Identifying Countries in Critical Need of Medical Care Using K-means Clustering

In this work, I used machine learning to identify nations that require immediate medical attention. To categorize nations according to their health profiles, I used **K-means clustering** on key healthcare indicators, such as life expectancy **(life_expec),** health expenditure **(health)**, and child mortality **(child_mort).** This study provides information about which nations need aid and assistance urgently.

Data Exploration

There are 10 columns and 163 rows in this dataset. Using correlation metrics, I looked at the correlations between three important health indicators: life expectancy, health expenditures, and child mortality. There are no missing or duplicate values. Higher healthcare spending was found to be strongly associated with improved health outcomes, including longer life expectancy and decreased child mortality. These observations served as a reference for grouping nations according to their healthcare characteristics.

Model: KMeans Clustering

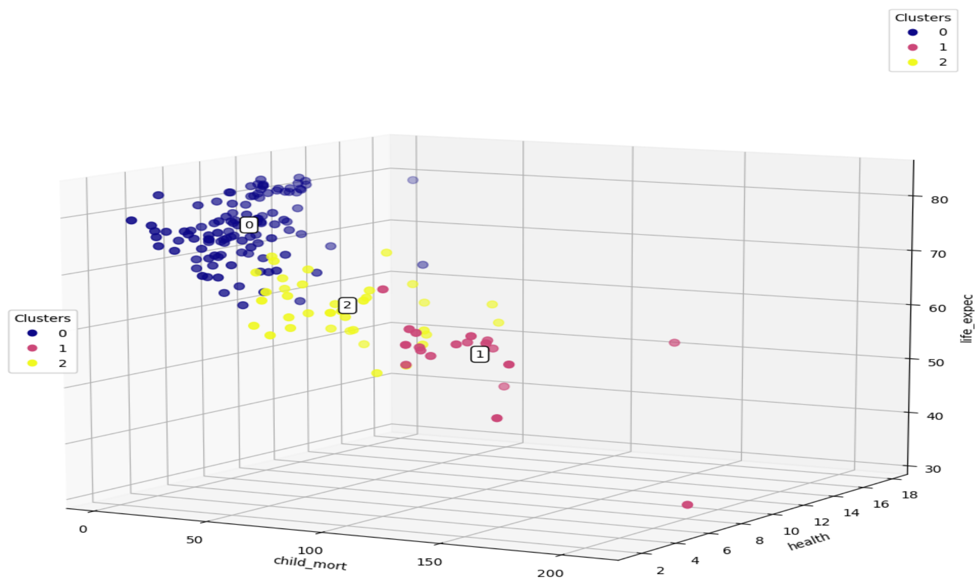
I used Python to implement K-means, specifying 3 clusters (n_clusters=3)

1. Child Mortality Rate (child_mort): Indicates the number of child deaths for every 1,000 live births. High numbers indicate insufficient medical care, especially for the health of mothers and children.

2. Health Expenditure (health): Shows the proportion of GDP that goes toward health spending. Lower values indicate less money spent on healthcare facilities.

3. Life Expectancy (life_expec): Indicates the effectiveness of a nation's healthcare system by reflecting the average number of years a person is expected to live.

Visualization: 3D visualization for the three clusters



Cluster Analysis and Results

Cluster 0: Low-Risk Countries (Blue) [Algeria, Zambia, Angola, Yemen]

Characteristics: High life expectancy (75.4 years), moderate health spending (7.2% of GDP), and low child mortality (average of 14.2 per 1,000 live births).

Conclusion: these countries can act as role models for other nations due to their efficient healthcare systems. Initiatives to exchange knowledge could aid in the improvement of healthcare in less developed nations**.**

Cluster 1: High-Risk Countries (Pink) [Switzerland, Singapore, Norway, Kuwait]

Characteristics: Poor life expectancy (56.0 years), poor health spending (6.0% of GDP), and high child mortality (average of 124.7 per 1,000 live births).

Conclusion: these countries have serious healthcare issues that need quick action to improve mother and child health services as well as healthcare access.

Cluster 2: Moderate Risk Countries (Yellow) [United Kingdom, Spain, Italy, France]

Characteristics: Moderate life expectancy (63.0 years), modest health spending (6.0% of GDP), and a moderate child mortality rate (average of 67.5 per 1,000 live births).

Conclusion: Although these countries are making progress, they still have difficulties. To improve healthcare outcomes, targeted interventions are required, such as immunization programs and preventative healthcare.

Recommendations

Adding income and fertility rates as features made it easier to differentiate between nations, particularly those whose economic difficulties are causing them to have bad health outcomes. These extra characteristics made recommendations more focused and successful by highlighting the relationship between healthcare quality, fertility rates, and economic capability.

Conclusion

The K-means clustering technique offers an analytical approach to determine which countries require healthcare interventions the most. I was able to identify three clusters that represent different healthcare needs by concentrating on life expectancy, health spending, and child mortality. In order to improve healthcare outcomes worldwide, **WHO** can use these clusters as a reference when allocating resources and creating focused programs.