Cycle Test 3- Assignment

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About the dataset (Life Expectancy Data)

The dataset contains the health data of 2938 individuals useful for predicting the life expentency of the individuals. The features are related to economical factors, immunity realted factors, social factors and so on.

Attribute Information:

Country: Country of the recorded data

Year: Year of the recorded data

Status: Status of the country

Life expectancy: Life expectancy in age (target/dependent variable)

Adult mortality: Rate of adult mortality

Infant deaths: Number of Infant Deaths per 1000 population

Alcohol: Alcohol consumption (in litres of pure alcohol)

Percentage expenditure: Expenditure on health as a percentage of GDP

Hepatitis B: Hepatitis B immunization coverage among 1-year-olds (%)

Measles: Number of reported cases per 1000 population

BMI: Average BMI of entire population

Under-five deaths: Number of under-five deaths per 1000 population

Polio: Polio immunization coverage among 1-year-olds (%)

Total expenditure: Government expenditure on health as a percentage of total government expenditure (%)

Diphtheria: DTP3 immunization coverage among 1-year-olds (%)

HIV/AIDS: Deaths per 1000 live births HIV/AIDS (0-4 years)

GDP: Gross Domestic Product per capita (in USD)

Population: Population of the country

Thinness 1-19 years: Prevalence of thinness for age 1 to 19 (%)

Thinness 5-9 years: Prevalence of thinness for age 5 to 9 (%)

Income composition of resources: Human Development Index in terms of income composition of resources

Schooling: Number of years of Schooling

Import the required libraries

In [5]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [6]:
```
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
/kaggle/input/LifeExpectancyData/LifeExpectancyData.csv
```

In [7]:
```
import warnings
warnings.filterwarnings(action='ignore')
```

In [8]:
```
from sklearn.model_selection import train_test_split
from sklearn.impute import KNNImputer
```

Load the life expectancy dataset and print the first five observations

In [67]:
```
# type your code here
df_life_exp = pd.read_csv('../input/LifeExpectancyData/LifeExpectancyData.csv')
df_life_exp.head()
```

Out[67]:

	Country	Year	Status	Life expectancy	Adult mortality	Infant deaths	Alcohol	Percentage expenditure	Hepatitis B	Measles	...	Polio	Total expenditure	Diphther
0	Afghanistan	2015	Developing	65.0	263.0	62	0.01	71.279624	65.0	1154	...	6.0	8.16	65
1	Afghanistan	2014	Developing	59.9	271.0	64	0.01	73.523582	62.0	492	...	58.0	8.18	62
2	Afghanistan	2013	Developing	59.9	268.0	66	0.01	73.219243	64.0	430	...	62.0	8.13	64
3	Afghanistan	2012	Developing	59.5	272.0	69	0.01	78.184215	67.0	2787	...	67.0	8.52	67
4	Afghanistan	2011	Developing	59.2	275.0	71	0.01	7.097109	68.0	3013	...	68.0	7.87	68

5 rows × 22 columns

Plot the following plots and write the inferences (5 marks)

(i) Pair plot

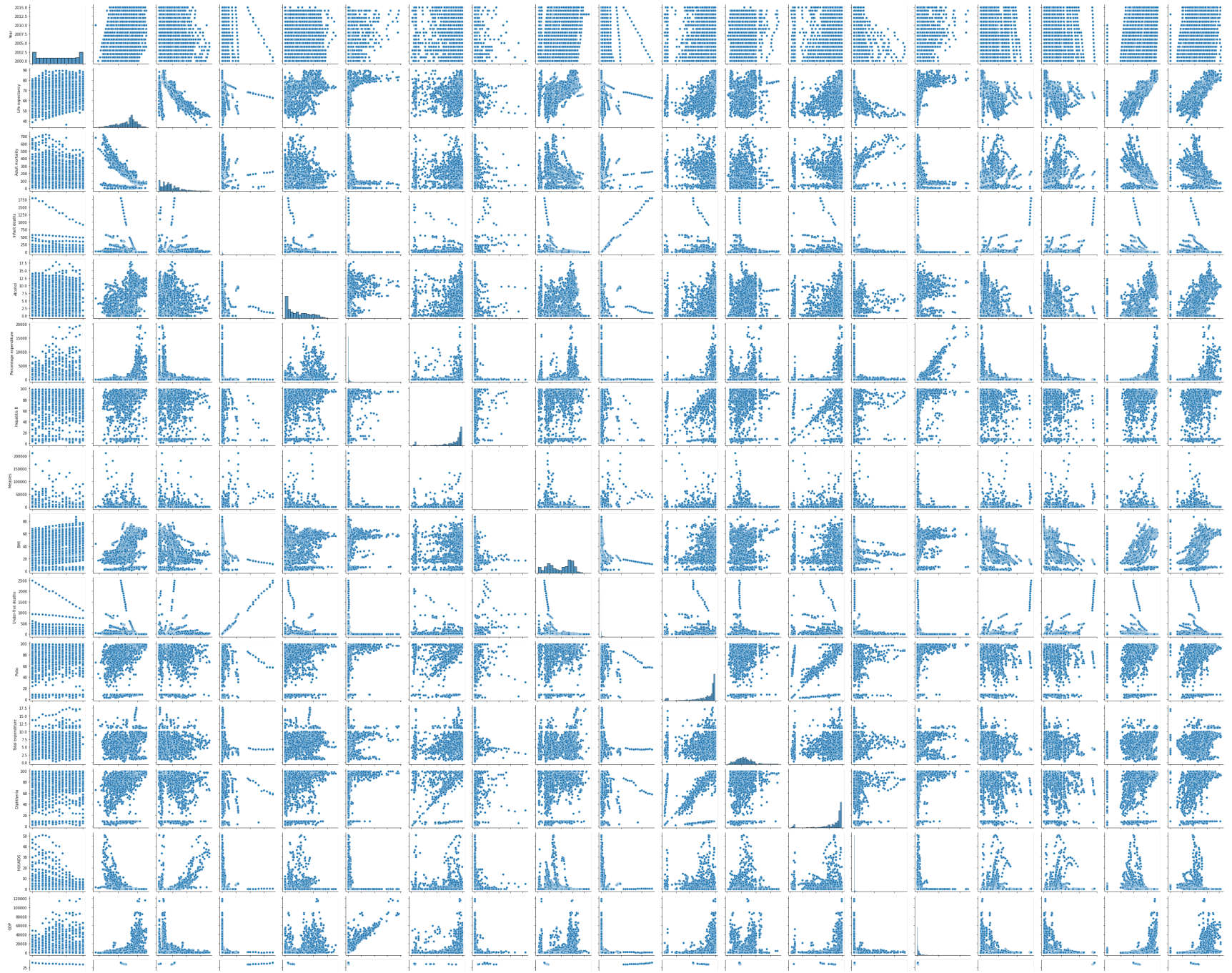
(ii) Dist Plot

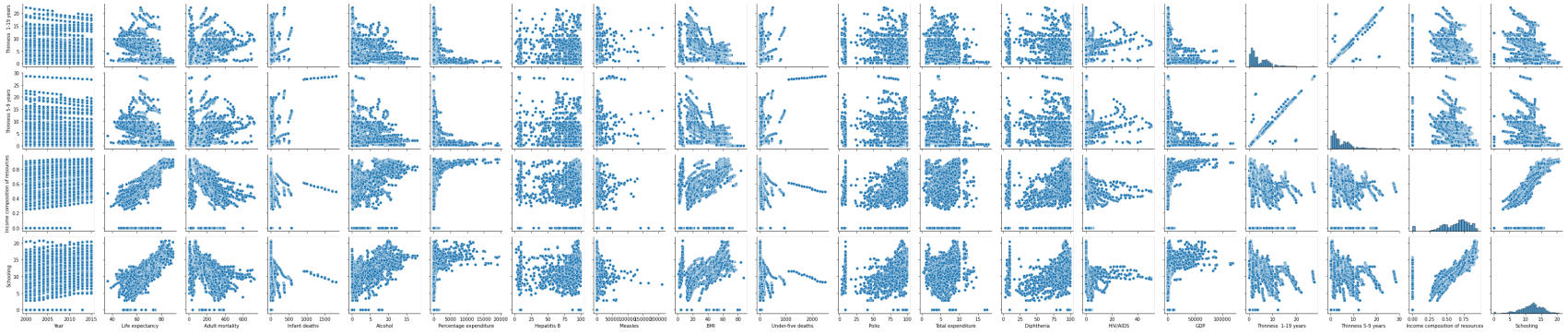
(iii)Box plot

(iv) Violin plot

(v) swarn plot

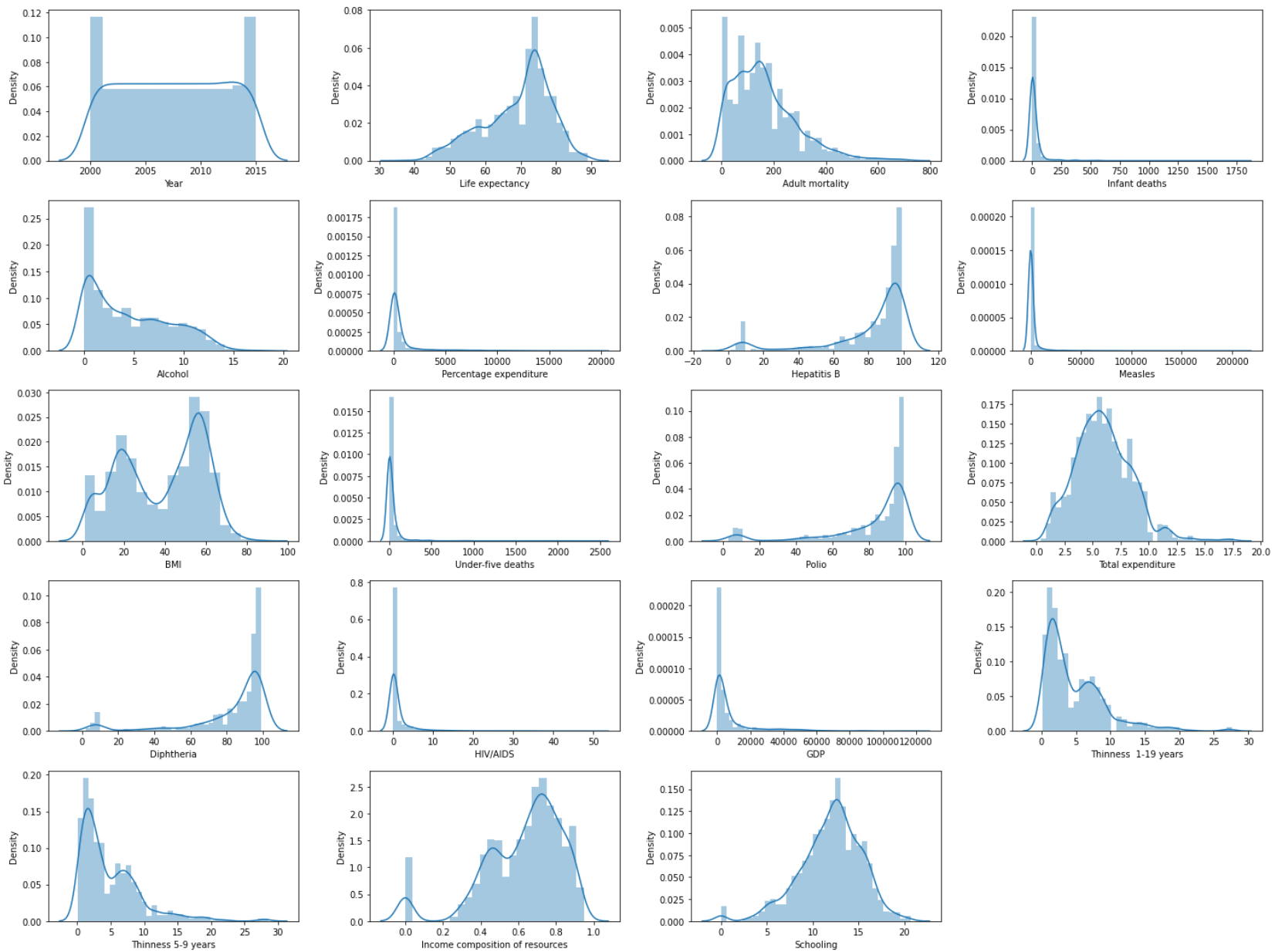
In [10]:
```
sns.pairplot(df_life_exp.select_dtypes(exclude='object'))
plt.show()
```





INFERENCE: Pairplot allows us to plot pairwise relationships between variables within a dataset. It helps us understand data by summarising large amount of data in a single picture.The main-diagonal subplots are the univariate distributions (here kernel density estimate (KDE) for each attribute.

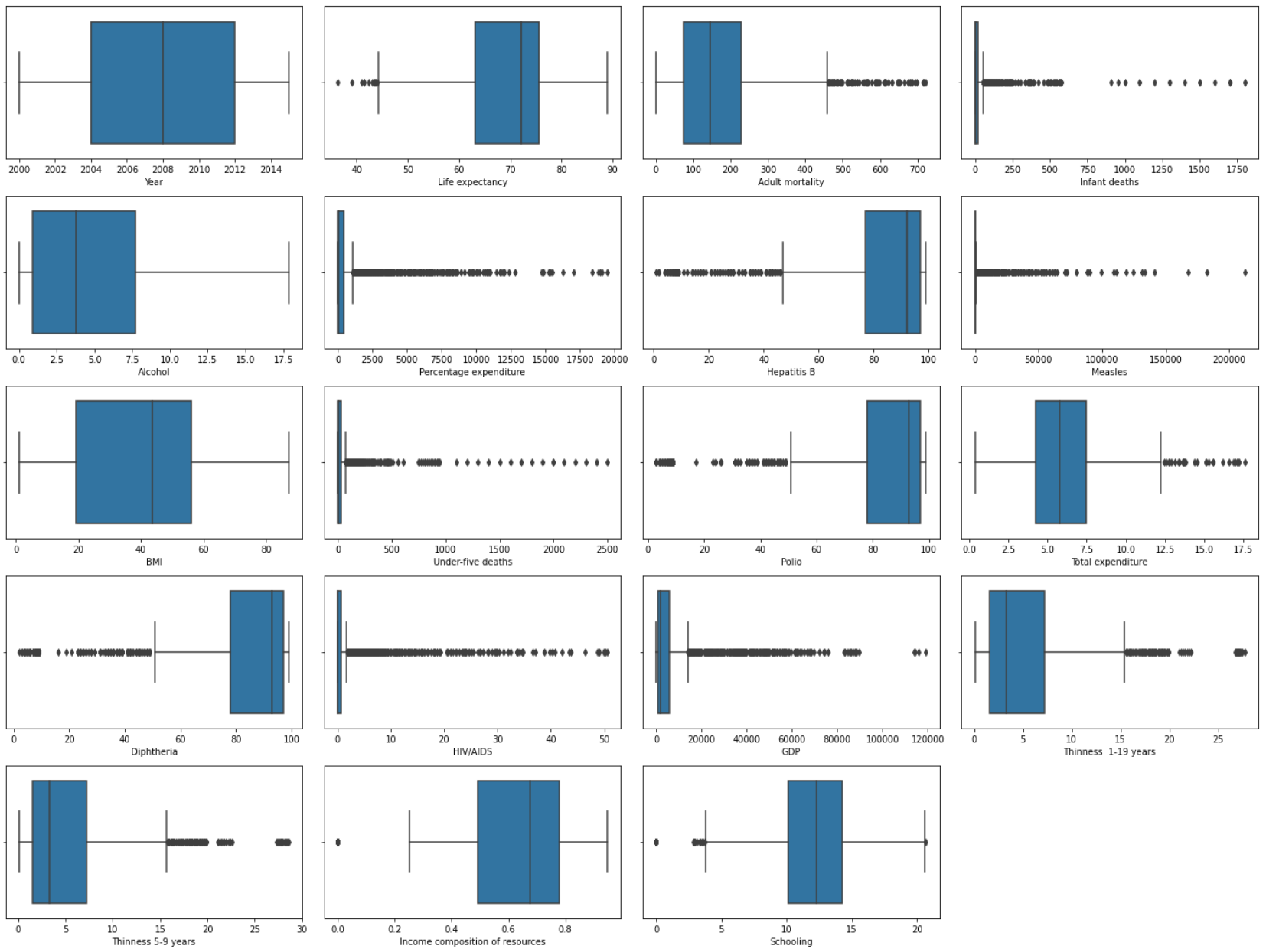
In [11]:
```
col = df_life_exp.select_dtypes(exclude='object').columns
plt.figure(figsize=(20,15))
for i in range(len(col)):
    plt.subplot(round(len(col)/4),4,i+1)
    sns.distplot(df_life_exp[col[i]])
plt.tight_layout()
plt.show()
```



INFERENCE: Distplot or distribution plot, depicts the variation in the data distribution. It represents distribution for continuous data variables. It depicts data by a histogram and a line in combination to it. The distplot represents the univariate distribution i.e. data distribution of a variable against

the density distribution. The y-axis is the probability density function for the kernel density estimation.

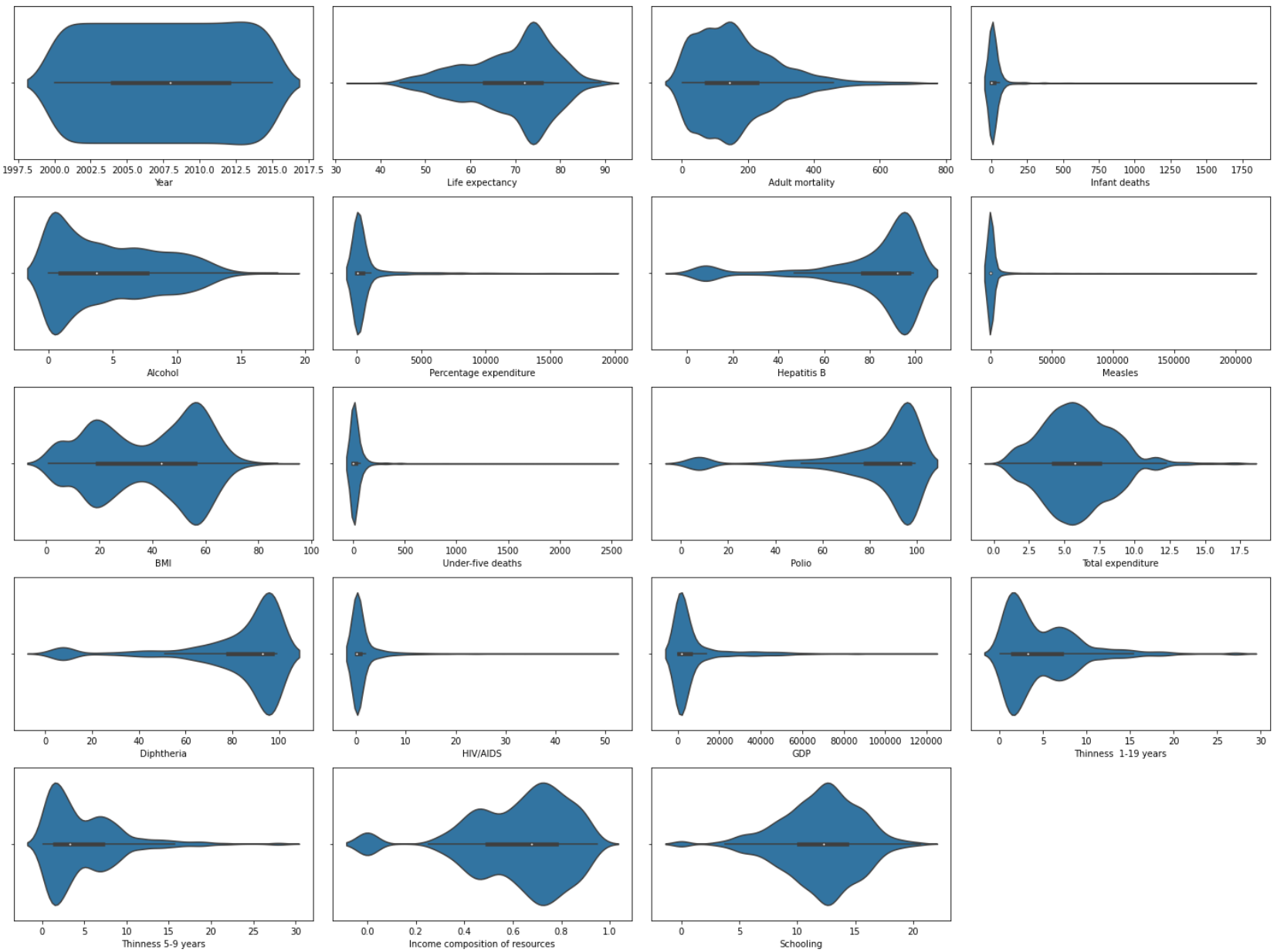
In [12]:
```
col = df_life_exp.select_dtypes(exclude='object').columns
plt.figure(figsize=(20,15))
for i in range(len(col)):
    plt.subplot(round(len(col)/4),4,i+1)
    sns.boxplot(df_life_exp[col[i]])
plt.tight_layout()
plt.show()
```



INFERENCE: Box plot shows the distribution of quantitative data. Commonly used for Univariate analysis. It can also be used in comparison with one or more categorical variables.The other name for box plot is 'box-and-whisker' plot. It is usefult to visualize the descriptive statistics of a variable.

The 'box' shows quartiles of the dataset while 'whiskers' shows the rest of the distribution. Boxplot are very good to visualize distributions and have a look on the minimum, maximum, 1st quartile and 3rd quartile values of the data.

In [13]:
```
col = df_life_exp.select_dtypes(exclude='object').columns
plt.figure(figsize=(20,15))
for i in range(len(col)):
    plt.subplot(round(len(col)/4),4,i+1)
    sns.violinplot(df_life_exp[col[i]])
plt.tight_layout()
plt.show()
```



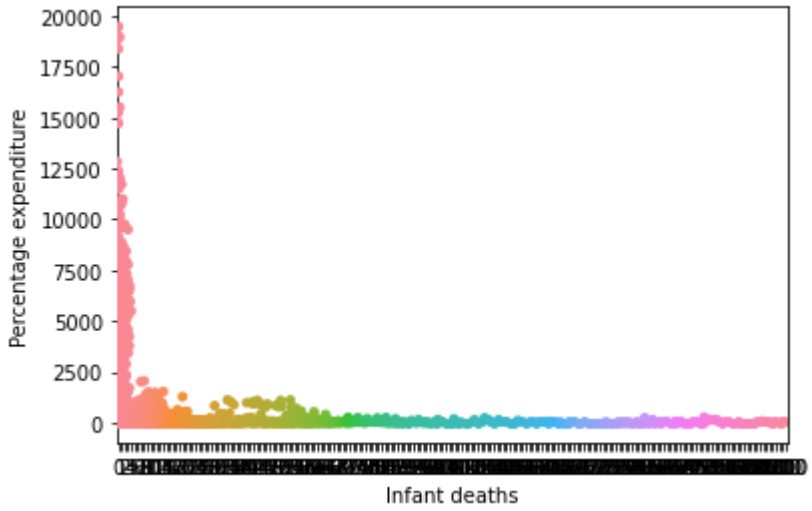
INFERENCE: **Violin plot is a combination of boxplot and kernel density estimate. It shows the distribution of quantitative data across several levels of one (or more) categorical variables so that the distributions can be compared. In box plot, we analyze with actual datapoints but the violin plot uses a kernel density estimation of that distribution.**

In [14]:
```
col = []
for i in df_life_exp.columns:
    if df_life_exp[i].isnull().sum() == 0:
        col.append(i)

lst = []
for i in range(len(col)):
    for j in range(len(col)):
        if i==j:
            continue
        lst.append(tuple(sorted([col[i],col[j]])))
combinations = list(set(lst))
combinations
```

Out[14]:
```
[('Infant deaths', 'Percentage expenditure'),
 ('Under-five deaths', 'Year'),
 ('Percentage expenditure', 'Population'),
 ('Measles', 'Year'),
 ('Infant deaths', 'Year'),
 ('Country', 'Infant deaths'),
 ('Country', 'HIV/AIDS'),
 ('Country', 'Percentage expenditure'),
 ('HIV/AIDS', 'Measles'),
 ('Measles', 'Percentage expenditure'),
 ('Infant deaths', 'Population'),
 ('Population', 'Under-five deaths'),
 ('HIV/AIDS', 'Year'),
 ('Percentage expenditure', 'Under-five deaths'),
 ('Measles', 'Under-five deaths'),
 ('Country', 'Under-five deaths'),
 ('HIV/AIDS', 'Infant deaths'),
 ('Measles', 'Population'),
 ('Country', 'Population'),
 ('Country', 'Measles'),
 ('HIV/AIDS', 'Percentage expenditure'),
 ('Infant deaths', 'Under-five deaths'),
 ('Population', 'Year'),
 ('Infant deaths', 'Measles'),
 ('HIV/AIDS', 'Under-five deaths'),
 ('Percentage expenditure', 'Year'),
 ('HIV/AIDS', 'Population'),
 ('Country', 'Year')]
```

In [15]:
```
combinations[0][1]
sns.swarmplot(x = combinations[0][0] , y = combinations[0][1], data= df_life_exp)
```

Out[15]: <AxesSubplot:xlabel='Infant deaths', ylabel='Percentage expenditure'>



INFERENCE: Swarmplot is like a categorical scatterplot with points adjusted to be non-overlapping. Here the points are adjusted (only along the categorical axis) so that they don't overlap. This gives a better representation of the distribution of values. It is sometimes called a 'beeswarm'. Swarm plot is not efficient in plotting for large number of features.

In [16]:
```
# plt.figure(figsize=(20,15))
# for i in range(len(combinations)):
#     plt.subplot(round(len(combinations)/4),4,i+1)
#     sns.swarmplot(x = combinations[i][0] , y = combinations[i][1], data= df_life_exp)
# plt.tight_layout()
# plt.show()
```

Let's begin with some hands-on practice exercises

1. Check the data type of each variable and if any variable is wrongly identified, do the needful (1 mark)

In [17]:
```
# type your code here
pd.DataFrame({'Dtype': df_life_exp.dtypes,'1st row Values': df_life_exp.iloc[1], 'Null Values': df_life_exp.isnu
```

Out[17]:

	Dtype	1st row Values	Null Values
Country	object	Afghanistan	0
Year	int64	2014	0
Status	object	Developing	16
Life expectancy	float64	59.9	10
Adult mortality	float64	271.0	10
Infant deaths	int64	64	0
Alcohol	float64	0.01	194
Percentage expenditure	float64	73.523582	0
Hepatitis B	float64	62.0	553
Measles	int64	492	0
BMI	float64	18.6	34
Under-five deaths	int64	86	0
Polio	float64	58.0	19
Total expenditure	float64	8.18	226
Diphtheria	float64	62.0	19
HIV/AIDS	float64	0.1	0
GDP	float64	612.696514	448
Population	object	327582	0
Thinness 1-19 years	float64	17.5	34
Thinness 5-9 years	float64	17.5	34
Income composition of resources	float64	0.476	167
Schooling	float64	10.0	163

In [18]:
```
df_life_exp.Population.value_counts(dropna=False)
```

Out[18]:
```
#           652
444           4
718239        2
1141          2
26868         2
             ...
4136          1
482           1
43            1
3978          1
12222251      1
Name: Population, Length: 2279, dtype: int64
```

In [19]:
```
# #changing the '#' to 'null'
df_life_exp.Population.replace(to_replace='#', value= np.nan, inplace=True)
```

In [20]:
```
df_life_exp['Population'] = df_life_exp['Population'].astype('float64')
```

INFERENCE: When checked the dataset, we found column 'Population' was in 'object' datatype. And it had value '#' in 652 places. So we have first replaced '#' value with 'NaN' and then converted it to 'float' datatype. Now we can see that there are 652 null values in 'Population' feature.

2. Create a DataFrame containing the count and percentage of missing entries in each variable (2 marks)

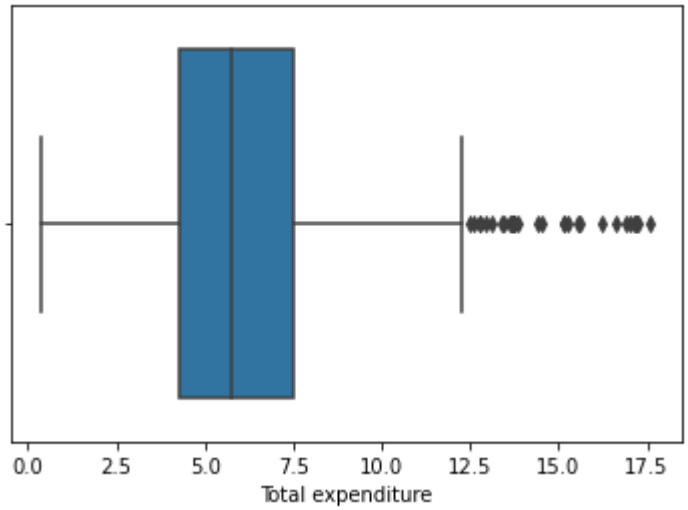
In [21]:
```
column_count = [df_life_exp[x].count() for x in df_life_exp]
column_name = [x for x in df_life_exp]
null_percent = [str(round((df_life_exp[x].isnull().sum()/len(df_life_exp))*100,2))+'%' for x in df_life_exp]

pd.DataFrame({'Varaible' : column_name, 'Variable_count' : column_count, 'Null_value%' : null_percent})
```

Out[21]:

	Varaible	Variable_count	Null_value%
0	Country	2938	0.0%
1	Year	2938	0.0%
2	Status	2922	0.54%
3	Life expectancy	2928	0.34%
4	Adult mortality	2928	0.34%
5	Infant deaths	2938	0.0%
6	Alcohol	2744	6.6%
7	Percentage expenditure	2938	0.0%
8	Hepatitis B	2385	18.82%
9	Measles	2938	0.0%
10	BMI	2904	1.16%
11	Under-five deaths	2938	0.0%
12	Polio	2919	0.65%
13	Total expenditure	2712	7.69%
14	Diphtheria	2919	0.65%
15	HIV/AIDS	2938	0.0%
16	GDP	2490	15.25%
17	Population	2286	22.19%
18	Thinness 1-19 years	2904	1.16%
19	Thinness 5-9 years	2904	1.16%
20	Income composition of resources	2771	5.68%
21	Schooling	2775	5.55%

3a. Are there any extreme values present in the government's total expenditure on health? (2 marks)

In [22]:
```
# type your code here
sns.boxplot(df_life_exp['Total expenditure'])
plt.show()
print(df_life_exp['Total expenditure'].describe())
```




```
count    2712.00000
mean        5.93819
std         2.49832
min         0.37000
25%         4.26000
50%         5.75500
75%         7.49250
max        17.60000
Name: Total expenditure, dtype: float64
```

In [23]:
```
def get_extreme_val(data):
    q1, q3 = data.quantile([.25, .75])
    iqr = q3-q1
    lb = q1 - (1.5*iqr)
    ub = q3 + (1.5*iqr)
    extreme_Values = [x for x in data
                      if ((x < lb) | (x > ub))]
    print("Q1 :" ,q1, "\tQ3 :" ,q3,"\nIQR :" ,iqr, "\tLB :" ,lb,"\tUB :", ub, "\nNumber of extVals :", len(extre
    print('Exteme Values :',extreme_Values)
    return extreme_Values
```

In [24]:
```
ext_vals = get_extreme_val(df_life_exp['Total expenditure'])
```

```
Q1 : 4.26       Q3 : 7.4925
IQR : 3.2325    LB : -0.5887500000000001        UB : 12.341249999999999
Number of extVals : 32
Exteme Values : [13.66, 14.39, 12.6, 13.73, 17.24, 13.71, 13.38, 12.77, 13.76, 13.83, 13.44, 12.94, 12.8, 12.4
9, 13.13, 13.63, 16.61, 17.14, 16.9, 17.2, 17.6, 17.2, 17.0, 16.2, 15.57, 15.27, 15.15, 15.14, 15.6, 14.55, 1
3.73, 13.7]
```

In [25]:
```
print("Yes, there are '", len(ext_vals), "' extreme values in 'Total expenditure'")
```

```
Yes, there are ' 32 ' extreme values in 'Total expenditure'
```

INFERENCE: Box plot of 'Total expenditure' shows that there are some values outside of Upper bound.

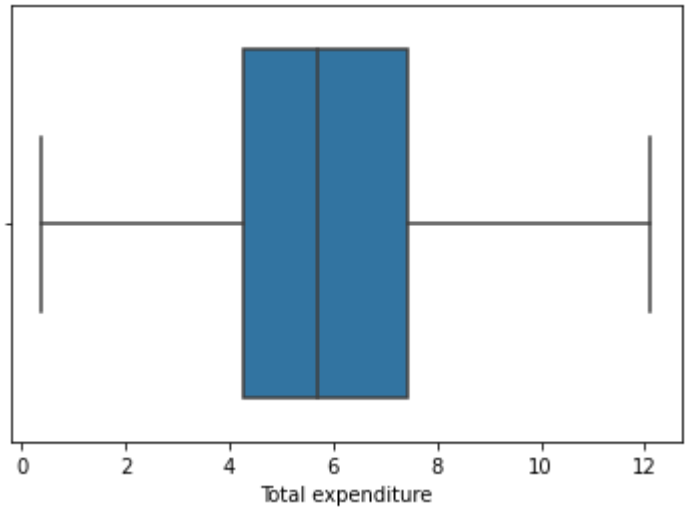
3b. Remove the outliers present in 'Total expenditure' using the quartiles of the variable (2 marks)

In [26]:
```
def index_of_extreme_values(data, extreme_Values):
    return [ data[data['Total expenditure'] == x].index[0]
                          for x in data['Total expenditure']
                          if (x in extreme_Values)]
```

In [27]:
```
# type your code here
while (len(ext_vals) > 0):
    ext_vals = get_extreme_val(df_life_exp['Total expenditure'])
    indexes = index_of_extreme_values(df_life_exp, ext_vals)
    print(indexes,'\n----------------------------------------------------------\n\n')
    df_life_exp.drop(index = indexes, inplace=True)
    df_life_exp.reset_index(inplace=True, drop=True)
```

```
Q1 : 4.26       Q3 : 7.4925
IQR : 3.2325    LB : -0.5887500000000001        UB : 12.341249999999999
Number of extVals : 32
Exteme Values : [13.66, 14.39, 12.6, 13.73, 17.24, 13.71, 13.38, 12.77, 13.76, 13.83, 13.44, 12.94, 12.8, 12.4
9, 13.13, 13.63, 16.61, 17.14, 16.9, 17.2, 17.6, 17.2, 17.0, 16.2, 15.57, 15.27, 15.15, 15.14, 15.6, 14.55, 1
3.73, 13.7]
[1386, 1496, 1573, 1603, 1650, 1700, 1701, 1702, 1703, 1704, 1705, 1706, 2108, 2109, 2303, 2312, 2713, 2795, 2
796, 2797, 2798, 2797, 2800, 2801, 2802, 2803, 2804, 2805, 2806, 2807, 1603, 2809]
----------------------------------------------------------


Q1 : 4.2524999999999995         Q3 : 7.43
IQR : 3.1775    LB : -0.5137500000000008        UB : 12.19625
Number of extVals : 5
Exteme Values : [12.24, 12.23, 12.25, 17.2, 13.73]
[1384, 1385, 2292, 2778, 2779]
----------------------------------------------------------


Q1 : 4.25       Q3 : 7.43
IQR : 3.1799999999999997        LB : -0.5199999999999996        UB : 12.2
Number of extVals : 0
Exteme Values : []
[]
----------------------------------------------------------
```

In [28]:
```
sns.boxplot(df_life_exp['Total expenditure'])
plt.show()
print(df_life_exp['Total expenditure'].describe())
```




```
count    2677.000000
mean        5.825771
std         2.303350
min         0.370000
25%         4.250000
50%         5.710000
75%         7.430000
max        12.110000
Name: Total expenditure, dtype: float64
```

INFERENCE: There are some extreme values outside of upper/lower bound and it was removed in a loop, till the external values gets removed.

4. Split the data such that 'X' will contain all the independent variables and 'y' will contain the target variable (2 mark)

Hint: 'Life expectancy' is the target variable depending on the remaining variables.

In [29]:
```
# type your code here
df_x = df_life_exp.drop(['Life expectancy'], axis=1)
df_x.columns
```

Out[29]:
```
Index(['Country', 'Year', 'Status', 'Adult mortality', 'Infant deaths',
       'Alcohol', 'Percentage expenditure', 'Hepatitis B', 'Measles', 'BMI',
       'Under-five deaths', 'Polio', 'Total expenditure', 'Diphtheria',
       'HIV/AIDS', 'GDP', 'Population', 'Thinness  1-19 years',
       'Thinness 5-9 years', 'Income composition of resources', 'Schooling'],
      dtype='object')
```

In [30]:
```
df_y = df_life_exp['Life expectancy']
```

INFERENCE: 'df_x' contains all independent variables (21 features) except 'Life expectancy'. 'df_y' has only target variable (1 feature) 'Life expectancy'.

5. Split the independent variables into two sets with the proportion of 70:30 (2 mark)

In [31]:
```
# type your code here
df_x_1, df_x_2 = train_test_split(df_x, test_size=0.30, random_state=40)
print(df_x_1.shape)
print(df_x_2.shape)
```

```
(2032, 21)
(871, 21)
```

INFERENCE: 'xtrain' has 70 percentage of input data i.e., 2032/2903 rows and 'xtest' contains 30 percentage of input data i.e., 871/2903 rows .

6. How would you treat the missing values in the variable 'GDP'? (2 marks)

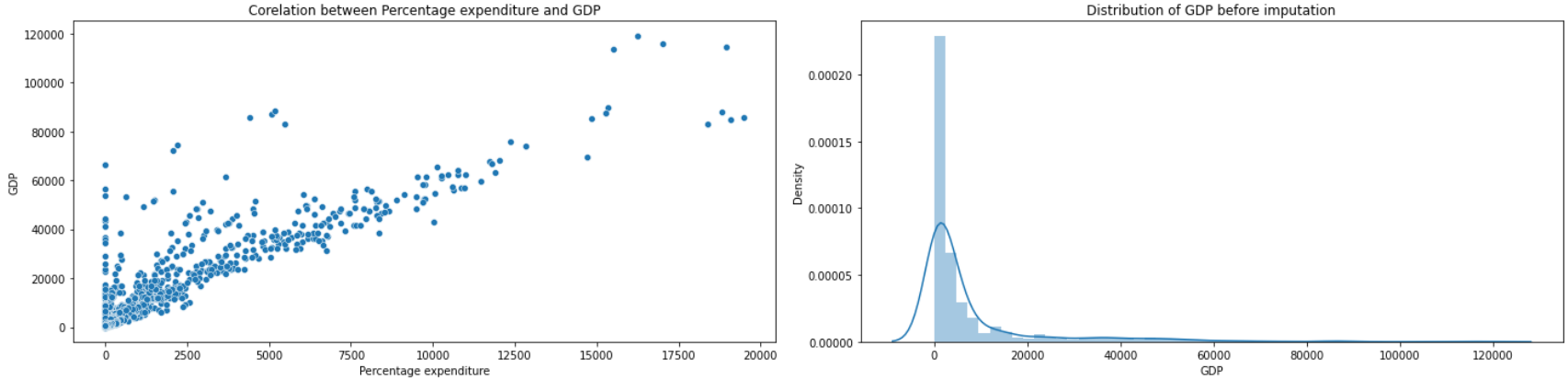
In [32]:
```
# type your code here
df_life_exp['GDP'].isnull().sum()
```

Out[32]:
```
424
```

In [33]:
```
df_life_exp['GDP'].describe()
```

Out[33]:
```
count      2479.000000
mean       7508.225266
std       14296.068366
min           1.681350
25%         464.674822
50%        1774.336730
75%        5937.373389
max      119172.741800
Name: GDP, dtype: float64
```

In [34]:
```
plt.figure(figsize=(20,5))
plt.subplot(1,2,1)
plt.title("Corelation between Percentage expenditure and GDP")
sns.scatterplot(data=df_life_exp, x='Percentage expenditure', y ='GDP')
plt.subplot(1,2,2)
plt.title("Distribution of GDP before imputation")
sns.distplot(df_life_exp['GDP'])
plt.tight_layout()
plt.show()
print("corr : ",df_life_exp['Percentage expenditure'].corr(df_life_exp['GDP']))
```

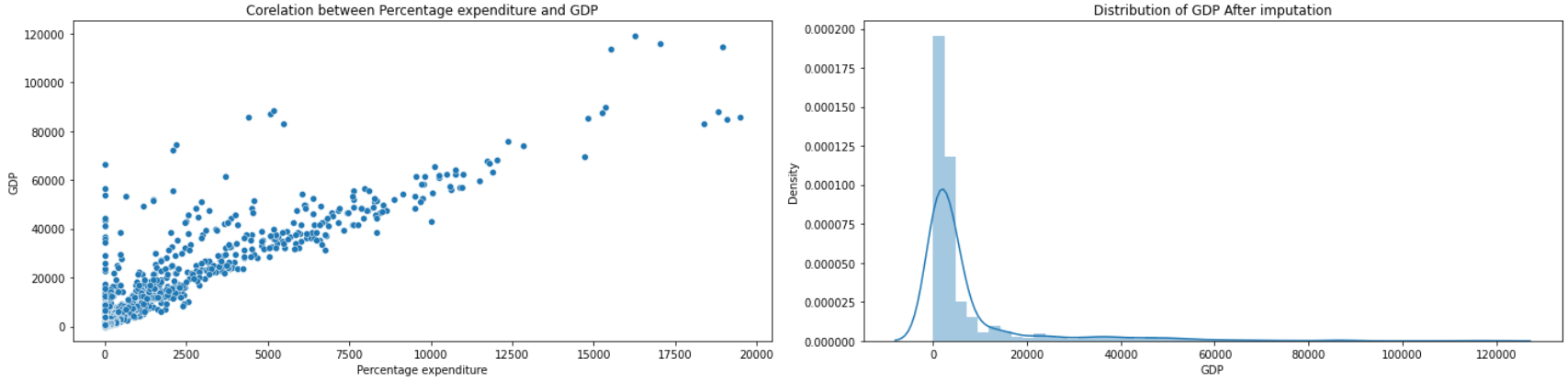



```
corr :  0.899396380118142
```

In [35]:
```
imp = KNNImputer(n_neighbors=2)
after_imp = pd.DataFrame(imp.fit_transform(df_life_exp[['Percentage expenditure', 'GDP']]))
df_life_exp['GDP'] = list(after_imp[1])
df_life_exp['GDP'].describe()
```

Out[35]:
```
count      2903.000000
mean       6983.308456
std       13271.333568
min           1.681350
25%         575.384106
50%        2977.115300
75%        4855.459715
max      119172.741800
Name: GDP, dtype: float64
```

In [36]:
```
plt.figure(figsize=(20,5))
plt.subplot(1,2,1)
plt.title("Corelation between Percentage expenditure and GDP")
sns.scatterplot(data=df_life_exp, x='Percentage expenditure', y ='GDP')
plt.subplot(1,2,2)
plt.title("Distribution of GDP After imputation")
sns.distplot(df_life_exp['GDP'])
plt.tight_layout()
plt.show()
print("corr : ",df_life_exp['Percentage expenditure'].corr(df_life_exp['GDP']))
```




```
corr :  0.8993058263925546
```

INFERENCE: While analysing the dataset, we saw 'Percentage expenditure' was calculated based on GDP and it had zero null values. We found correlation between 'Percentage expenditure' and 'GDP', which showed high correation. (nearly 90%). So we imputed null values in 'GDP' using KNN imputation.

7.There are 16 observations for which the status of the corresponding country is unknown, impute this status with an appropriate values (2 marks)

In [37]:
```
df_life_exp['Status'].isnull().sum()
```

Out[37]:
```
16
```

In [68]:
```
set_of_developing_countries = set(df_life_exp[df_life_exp['Status'] == 'Developing']['Country'].unique())
set_of_developed_countries = set(df_life_exp[df_life_exp['Status'] == 'Developed']['Country'].unique())
print('\nNumber of countries :', len(df_life_exp['Country'].unique()))
print('\nCount of unique developing countries : ', len(set_of_developing_countries))
print('Count of unique developed countries : ', len(set_of_developed_countries))
print('\nNumber of null values in status :' ,df_life_exp['Status'].isnull().sum())
print('\nIntersection between them : ', len(set_of_developing_countries.intersection(set_of_developed_countries)
```

```
Number of countries : 193

Count of unique developing countries :  161
Count of unique developed countries :  32

Number of null values in status : 16

Intersection between them :  0
```

In [38]:
```
df_life_exp.groupby(by='Country').describe(include = 'object')['Status']['top']['Afghanistan']
```

Out[38]:
```
'Developing'
```

In [39]:
```
index_of_null_status = df_life_exp[df_life_exp['Status'].isnull()].index
for i in index_of_null_status:
    if np.isnan(df_life_exp['Status'][i]):
        df_life_exp['Status'][i] =  df_life_exp.groupby(by='Country').describe(include = 'object')['Status']['to
```

In [40]:
```
df_life_exp.iloc[index_of_null_status]
```

Out[40]:

	Country	Year	Status	Life expectancy	Adult mortality	Infant deaths	Alcohol	Percentage expenditure	Hepatitis B	Measles	...	Polio	Total expenditure	Diph
6	Afghanistan	2009	Developing	58.6	281.0	77	0.01	56.762217	63.0	2861	...	63.0	9.42	
15	Afghanistan	2000	Developing	54.8	321.0	88	0.01	10.424960	62.0	6532	...	24.0	8.20	
27	Albania	2004	Developing	73.0	17.0	1	4.54	221.842800	99.0	7	...	98.0	6.38	
46	Algeria	2001	Developing	71.4	145.0	20	0.23	147.986071	NaN	2686	...	89.0	3.84	
65	Antigua and Barbuda	2014	Developing	76.2	131.0	0	8.56	2422.999774	99.0	0	...	96.0	5.54	
75	Antigua and Barbuda	2004	Developing	74.4	149.0	0	7.28	22.862952	97.0	0	...	97.0	4.21	
82	Argentina	2013	Developing	76.0	119.0	8	8.28	1001.796332	94.0	0	...	99.0	4.99	
93	Argentina	2002	Developing	74.1	138.0	12	7.81	470.186915	66.0	0	...	94.0	8.31	
104	Armenia	2007	Developing	73.5	132.0	1	3.99	44.572200	85.0	1	...	9.0	4.31	
118	Australia	2009	Developed	81.7	66.0	1	10.62	7172.275229	94.0	104	...	92.0	9.50	
136	Austria	2007	Developed	81.0	8.0	0	12.50	7453.864400	85.0	20	...	85.0	1.40	
148	Azerbaijan	2011	Developing	71.6	125.0	5	1.98	263.142699	84.0	0	...	91.0	5.10	
458	Cabo Verde	2005	Developing	71.8	134.0	0	4.26	3.349817	93.0	0	...	95.0	4.86	
1129	Haiti	2008	Developing	62.1	259.0	16	5.95	63.831957	NaN	0	...	64.0	5.92	
1989	Paraguay	2003	Developing	71.7	166.0	4	6.64	155.423308	86.0	0	...	86.0	5.99	
2054	Portugal	2002	Developed	77.2	17.0	1	12.00	1904.002310	82.0	8	...	96.0	9.15	

16 rows × 22 columns

INFERENCE: First we found out if there is any country with both 'Developed' and 'Developing' status through intersection and output was zero. Then we checked the dataset and found that 'Status' value was missing for countries for few years and it was present in another year. For eg: For country 'Afghanisthan' Status was missing for years '2000' and '2009' but status is 'Developing' for rest all years for Afghanistan.

8. Define a function to find the extreme values in alcohol consumption (2 marks)

In [41]:
```
ext_values  = get_extreme_val(df_life_exp['Alcohol'])
print("\n\nYes, there are '", len(ext_values), "' extreme values in 'Total expenditure'")
```

```
Q1 : 0.87       Q3 : 7.65
IQR : 6.78      LB : -9.3       UB : 17.82
Number of extVals : 1
Exteme Values : [17.87]


Yes, there are ' 1 ' extreme values in 'Total expenditure'
```

INFERENCE: Column 'Alcohol' has only one extreme value i.e., '17.87'and it lies outside Upper bound. Value of Upper bound is '17.82'.

9. Create a column 'Life_expectancy_level' such that it will contain three levels (High, Medium, Low) based on the life expectancy (3 marks)

In [42]:
```
# type your code here
df_life_exp['Life expectancy'].describe()
```

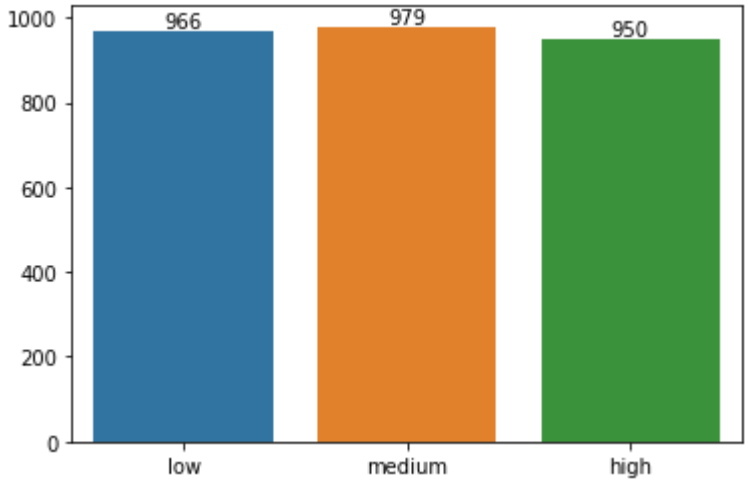
Out[42]:
```
count    2895.000000
mean       69.217133
std         9.511732
min        36.300000
25%        63.050000
50%        72.100000
75%        75.600000
max        89.000000
Name: Life expectancy, dtype: float64
```

In [43]:
```
df_life_exp['Life expectancy'].fillna(np.nan, inplace=True)
```

In [44]:
```
q0,q1,q2,q3 = df_life_exp['Life expectancy'].quantile([0,1/3,2/3,1])
df_life_exp['Life_expectancy_level'] = pd.cut(df_life_exp['Life expectancy'], [q0-1,q1,q2,q3], labels=['low', 'm
```

In [45]:
```
df_temp = df_life_exp['Life_expectancy_level'].value_counts(dropna=True)
```

In [46]:
```
ax = sns.barplot(x = df_temp.index, y = df_temp.values)
plt.bar_label(ax.containers[0])
plt.show()
```



Life expectancy level 'Low' has values from 0 to first quartile (i.e., 66.6).

Life expectancy level 'Medium' has values from 66.7 to second quartile (i.e., 74.4).

Life expectancy level 'High' has values from 74.5 to maximum value (i.e., 89).

10. Check how life expectancy has changed over the years in China (2marks)

In [47]:
```
# type your code here
df_life_exp_china = df_life_exp[df_life_exp['Country'] == 'China']
df_life_exp_china
```

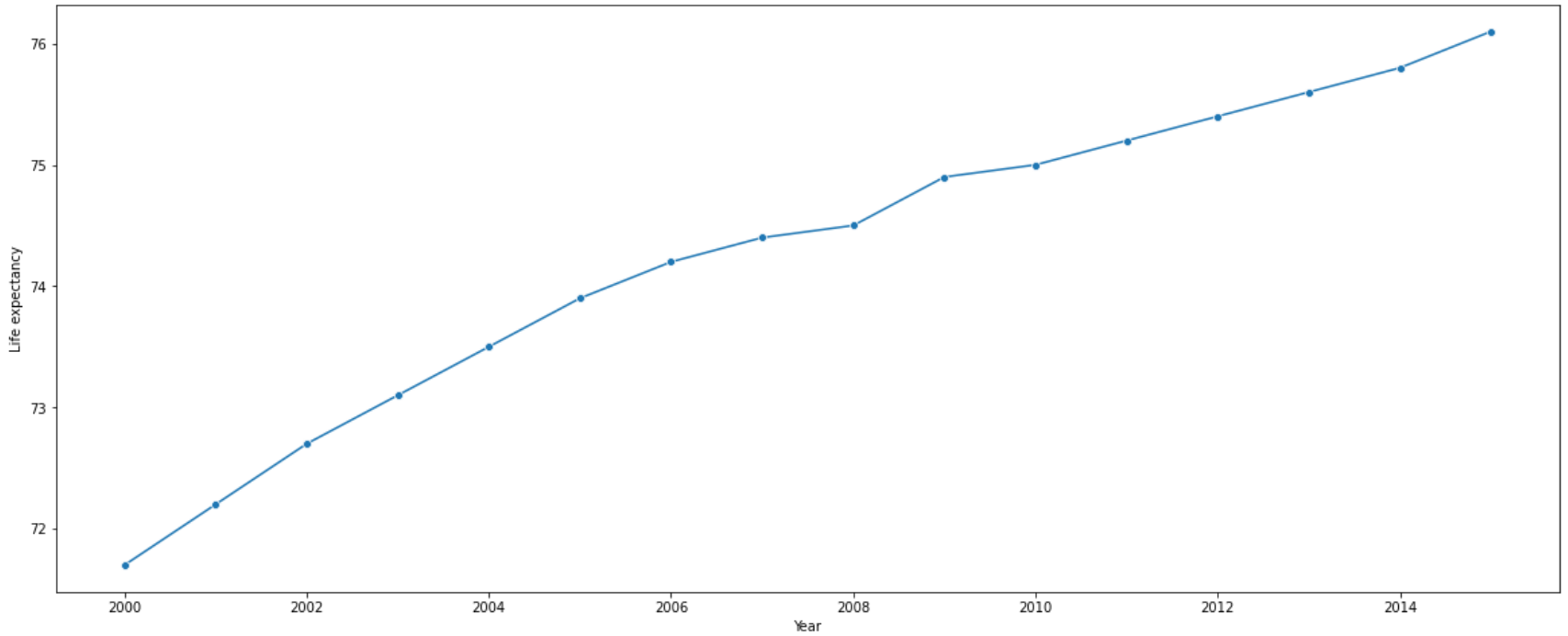
Out[47]:

	Country	Year	Status	Life expectancy	Adult mortality	Infant deaths	Alcohol	Percentage expenditure	Hepatitis B	Measles	...	Total expenditure	Diphtheria	HIV/
560	China	2015	Developing	76.1	85.0	157	NaN	0.000000	99.0	42361	...	NaN	99.0	
561	China	2014	Developing	75.8	86.0	171	5.78	109.874390	99.0	52628	...	5.55	99.0	
562	China	2013	Developing	75.6	88.0	185	5.79	9.955532	99.0	26883	...	5.39	99.0	
563	China	2012	Developing	75.4	89.0	201	5.74	94.434457	99.0	6183	...	5.26	99.0	
564	China	2011	Developing	75.2	91.0	215	5.63	91.267498	99.0	9943	...	5.30	99.0	
565	China	2010	Developing	75.0	92.0	231	5.75	5.660755	99.0	38159	...	4.89	99.0	
566	China	2009	Developing	74.9	93.0	248	4.88	50.283489	99.0	52461	...	5.80	99.0	
567	China	2008	Developing	74.5	97.0	266	4.27	39.225097	95.0	131441	...	4.59	97.0	
568	China	2007	Developing	74.4	96.0	285	3.88	312.662482	92.0	109023	...	4.32	93.0	
569	China	2006	Developing	74.2	98.0	307	3.28	29.743430	91.0	99602	...	4.52	93.0	
570	China	2005	Developing	73.9	99.0	332	2.92	171.659603	84.0	124219	...	4.66	87.0	
571	China	2004	Developing	73.5	11.0	360	3.04	1.586685	79.0	70549	...	4.72	87.0	
572	China	2003	Developing	73.1	13.0	391	2.96	122.936535	75.0	71879	...	4.82	86.0	
573	China	2002	Developing	72.7	16.0	422	2.91	106.359036	7.0	58341	...	4.79	86.0	
574	China	2001	Developing	72.2	11.0	457	2.84	14.230645	65.0	88962	...	4.56	86.0	
575	China	2000	Developing	71.7	115.0	490	3.06	17.460574	6.0	71093	...	4.60	85.0	

16 rows × 23 columns

In [48]:
```
df_life_exp_china.sort_values(by='Year', inplace=True)
```

In [49]:
```
plt.figure(figsize=(20,8))
sns.lineplot(x ='Year', y ='Life expectancy', data=df_life_exp_china, marker='o')
plt.show()
```



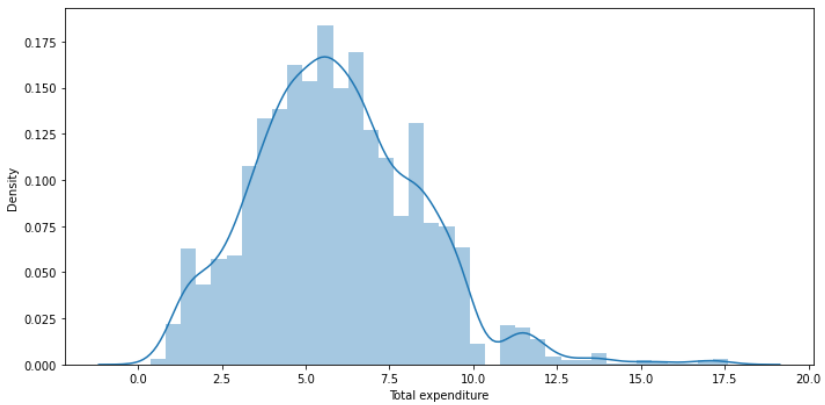
INFERENCE: From the above line plot, we can conclude that 'Life expectancy' of China has increased over the years. In other words, in a span of 14 years, life expectancy of people has increased from 71 to 76.

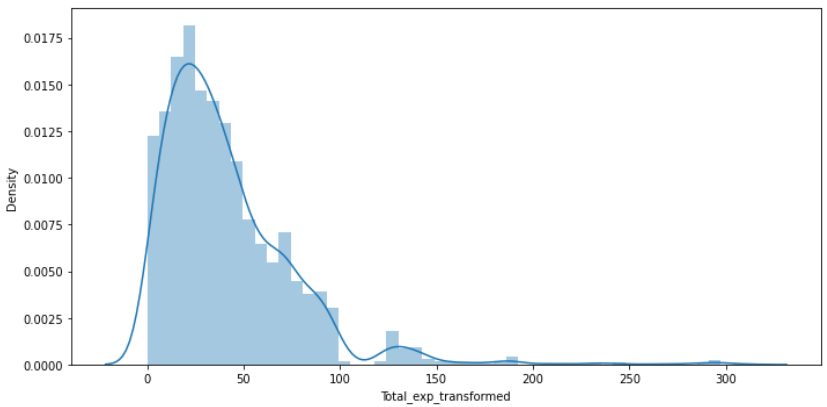
11. How transformation affect the distribution of the data points, take any one column and explore it? (3 marks)

In [70]:
```
# type your code here
df_life_exp['Total_exp_transformed']=df_life_exp['Total expenditure'].transform(func='square')
```

In [80]:
```
plt.figure(figsize=(20,5))
plt.subplot(1,2,1)
sns.distplot(df_life_exp['Total expenditure'])
print('Before Transformation \n')
print(df_life_exp['Total expenditure'].describe())
plt.subplot(1,2,2)
sns.distplot(df_life_exp['Total_exp_transformed'])
print('\n\n-----------------------------------------\nAfter Transformation \n')
print(df_life_exp['Total_exp_transformed'].describe())
plt.tight_layout()
plt.show()
```

```
Before Transformation

count    2712.00000
mean        5.93819
std         2.49832
min         0.37000
25%         4.26000
50%         5.75500
75%         7.49250
max        17.60000
Name: Total expenditure, dtype: float64


-----------------------------------------
After Transformation

count    2712.000000
mean       41.501395
std        35.101272
min         0.136900
25%        18.147600
50%        33.120050
75%        56.137575
max       309.760000
Name: Total_exp_transformed, dtype: float64
```





INFERENCE: **The transform() function is used to call function on self producing a Series with transformed values and that has the same axis length. This function is used for transforming the data. If a function, must either work when passed a Series or when passed to Series.**

Lets consider feature 'Total expenditure' and square the values of data points through 'transform' function. When we compare 'Total expenditure' and 'Total_exp_transformed' through describe(),we can see that each data point has been squared. Mean has increased 6.5 times from original value and standard deviation has increased drastically (18 times) from original value. The distribution has been affected for the transformed feature, as we are unable to see a proper bell-shaped curve.