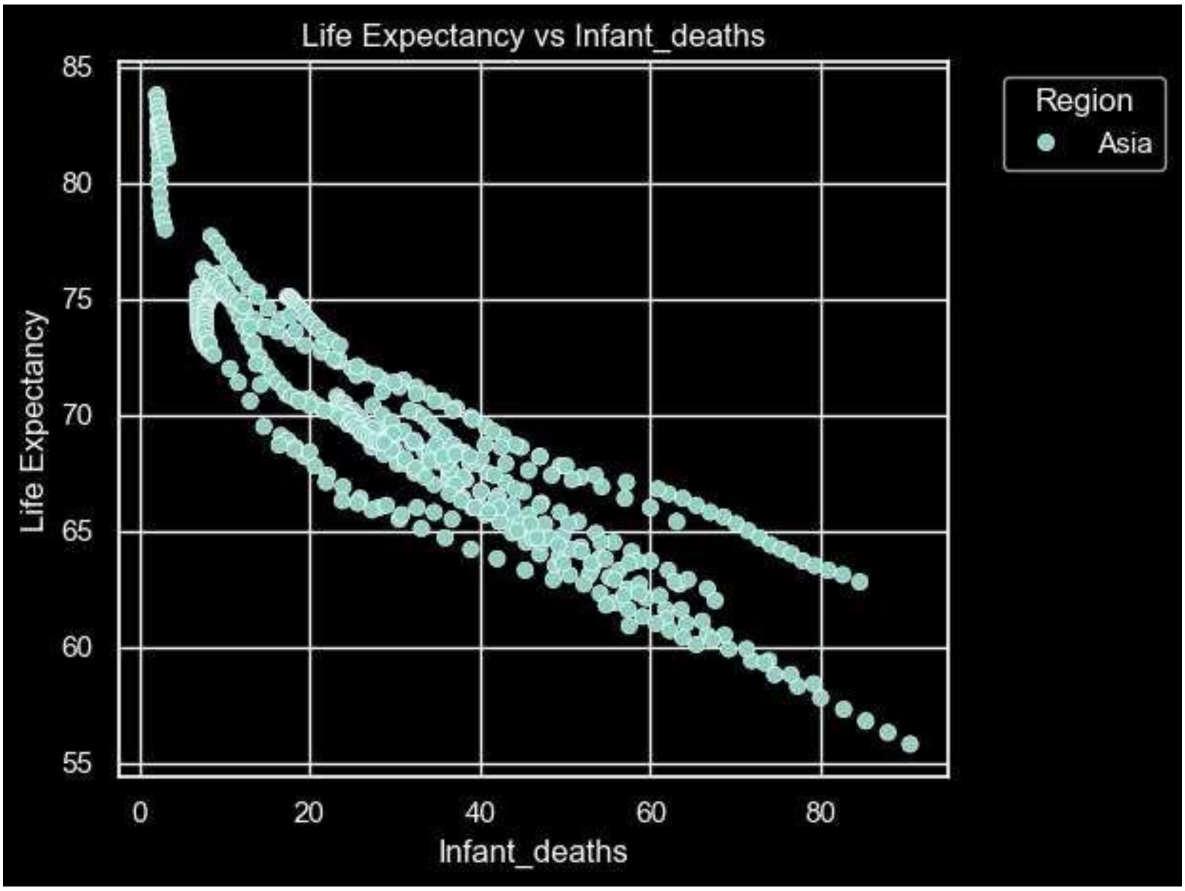
In [18]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
df=pd.read excel('dataset.xlsx')
df.head(5)
```

Out[18]:

	Country	Region	DEV/UNDEV	Year	Infant_deaths	Under_five_deaths	Adult_mor
0	Latvia	European Union	Developed	2014	4.6	5.5	165
1	Bulgaria	European Union	Developed	2014	7.3	8.7	139
2	Lithuania	European Union	Developed	2014	4.0	4.9	167
3	Romania	European Union	Developed	2014	8.3	9.9	130
4	Hungary	European Union	Developed	2014	4.5	5.4	131

5 rows × 22 columns

In [48]:
```
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
plt.style.use('dark background')

# Scal ten  pLof  of  Life  Expectancy  vs  GDP  per  Capt ta
#pLt.  fi   gure(fi gs ize-—(18,   6))
sns.scatterplot(x='Infant_deaths', y='Life_expectancy', data=df, hue='Region')
plt.title('Life Expectancy vs Infant deaths')
plt.xlabel('Infant_deaths')
plt.ylabel('Life Expectancy')
plt.legend(title='Region',bbox_to_anchor=(1.05, 1),loc='upper left')
plt.tight_layout()
plt.show()
```

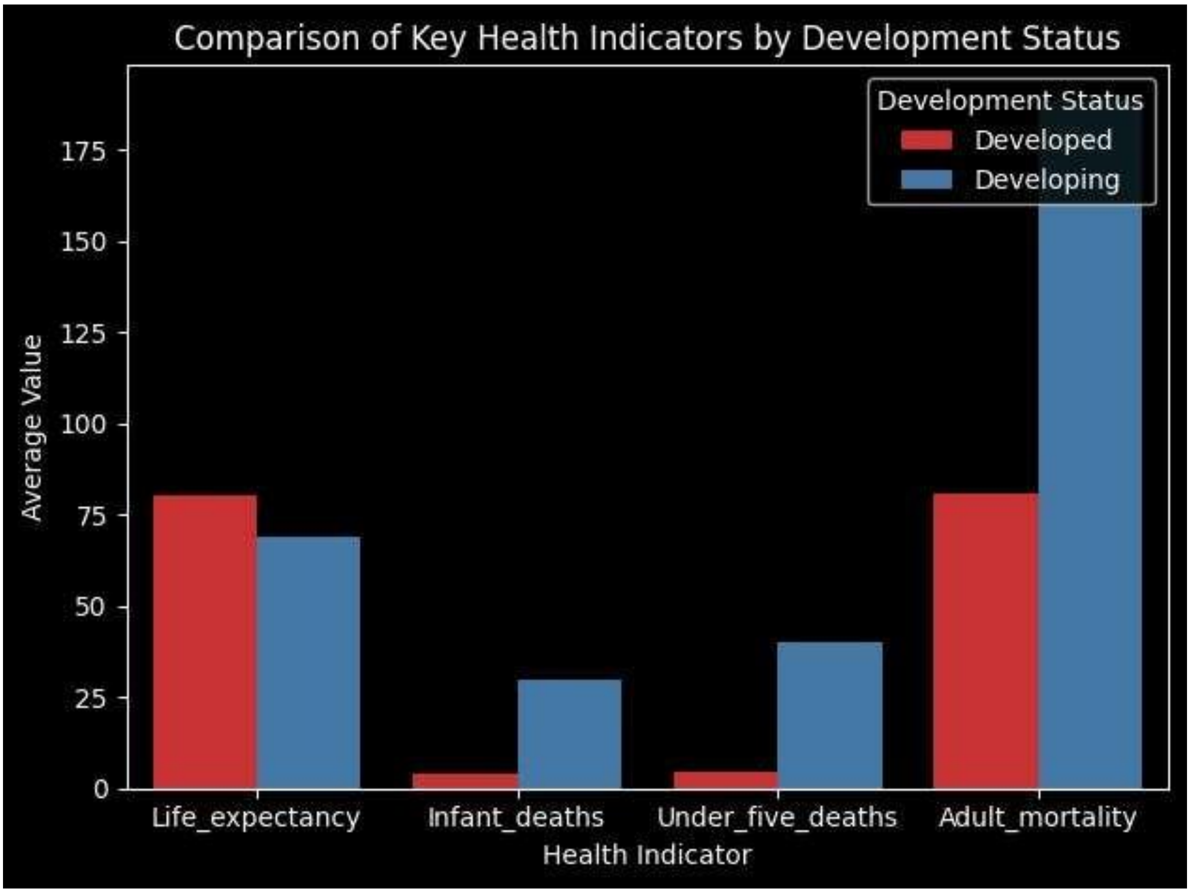


Inference for Life Expectancy Vs Infant_deaths

There is a negative correlation between Life Expectancy and Infant_deaths which means that when the infant deaths are more the life expectancy decreases and when infant deaths are less the life expectancy increases across the region asia.

In [43]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Assurriing the dataset is aLready Loaded into a datafra/re caLLed df

# Group data b'y deveLopment status (DeveLoped vs. DeveLoping) and caLcuLate the
health indicators = ['Life expectancy', 'Infant deaths', 'Under five deaths', '#
development comparison   df.groupby('DEV/UNDEV')[health indicators].mean().reset

# NeLt the dataframe for easier pLottirig
development_comparison_melted   development_comparison.melt(id_vars='DEV/UNDEV',

# PLotling the cornparison
#pLt./igure(figsize——(12, 6))
sns.barplot(x='Health Indicator', y='Average Value', hue='DEV/UNDEV', data=deve1

# Add LabeLs and titLe
plt.title('Comparison of Key Health Indicators by Development Status')
plt.xlabel('Health Indicator')
plt.ylabel('Average Value')
plt.legend(title='Development Status', loc='upper right')
```

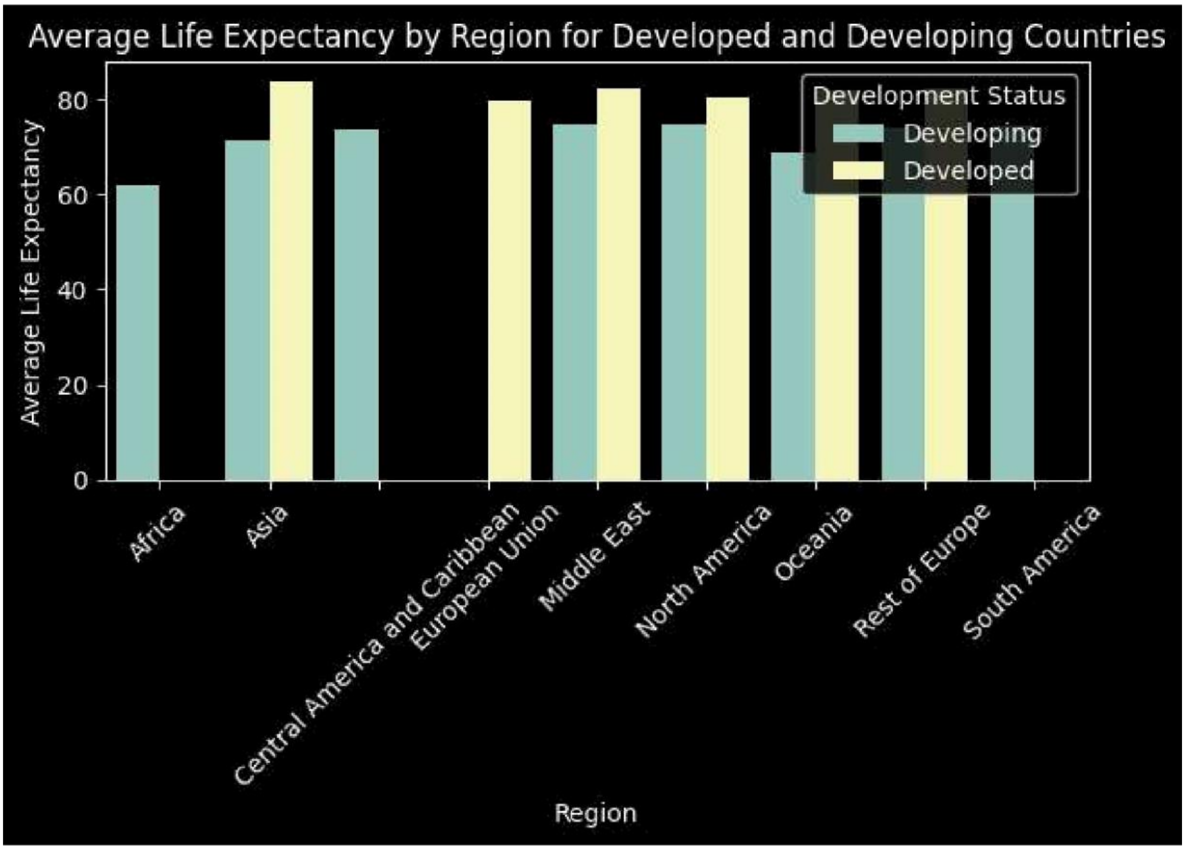
```
# Shoir the p Lot
plt.tight layout()
plt.show()
```



Inference: 1-Health disparities exist between the developed and developing nations. The life expectancy is way higher in the developed nations, with infant deaths, under-five deaths, and adult mortality rates being at very low rates compared to the developing world. 2-Influence of Development: That would go to underline how health indicators are influenced by development status, with the developed countries generally enjoying better health outcomes across all indicators. 3-It underlines the irreconcilable difference between the two: the extent of critical improvement needed in healthcare and related infrastructure in developing nations for the reduction of infant and child mortality, with an increase in life expectancy.

In [44]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Assums ng the dataset is aL ready Loaded tnto a datafra/re caL Led df

# Group the data by Regi on and Deve Lopulent Status, then caL cuL aie the ruean L ice
life_expectancy_by_region    df.groupby(['Region', 'DEV/UNDEV'])['Life_expectancy

# Bar pLof to compare Life Expectancy across diff-erent regions for Deve Loped and
# pLt. figure(figs ize——(14, 8))
sns.barplot(x='Region', y='Life expectancy', hue='DEV/UNDEV', data=life expectan

# Add Labe Ls and UI Le
plt.title('Average Life Expectancy by Region for Developed and Developing Countr
```

```
plt.xlabel('Region')
plt.ylabel('Average Life Expectancy')
plt.xticks(rotation=45)
plt.legend(title='Development Status', loc='upper right')

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

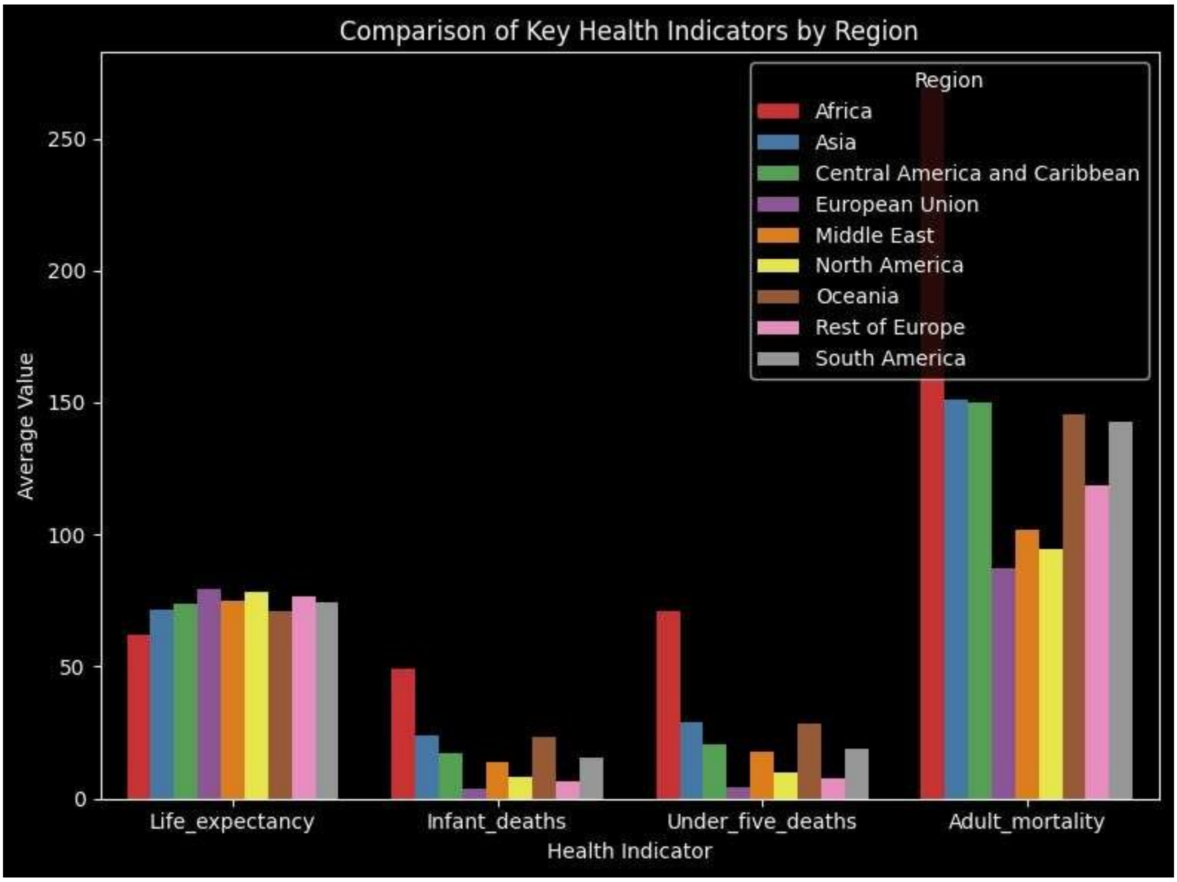


inference for the Graph Average Life Expectancy Vs Region for developed and developing countries

1-Status of Development as a Key Determinant: The graph puts in clear terms that by large, developed countries exhibit greater life expectancy in all regions. This then makes it an indication that the determinant factors of development, such as healthcare systems, standards of living, and resources, greatly contribute to life expectancy. 2-The venture of narrowing down the gap of life expectancies taken for developing and developed nations would apply to those regions experiencing a wide disparity, like Africa and Asia, and those with the most urgent need for change through interventions focused on achieving health care, nutrition, and uplift in living standards. 3-This comparison emphasizes the need to take up forward actions on regional and developmental imbalances for the improvement in global life expectancy.

In [68]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

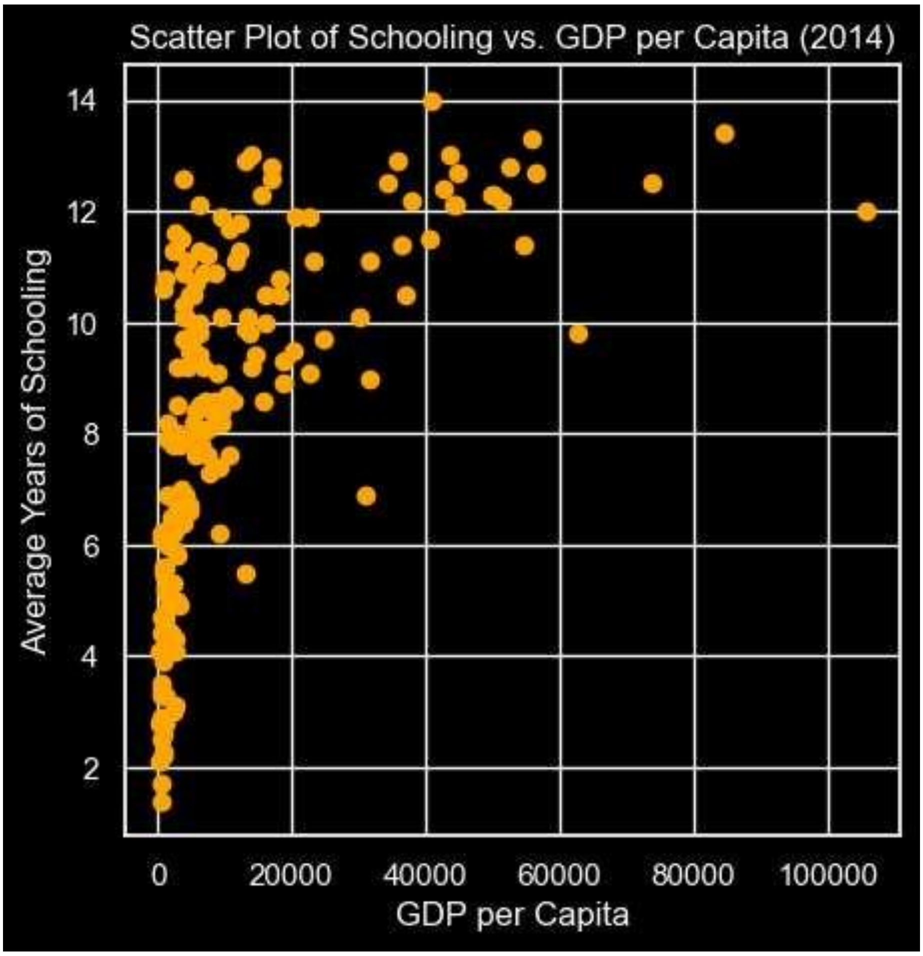
```
# Assurling the dataset is aLready Loaded into a datafnarne caLLed df

It Group data b'y deveLopment status (DeveLoped vs. DeveLoping) and caLcuLate the
health indicators = ['Life expectancy', 'Infant deaths', 'Under five deaths', '
development_comparison   df.groupby('Region')[health_indicators].mean().reset_in

# NeLt the dataframe for easier pLottirig
development_comparison_melted   development_comparison.melt(id_vars='Region', va

# PLolIing the cornparison
plt.figure(figsize=(8, 6))
sns.barplot(x='Health Indicator', y='Average Value', hue='Region', data=develop

# Add LabeLs and UI Le
plt.title('Comparison of Key Health Indicators by Region')
plt.xlabel('Health Indicator')
plt.ylabel('Average Value')
plt.legend(title='Region', loc='upper right')

# Show the pLot
plt.tight_layout()
plt.show()
```



Inference for the graph Comparison of Key Health indicator by Region.

Life expectancy is relatively homogenous across regions, showing minor differences. Infant deaths and Under-five deaths are appreciably higher in Africa as opposed to other regions, pointing out the challenges in child health. While countries in Africa and the Middle Eastern region are way far higher in adult mortality, European Union and Oceania have lower values, hence indicating good health outcomes for adults. The table highlights health inequalities within the regions, especially in the overall infant and adult mortality rates.

In [58]:
```
#Scatter pLof between SchooLing and GDP per capita
import pandas as pd
import matplotlib.pyplot as plt

It Load the ExceL fi Le
#fi Le path —— 'your fi Le path here.xLsx'  # RepLace with your fi Le path
data = pd.read_excel('dataset.xlsx')

# Extract weLevant coLurnns
gdp_per_capita = data['GDP_per_capita']
schooling = data['Schooling']

It Create the scatter pLot
plt.figure(figsize=(5, 5))
plt.scatter(gdp per capita, schooling, color='orange')

# Addlng LobeLs and UI Le
plt.xlabel('GDP per Capita')
plt.ylabel('Average Years of Schooling')
plt.title('Scatter Plot of Schooling vs. GDP per Capita (2014)')
plt.grid(True)

# DCspLay the pLot
plt.show()
```



Inference of Average Years of schooling Vs GDP per Capita

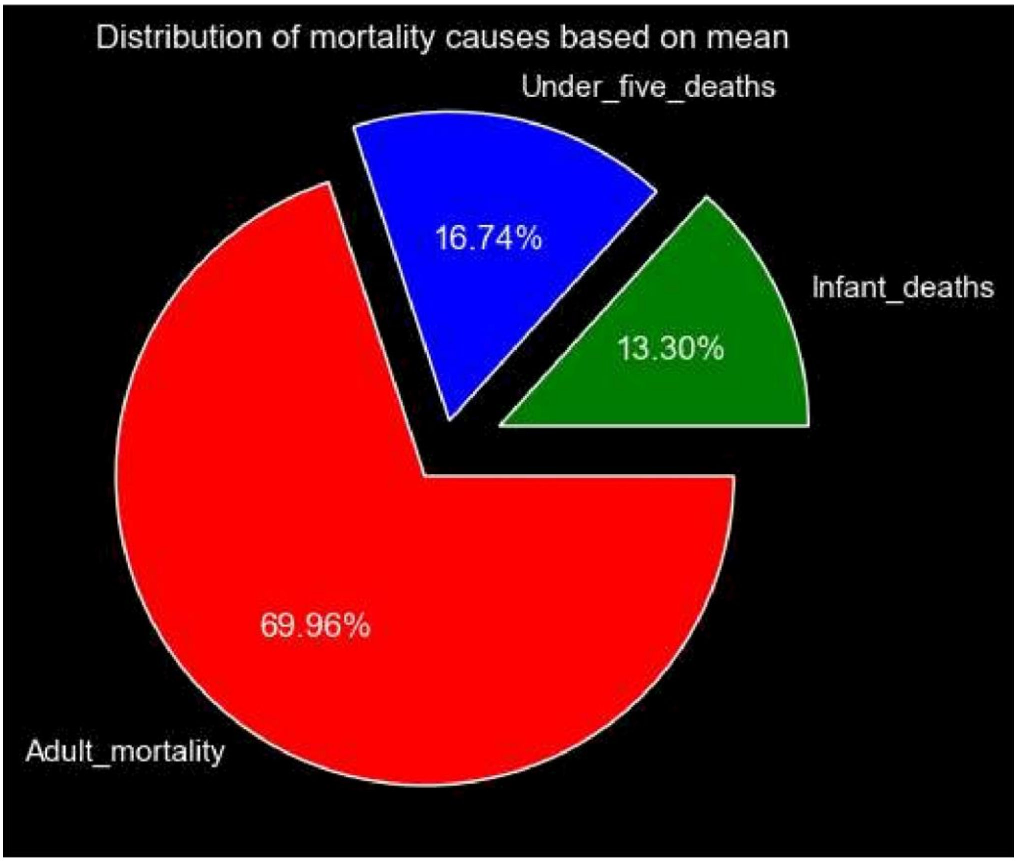
1-Positive Correlation: GDP per capita appears to be positively correlated with average years of schooling. Generally, when GDP per capita goes up, so do average years of schooling. This suggests that on average, the richer countries invest more in education, leading to a larger number of years of schooling.

2-Low GDP Cluster: Most of the data points cluster at the low end of the GDP per capita axis, below $20,000. These have a wide range in schooling years, ranging from about 4 to 12 years. This indicates that there is a lot of variability in the educational outcome, even within countries with low per capita GDP.

3-High Schooling in High GDP Countries: Countries with a high GDP per capita, above $40,000, have average years of schooling ranging from 10 or more. From this, it can be induced that the richer countries would hold more developed and accessible education systems, hence higher education.

4-Outliers: There are a few outliers that have very high GDP per capita—close to $100,000—with the years of schooling varying. It could mean that rich countries do not necessarily imply higher average schooling; it can reflect differences in educational or economic structures.

In [57]:
```
#creating a pie chart for the anaLysis of the heaLth indicators
 u
p l e gure(figsize=(5,5))
health_indicators = [ 'Infant deaths', 'Under five deaths', 'Adult mortality']
                                   e
e p ode_vG een=[0B2u0.1,0 d]'
ltx——dyLife expectancy ') . mean()
y=df['Infant deaths'].mean()
z=df['Under five deaths'].mean()
p=df['Adult_mortality'].mean()
#vaLues . append(x)
values.append(y)
values.append(z)
values.append(p)
plt.pie(values,labels=health_indicators,colors=colors,explode=explode_values,aut
plt.title('Distribution of mortality causes based on mean')
plt.show()
```



Inference of mortality causes based on mean

1- Adult mortality is the single largest share of the pie chart, contributing 56.50% of the total. This means that adult mortality is the most significant of the factors shown in this series of categories.

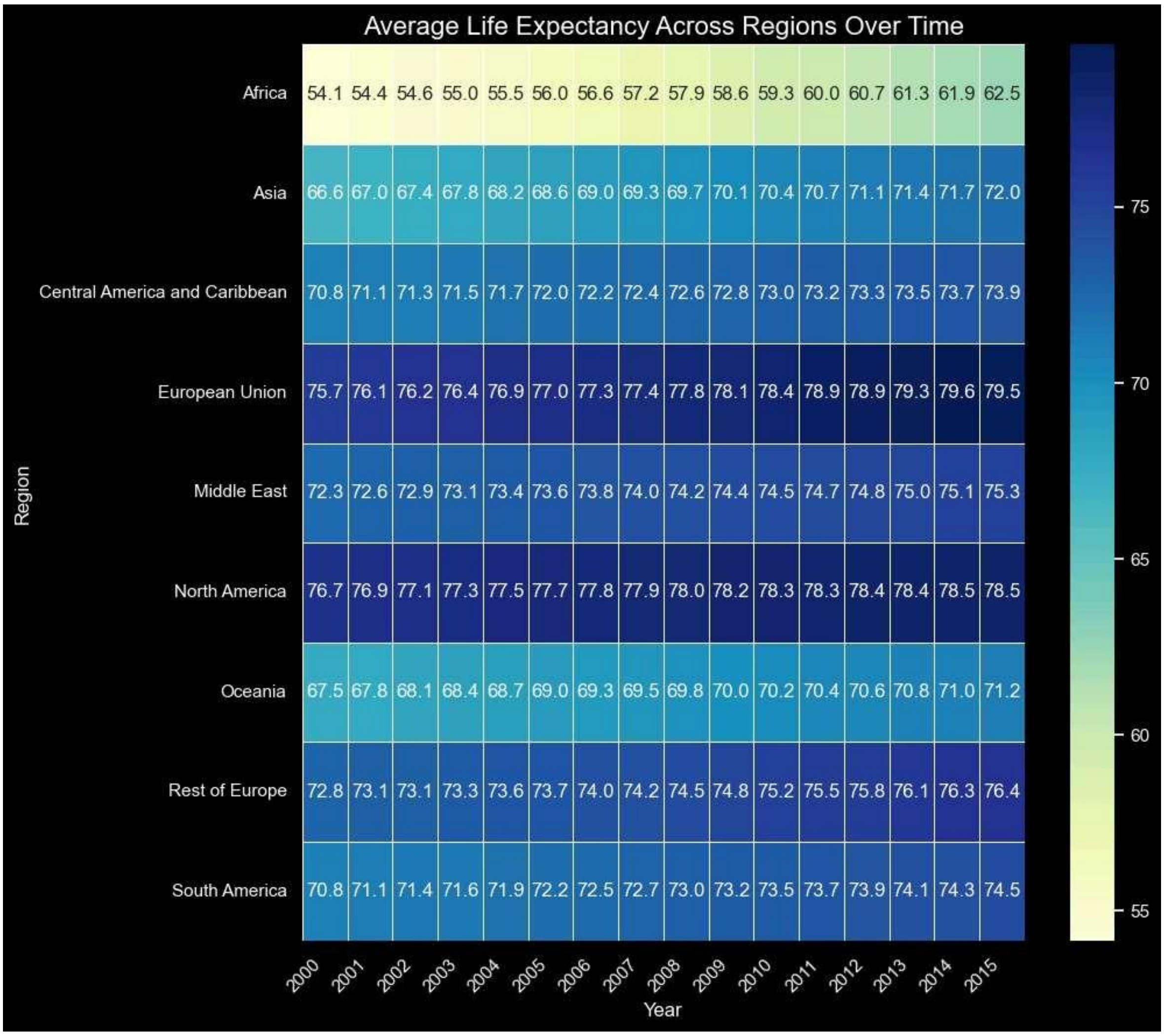
2- Under-Five Deaths: Under-five deaths account for 11.11°/oof the distribution, hence child mortality also becomes a significant factor.

3- Infant Deaths: This is the smallest portion, 8.22%, having to do with infant deaths, and this particularly showcases mortality in the first year of life.

In summary, adult mortality dominates, with over half of the distribution, while life expectancy, under-five deaths, and infant deaths make up a smaller although still important part of the distribution. This chart puts into perspective the position of adult mortality within the overall health landscape.

In [42]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Load your dataset
ryi Le_path —- 'your_fi Le_path. xLsx     # RepLace h/ith your actuaL fi Le path
data   pd.read_csv('Life-Expectancy-Data-Updated.csv')

# CaLcuLate the average L!fe expectancy per negion for each year
average_life_expectancy   data.groupby(['Region', 'Year'])['Life_expectancy'].me
```

```
# Set up the natpLotLib fi gure
plt.figure(figsize=(10, 10))

# Draw the heatmap
sns.heatmap(average_life_expectancy, annot=True, fmt=”.1f”, cmap=”YlGnBu", lines

it TOt Le fon the heatmap
plt.title(”Average Life Expectancy Across Regions Over Time”, fontsize=16)

# LabeL the axes
plt.xlabel(“Year”)
plt.ylabel(“Region”)

# Rotate the x-axis LabeLs for better readabiLQty
plt.xticks(rotation=45, ha='right')

It DispLay the heatiflap
plt.show()
```

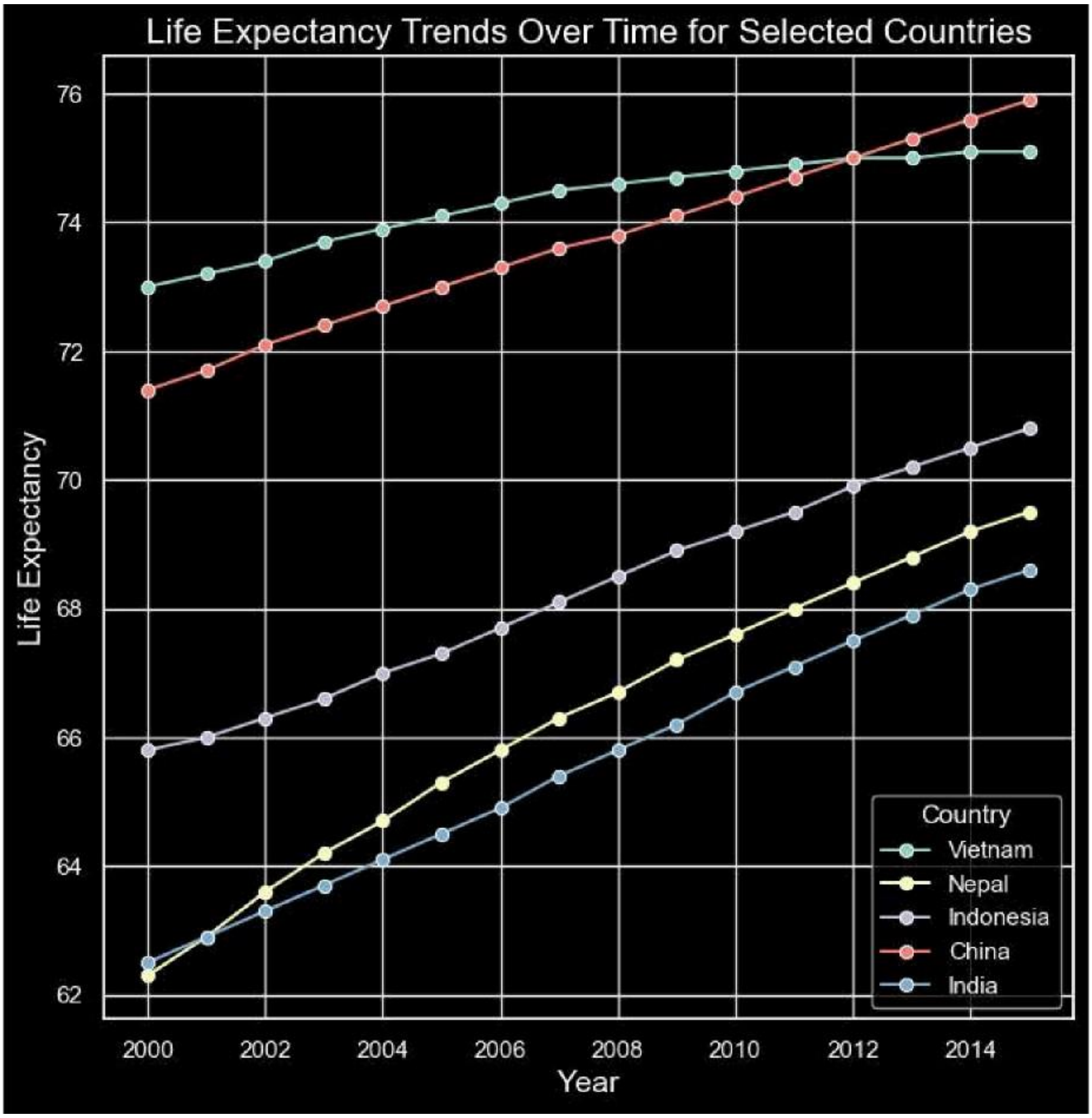


Inference for the Heatmap of average life expectancy Vs regions over time

1- For all the regions the average life expectancy increaed from 2000 to 2015 which is due to the advancements of medical science and technology.

2- In 2015, European Union have the highest life expectancy which may be because of their healthy eating and sleeping habits and availability of advanced medical facilities whereas Africa is having the least life expectancy maybe because of the non availability of advanced medical facilities.

In [56]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
df = pd.read excel('hotspot analysis.xlsx')
plt.style.use('dark background')

# FiLter  the  data for  seLected  countri es
selected_countries = ['Vietnam', 'Nepal', 'Indonesia', 'China', 'India']
df_filtered  df[df['Country'].isin(selected_countries)]

it Set  the  pLot styLe
#sns.set(styIe—-"ahitegrid")

# Create the  Li ne pLot
plt.figure(figsize=(8, 8))
sns.lineplot(data=df filtered, x='Year', y='Life expectancy', hue='Country', mar

it Set  pLot titLe and IabeIs
plt.title('Life Expectancy Trends Over Time for Selected Countries', fontsize=1f
plt.xlabel('Year', fontsize=14)
plt.ylabel('Life Expectancy', fontsize=14)

# Show the  pLot
plt.legend(title='Country')
plt.show()
```



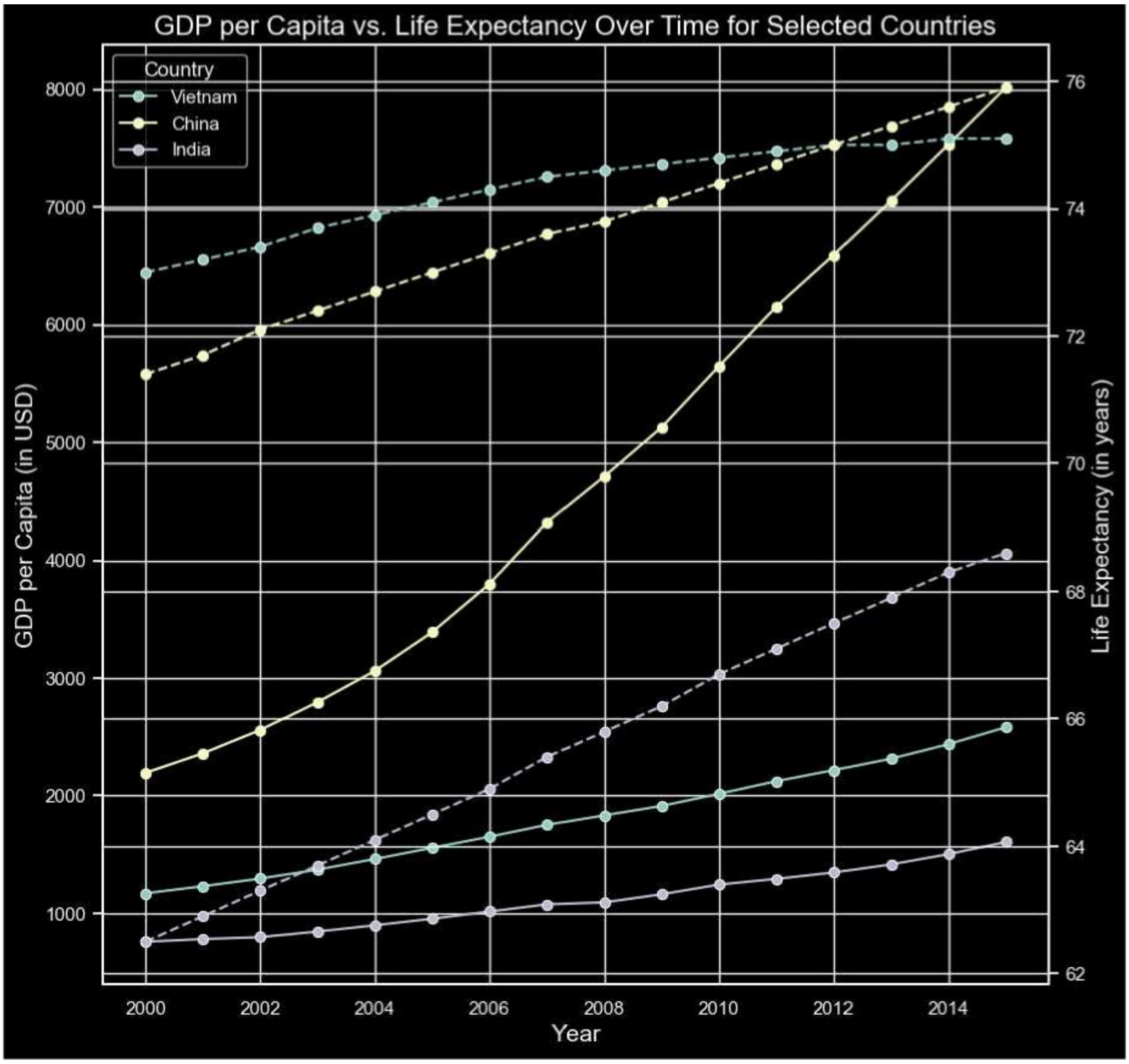
Inference for the above graph Life Expectancy Vs Year

1- For almost all the countries selected for analysis the life expectancy increases over the time period from 2000 to 2014 showing that there have been significant advancements in the medical field with people recieving advanced treatments over the time period.

2- If there is a comparison of life expectancy between countries then vietnam has the highest life expectancy amongst all countries depicting that people in vietnam are strict and disciplined in terms of eating and sleeping habits, whereas india have the least life expectancy depicting indians may not follow a strict regime when it comes to diet and sleep.

In [45]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load the data Iron the ExceL fi Le
```

```
#fi Le_path —— '/rnnt/data/hotspot anaLpsis. xLsx'
df = pd.read_excel('hotspot analysis.xlsx')
plt.style.use('dark background')

# FT Lten the data for seLected countsies
selected_countries = ['Vietnam', 'China', 'India']
df_filtered   df[df['Country'].isin(selected_countries)]

# Set the pLof st'yLe
#sns . set(slyLe--”ahi legal d”)

# Create a LOne pLot with two y-axes
fig, ax1 = plt.subplots(figsize=(10,10))

# PLot GDP per capita on the Left y-axis
sns.lineplot(
    data=df filtered,
    x='Year',
    y='GDP per capita',
    hue='Country',
    marker=”o”,
    ax=ax1


ax1.set_xlabel('Year', fontsize=14)
ax1.set_ylabel('GDP per Capita (in USD)', fontsize=14, color='white')
ax1.tick_params(axis='y', labelcolor='white')

# Create a second y-axis gon Life Expectanc'y
ax2 = ax1.twinx()

sns.lineplot(
    data=df filtered,
    x='Year',
    y='Life expectancy',
    hue='Country',
    marker=”o”,
    linestyle=”--”,
    ax=ax2,
    legend=False


ax2.set_ylabel('Life Expectancy (in years)', fontsize=14, color='white')
ax2.tick params(axis='y', labelcolor='white')

it Set  pLot  titLe
plt.title('GDP per Capita vs. Life Expectancy Over Time for Selected Countries',

# DCspLay the pLot
plt.show()
```



inference for the GDP per capita Vs Year Graphs

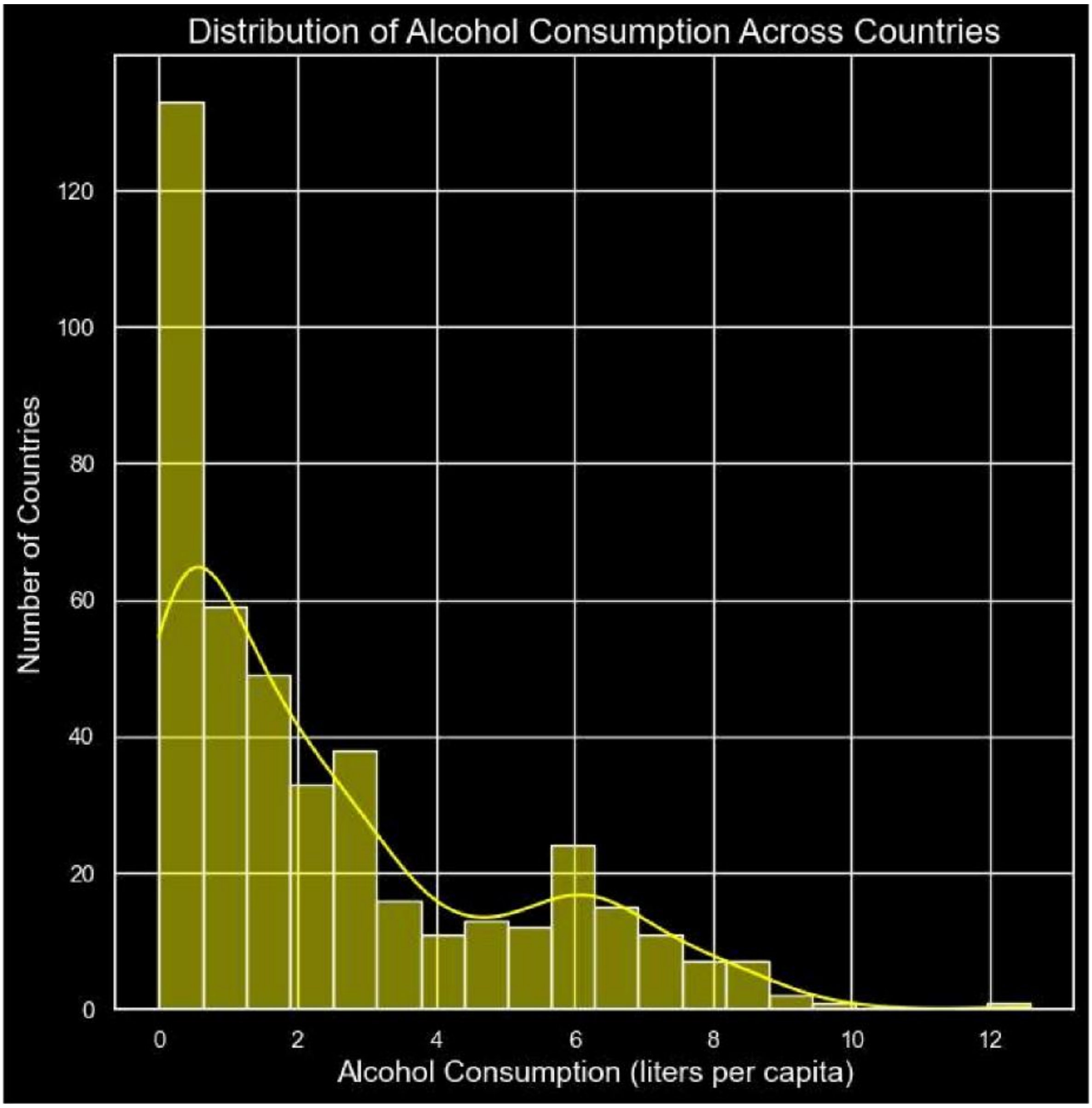
1-For all the selected countries there is a gradual increase in the GDP per Capita from 2000 to 2014 showing that there have been devlopments in all the countries over the period of time . 2- For china the rate to increase of GDP per Capita increases at a very increasing rate from 2005 to 2014 which shows the develpoment in china is more than all other countries in that given period of time.

inference for life Expectancy Vs Year Graphs

1- For almost all the countries selected for analysis the life expectancy increases over the time period from 2000 to 2014 showing that there have been significant advancements in the medical field with people recieving advanced treatments over the time period.

2- If there is a comparison of life expectancy between countries then vietnam has the highest life expectancy amongst all countries depicting that people in vietnam are strict and disciplined in terms of eating and sleeping habits, whereas india have the least life expectancy depicting indians may not follow a strict regime when it comes to diet and sleep.

In [55]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

It Load the  data from the ExceL fi  Le
#fi  Le path —— '/rnnt/data/hotspot anaLysis. xLsx'
df = pd.read_excel('hotspot analysis.xlsx')

# PLot a hi stognarn for   ALcoho L  ConsuHpti on
plt.figure(figsize=(8, 8))
sns.histplot(df['Alcohol_consumption'], bins=20, color='yellow',kde=True)

it Set  p Lot  t i t Le and  I abe Ls
plt.title('Distribution of Alcohol Consumption Across Countries', fontsize=16)
plt.xlabel('Alcohol Consumption (liters per capita)', fontsize=14)
plt.ylabel('Number of Countries', fontsize=14)

# Show the  p Lot
plt.show()
```



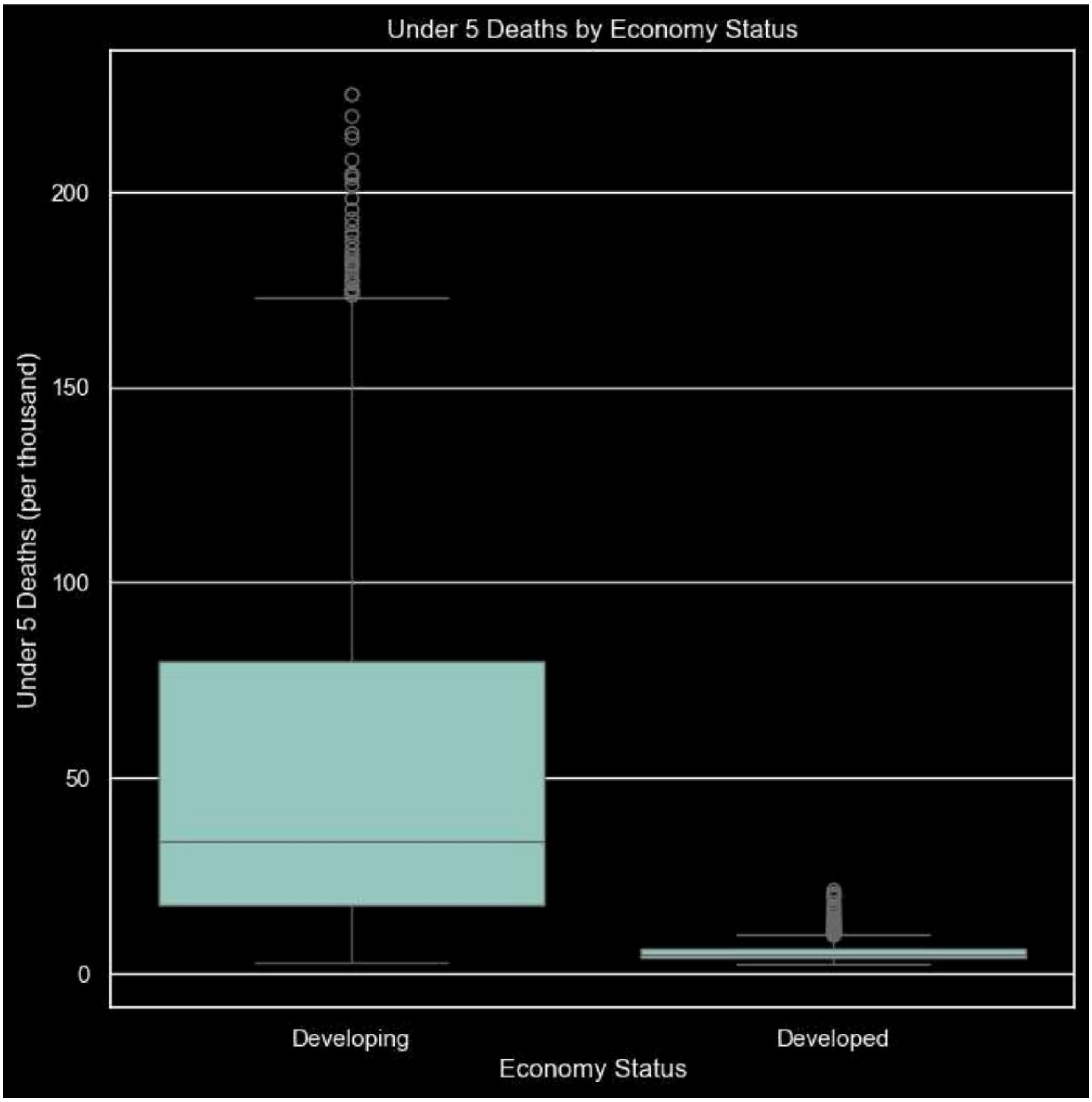
inference of graph between number of countries Vs alcohol consumption (liters per capita)

This is a histogram of alcohol consumption in liters per capita for different countries. From this histogram, the distribution is characterized by a strong right skew; thus, most countries are ranked at the low level of alcohol consumption, a big portion of which below 2 liters per capita. Very few of them have high consumption levels, with very few reaching even up to 12 or so liters per capita. This graph could then mean that high alcohol consumption rates are fairly low worldwide.

In [59]:

```
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
data=pd.read_csv('Life-Expectancy-Data-Updated.csv')
plt.style.use('dark_background')

# mapping economy status columns to a single categorical column for easier plott
```

```
data['Economy_Status'] = data.apply(lambda row: 'Developed' if row['Economy_stat

# PLofling the box pLot
plt.figure(figsize=(8, 8))
sns.boxplot(x='Economy_Status', y='Under_five_deaths', data=data)
plt.title('Under 5 Deaths by Economy Status')
plt.xlabel('Economy Status')
plt.ylabel('Under 5 Deaths (per thousand)')
plt.show()
```



inference for the Box plot of Under 5 Deaths Vs Economy Status

The number of Under S Deaths for developing countries is more than the developed countries which is mainly due to the less availability of advanced medical facilities in the developing regions (Like lack of skilled doctors ,unavailibility of quality medicines and other medical equipments).