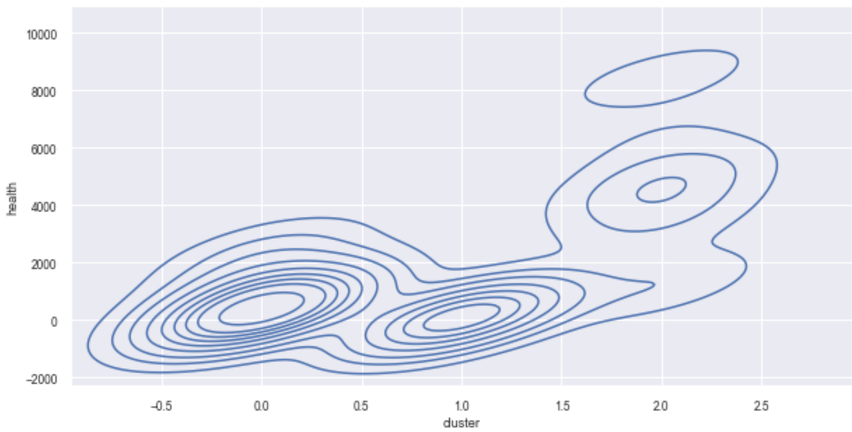
	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp	cluster
0	Afghanistan	90.2	55.30	41.9174	248.297	1610	9.44	56.2	5.82	553	1
1	Albania	16.6	1145.20	267.8950	1987.740	9930	4.49	76.3	1.65	4090	0
2	Algeria	27.3	1712.64	185.9820	1400.440	12900	16.10	76.5	2.89	4460	0
3	Angola	119.0	2199.19	100.6050	1514.370	5900	22.40	60.1	6.16	3530	1
4	Antigua and Barbuda	10.3	5551.00	735.6600	7185.800	19100	1.44	76.8	2.13	12200	0

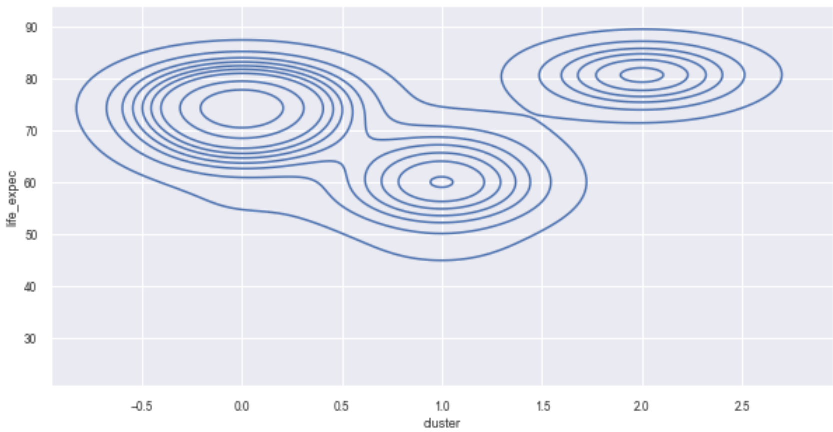
Visualizing Clusters Graphically

In [36]:
```
sns.kdeplot(x=df_cpy.cluster,y=df_cpy.gdpp)
plt.show()
sns.kdeplot(x=df_cpy.cluster,y=df_cpy.child_mort)
plt.show()
sns.kdeplot(x=df_cpy.cluster,y=df_cpy.health)
plt.show()
sns.kdeplot(x=df_cpy.cluster,y=df_cpy.life_expec)
plt.show()
```





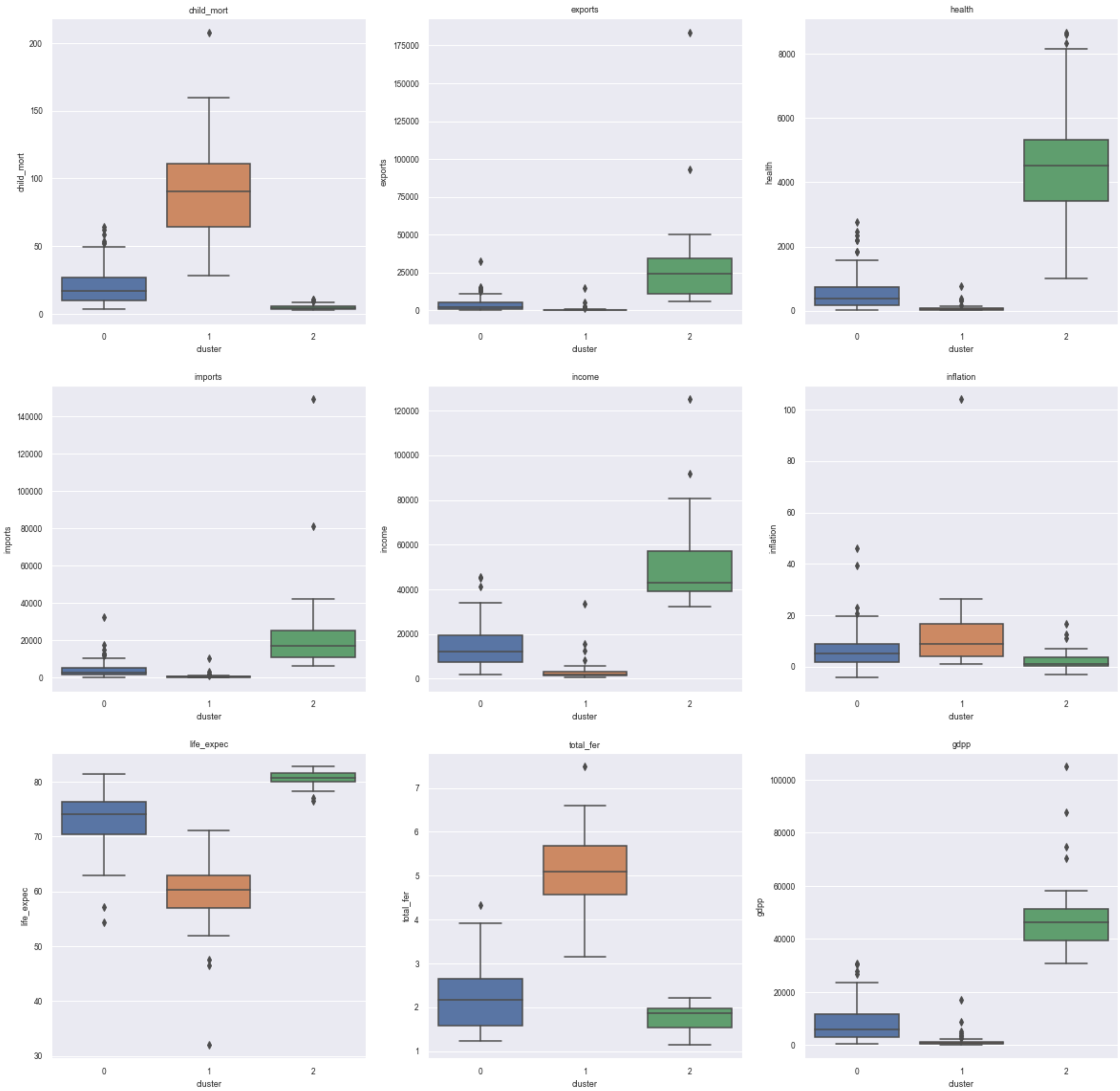




- **Now We analyse The Clusters on the basis of the features we have chosed in eda for selection of countries.**

In [37]:

```
import seaborn as sns
l=['child_mort', 'exports', 'health', 'imports', 'income',
       'inflation', 'life_expec', 'total_fer', 'gdpp']
plt.figure(figsize=(20,20))
for i in range(len(l)):
    plt.subplot(3,3,i+1)
    sns.boxplot(df_cpy.cluster,df_cpy[l[i]])
    plt.title(l[i])
```



As We can See from the boxplots Above that the countries in **Cluster 1** Having

1.Less GDPP

2.High Child Mort

3.High Total Fertility Rate Which Leads to More Population

4.Less Life Expectancy

5.High Inflation

6.Very Less Income

7.Very Less Exports

8.Very Less expenditure on Health

- So these are the Countries Definitely Need to be Focused By The Ngo.

In [38]:
```
Lowest_countries= df_cpy[df_cpy['cluster']==1]
```

In [39]:
```
Lowest_countries
```

Out[39]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp	cluster
0	Afghanistan	90.2	55.3000	41.9174	248.297	1610	9.440	56.2	5.82	553	1
3	Angola	119.0	2199.1900	100.6050	1514.370	5900	22.400	60.1	6.16	3530	1
17	Benin	111.0	180.4040	31.0780	281.976	1820	0.885	61.8	5.36	758	1
25	Burkina Faso	116.0	110.4000	38.7550	170.200	1430	6.810	57.9	5.87	575	1
26	Burundi	93.6	20.6052	26.7960	90.552	764	12.300	57.7	6.26	231	1
28	Cameroon	108.0	290.8200	67.2030	353.700	2660	1.910	57.3	5.11	1310	1
31	Central African Republic	149.0	52.6280	17.7508	118.190	888	2.010	47.5	5.21	446	1
32	Chad	150.0	330.0960	40.6341	390.195	1930	6.390	56.5	6.59	897	1
36	Comoros	88.2	126.8850	34.6819	397.573	1410	3.870	65.9	4.75	769	1
37	Congo, Dem. Rep.	116.0	137.2740	26.4194	165.664	609	20.800	57.5	6.54	334	1
38	Congo, Rep.	63.9	2331.7400	67.4040	1498.780	5190	20.700	60.4	4.95	2740	1
40	Cote d'Ivoire	111.0	617.3200	64.6600	528.260	2690	5.390	56.3	5.27	1220	1
49	Equatorial Guinea	111.0	14671.8000	766.0800	10071.900	33700	24.900	60.9	5.21	17100	1
50	Eritrea	55.2	23.0878	12.8212	112.306	1420	11.600	61.7	4.61	482	1
55	Gabon	63.7	5048.7500	306.2500	1653.750	15400	16.600	62.9	4.08	8750	1
56	Gambia	80.3	133.7560	31.9778	239.974	1660	4.300	65.5	5.71	562	1
59	Ghana	74.7	386.4500	68.3820	601.290	3060	16.600	62.2	4.27	1310	1
63	Guinea	109.0	196.3440	31.9464	279.936	1190	16.100	58.0	5.34	648	1
64	Guinea-Bissau	114.0	81.5030	46.4950	192.544	1390	2.970	55.6	5.05	547	1
66	Haiti	208.0	101.2860	45.7442	428.314	1500	5.450	32.1	3.33	662	1
72	Iraq	36.9	1773.0000	378.4500	1534.500	12700	16.600	67.2	4.56	4500	1
80	Kenya	62.2	200.1690	45.9325	324.912	2480	2.090	62.8	4.37	967	1
81	Kiribati	62.7	198.1700	168.3700	1190.510	1730	1.520	60.7	3.84	1490	1
84	Lao	78.9	403.5600	50.9580	562.020	3980	9.200	63.8	3.15	1140	1
87	Lesotho	99.7	460.9800	129.8700	1181.700	2380	4.150	46.5	3.30	1170	1
88	Liberia	89.3	62.4570	38.5860	302.802	700	5.470	60.8	5.02	327	1
93	Madagascar	62.2	103.2500	15.5701	177.590	1390	8.790	60.8	4.60	413	1
94	Malawi	90.5	104.6520	30.2481	160.191	1030	12.100	53.1	5.31	459	1
97	Mali	137.0	161.4240	35.2584	248.508	1870	4.370	59.5	6.55	708	1
99	Mauritania	97.4	608.4000	52.9200	734.400	3320	18.900	68.2	4.98	1200	1
106	Mozambique	101.0	131.9850	21.8299	193.578	918	7.640	54.5	5.56	419	1
108	Namibia	56.0	2480.8200	351.8820	3150.330	8460	3.560	58.6	3.60	5190	1
112	Niger	123.0	77.2560	17.9568	170.868	814	2.550	58.8	7.49	348	1
113	Nigeria	130.0	589.4900	118.1310	405.420	5150	104.000	60.5	5.84	2330	1
116	Pakistan	92.1	140.4000	22.8800	201.760	4280	10.900	65.3	3.85	1040	1
126	Rwanda	63.6	67.5600	59.1150	168.900	1350	2.610	64.6	4.51	563	1
129	Senegal	66.8	249.0000	56.6000	403.000	2180	1.850	64.0	5.06	1000	1
132	Sierra Leone	160.0	67.0320	52.2690	137.655	1220	17.200	55.0	5.20	399	1
136	Solomon Islands	28.1	635.9700	110.2950	1047.480	1780	6.810	61.7	4.24	1290	1
142	Sudan	76.7	291.5600	93.5360	254.560	3370	19.600	66.3	4.88	1480	1
147	Tanzania	71.9	131.2740	42.1902	204.282	2090	9.250	59.3	5.43	702	1
149	Timor-Leste	62.6	79.2000	328.3200	1000.800	1850	26.500	71.1	6.23	3600	1
150	Togo	90.3	196.1760	37.3320	279.624	1210	1.180	58.7	4.87	488	1
155	Uganda	81.0	101.7450	53.6095	170.170	1540	10.600	56.8	6.15	595	1
165	Yemen	56.3	393.0000	67.8580	450.640	4480	23.600	67.5	4.67	1310	1
166	Zambia	83.1	540.2000	85.9940	451.140	3280	14.000	52.0	5.40	1460	1

In [40]:

```
Developing = df_cpy[df_cpy['cluster']==0]
Developed = df_cpy[df_cpy['cluster']==2]
print(Lowest_countries.shape)
print(Developing.shape)
print(Developed.shape)
print(46+95+26)
print(df_cpy.shape)
```

```
(46, 11)
(95, 11)
(26, 11)
167
(167, 11)
```

We are Checking that Our Clustering Envolved all The Countries or Not

In [41]:
```
List_countries = Lowest_countries['country']
```

In [42]:
```
print(List_countries)
```

```
0      Afghanistan
3      Angola
17     Benin
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
136    Solomon Islands
142    Sudan
147    Tanzania
149    Timor-Leste
150    Togo
155    Uganda
165    Yemen
166    Zambia
Name: country, dtype: object
```

Creating Model - Hierchical Clustering

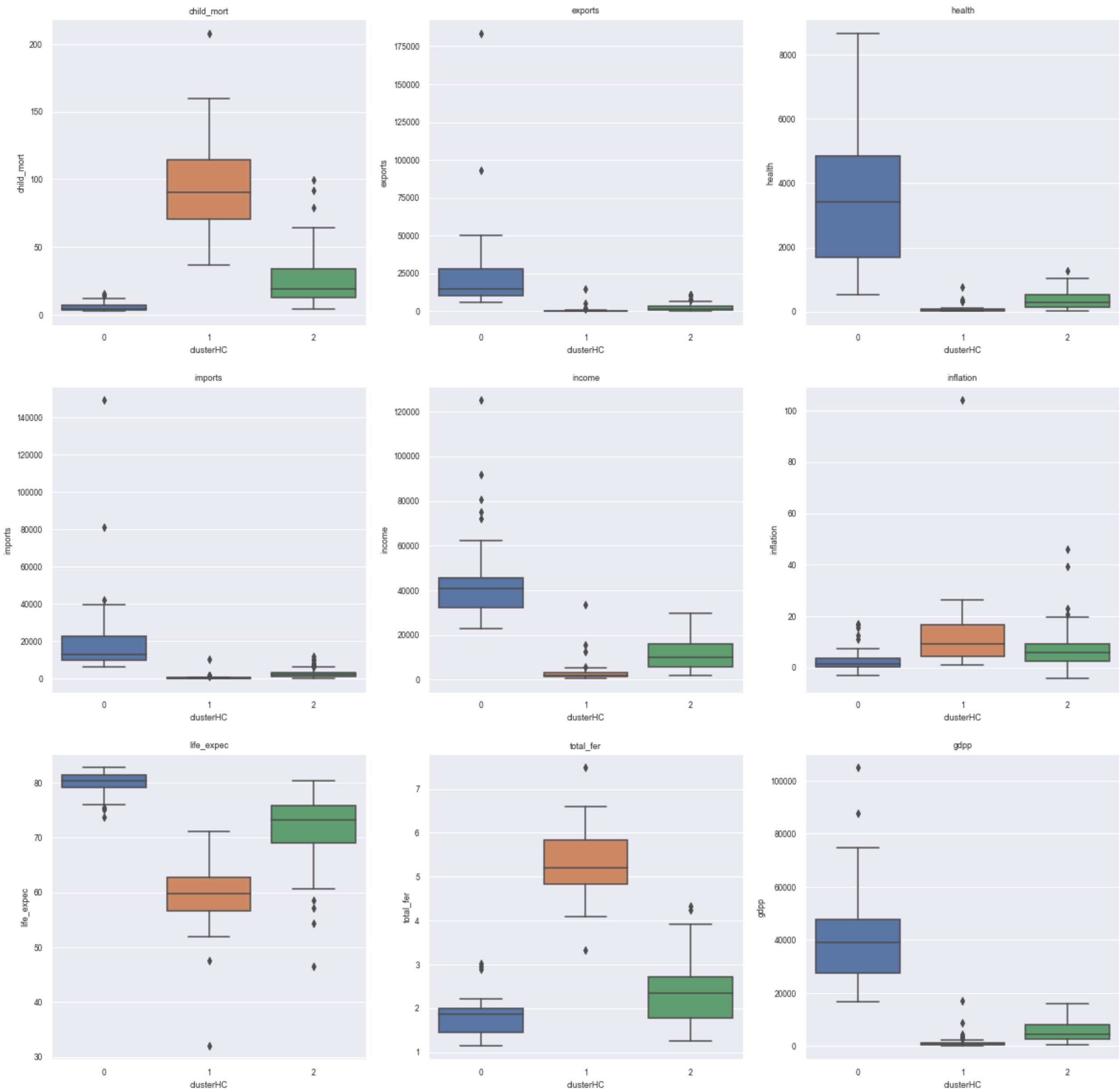
In [43]:
```
from sklearn.cluster import AgglomerativeClustering
model = AgglomerativeClustering(n_clusters=3, linkage='ward')
model.fit_predict(x2)
df_cpy['clusterHC']= model.labels_
```

In [44]:
```
df_cpy.head()
```

Out[44]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp	cluster	clusterHC
0	Afghanistan	90.2	55.30	41.9174	248.297	1610	9.44	56.2	5.82	553	1	1
1	Albania	16.6	1145.20	267.8950	1987.740	9930	4.49	76.3	1.65	4090	0	2
2	Algeria	27.3	1712.64	185.9820	1400.440	12900	16.10	76.5	2.89	4460	0	2
3	Angola	119.0	2199.19	100.6050	1514.370	5900	22.40	60.1	6.16	3530	1	1
4	Antigua and Barbuda	10.3	5551.00	735.6600	7185.800	19100	1.44	76.8	2.13	12200	0	2

In [45]:
```
import seaborn as sns
l=['child_mort', 'exports', 'health', 'imports', 'income',
       'inflation', 'life_expec', 'total_fer', 'gdpp']
plt.figure(figsize=(20,20))
for i in range(len(l)):
    plt.subplot(3,3,i+1)
    sns.boxplot(df_cpy.clusterHC,df_cpy[l[i]])
    plt.title(l[i])
```



As We can See from the boxplots Above that the countries in Cluster 1 Having

1.Less GDPP

2.High Child Mort

3.High Total Fertility Rate Which Leads to More Population

4.Less Life Expectancy

5.High Inflation

6.Very Less Income

7.Very Less Exports

8.Very Less expenditure on Health

In [46]:
```
Lowest_countries= df_cpy[df_cpy['clusterHC']==1]
```

In [47]:
```
Lowest_countries
```

Out[47]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp	cluster	clusterHC
0	Afghanistan	90.2	55.3000	41.9174	248.297	1610	9.440	56.2	5.82	553	1	1
3	Angola	119.0	2199.1900	100.6050	1514.370	5900	22.400	60.1	6.16	3530	1	1
17	Benin	111.0	180.4040	31.0780	281.976	1820	0.885	61.8	5.36	758	1	1
25	Burkina Faso	116.0	110.4000	38.7550	170.200	1430	6.810	57.9	5.87	575	1	1
26	Burundi	93.6	20.6052	26.7960	90.552	764	12.300	57.7	6.26	231	1	1
28	Cameroon	108.0	290.8200	67.2030	353.700	2660	1.910	57.3	5.11	1310	1	1
31	Central African Republic	149.0	52.6280	17.7508	118.190	888	2.010	47.5	5.21	446	1	1
32	Chad	150.0	330.0960	40.6341	390.195	1930	6.390	56.5	6.59	897	1	1
36	Comoros	88.2	126.8850	34.6819	397.573	1410	3.870	65.9	4.75	769	1	1
37	Congo, Dem. Rep.	116.0	137.2740	26.4194	165.664	609	20.800	57.5	6.54	334	1	1
38	Congo, Rep.	63.9	2331.7400	67.4040	1498.780	5190	20.700	60.4	4.95	2740	1	1
40	Cote d'Ivoire	111.0	617.3200	64.6600	528.260	2690	5.390	56.3	5.27	1220	1	1
49	Equatorial Guinea	111.0	14671.8000	766.0800	10071.900	33700	24.900	60.9	5.21	17100	1	1
50	Eritrea	55.2	23.0878	12.8212	112.306	1420	11.600	61.7	4.61	482	1	1
55	Gabon	63.7	5048.7500	306.2500	1653.750	15400	16.600	62.9	4.08	8750	1	1
56	Gambia	80.3	133.7560	31.9778	239.974	1660	4.300	65.5	5.71	562	1	1
59	Ghana	74.7	386.4500	68.3820	601.290	3060	16.600	62.2	4.27	1310	1	1
63	Guinea	109.0	196.3440	31.9464	279.936	1190	16.100	58.0	5.34	648	1	1
64	Guinea-Bissau	114.0	81.5030	46.4950	192.544	1390	2.970	55.6	5.05	547	1	1
66	Haiti	208.0	101.2860	45.7442	428.314	1500	5.450	32.1	3.33	662	1	1
72	Iraq	36.9	1773.0000	378.4500	1534.500	12700	16.600	67.2	4.56	4500	1	1
80	Kenya	62.2	200.1690	45.9325	324.912	2480	2.090	62.8	4.37	967	1	1
88	Liberia	89.3	62.4570	38.5860	302.802	700	5.470	60.8	5.02	327	1	1
93	Madagascar	62.2	103.2500	15.5701	177.590	1390	8.790	60.8	4.60	413	1	1
94	Malawi	90.5	104.6520	30.2481	160.191	1030	12.100	53.1	5.31	459	1	1
97	Mali	137.0	161.4240	35.2584	248.508	1870	4.370	59.5	6.55	708	1	1
99	Mauritania	97.4	608.4000	52.9200	734.400	3320	18.900	68.2	4.98	1200	1	1
106	Mozambique	101.0	131.9850	21.8299	193.578	918	7.640	54.5	5.56	419	1	1
112	Niger	123.0	77.2560	17.9568	170.868	814	2.550	58.8	7.49	348	1	1
113	Nigeria	130.0	589.4900	118.1310	405.420	5150	104.000	60.5	5.84	2330	1	1
126	Rwanda	63.6	67.5600	59.1150	168.900	1350	2.610	64.6	4.51	563	1	1
129	Senegal	66.8	249.0000	56.6000	403.000	2180	1.850	64.0	5.06	1000	1	1
132	Sierra Leone	160.0	67.0320	52.2690	137.655	1220	17.200	55.0	5.20	399	1	1
142	Sudan	76.7	291.5600	93.5360	254.560	3370	19.600	66.3	4.88	1480	1	1
147	Tanzania	71.9	131.2740	42.1902	204.282	2090	9.250	59.3	5.43	702	1	1
149	Timor-Leste	62.6	79.2000	328.3200	1000.800	1850	26.500	71.1	6.23	3600	1	1
150	Togo	90.3	196.1760	37.3320	279.624	1210	1.180	58.7	4.87	488	1	1
155	Uganda	81.0	101.7450	53.6095	170.170	1540	10.600	56.8	6.15	595	1	1
165	Yemen	56.3	393.0000	67.8580	450.640	4480	23.600	67.5	4.67	1310	1	1
166	Zambia	83.1	540.2000	85.9940	451.140	3280	14.000	52.0	5.40	1460	1	1

In [48]:

```
cluster0 = df_cpy[df_cpy['clusterHC']==0]
cluster2 = df_cpy[df_cpy['clusterHC']==2]
print(Lowest_countries.shape)
print(cluster0.shape)
print(cluster2.shape)
print(40+39+88)
print(df_cpy.shape)
```

```
(40, 12)
(39, 12)
(88, 12)
167
(167, 12)
```

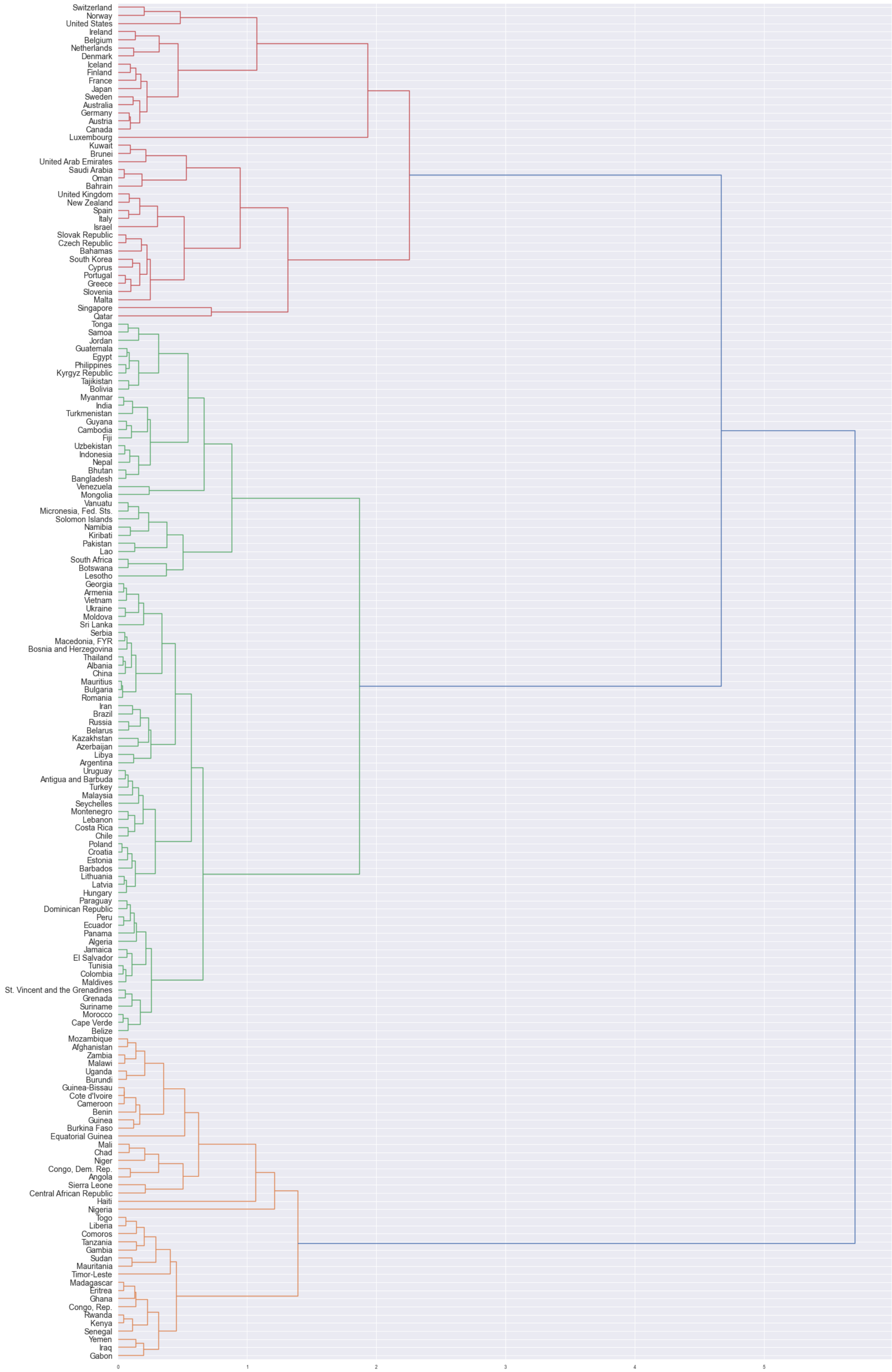
- We Can See That This have Classified 40 Countries and k means have Classified 46 but we can see that these above countries are in same cluster according to both clusters.

In [49]:

```
from scipy.cluster.hierarchy import linkage, dendrogram
import matplotlib.pyplot as plt
import numpy as np

plt.figure(figsize=(25, 45))
Z = linkage(x2, method='ward')

dendrogram(
    Z,
    orientation='right',
    labels=df_cpy['country'].values,
    distance_sort='assending',
    show_leaf_counts=True,
    leaf_font_size=14,
)
plt.show()
```



- **Green Color Are The Classified Cluster Dendogram**

Calculating Performance

For Hierchical clustering

In [50]:
```
from sklearn.metrics import silhouette_score, calinski_harabasz_score
```

In [51]:
```
silhouette_avg = silhouette_score(x2, model.labels_)
silhouette_avg
```

Out[51]:
```
0.4413193655673136
```

In [52]:
```
ch_score = calinski_harabasz_score(x2, model.labels_)
ch_score
```

Out[52]:
```
149.9860971231719
```

For K Means clustering

In [53]:
```
silhouette_avg = silhouette_score(x,clusters)
silhouette_avg
```

Out[53]:
```
0.4875688325246982
```

In [54]:
```
ch_score = calinski_harabasz_score(x, clusters)
ch_score
```

Out[54]:
```
168.89645031547616
```

Conclusion

The Countries Which are in Need of Aid Are

- Note That We are Considering Results Of K means Clustering as Final Result Because It has a good Score. There are 46 Countries that are in need of Aid.

In [55]:
```
Lowest_countries= df_cpy[df_cpy['cluster']==1]
```

In [56]:
```
C=[]
for country in Lowest_countries['country']:
    C.append(country)
data = {"S.No":[i for i in range(1,47)],"Country":C}
Result= pd.DataFrame(data=data)
Result.sort_values(by=['Country'],inplace=True)
```

In [57]:
```
Result
```

Out[57]:

	S.No	Country
0	1	Afghanistan
1	2	Angola
2	3	Benin
3	4	Burkina Faso
4	5	Burundi
5	6	Cameroon
6	7	Central African Republic
7	8	Chad
8	9	Comoros
9	10	Congo, Dem. Rep.
10	11	Congo, Rep.
11	12	Cote d'Ivoire
12	13	Equatorial Guinea
13	14	Eritrea
14	15	Gabon
15	16	Gambia
16	17	Ghana
17	18	Guinea
18	19	Guinea-Bissau
19	20	Haiti
20	21	Iraq
21	22	Kenya
22	23	Kiribati
23	24	Lao
24	25	Lesotho
25	26	Liberia
26	27	Madagascar
27	28	Malawi
28	29	Mali
29	30	Mauritania
30	31	Mozambique
31	32	Namibia
32	33	Niger
33	34	Nigeria
34	35	Pakistan
35	36	Rwanda
36	37	Senegal
37	38	Sierra Leone
38	39	Solomon Islands
39	40	Sudan
40	41	Tanzania
41	42	Timor-Leste
42	43	Togo
43	44	Uganda
44	45	Yemen
45	46	Zambia

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