Lung Cancer Patient Data Analysis

In [2]: # importing import libraries for data analysis
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

1. Read the Data

In [3]: Lung_cancer = pd.read_excel(r"C:\Users\ratho\.ipynb_checkpoints\DATA\Lung Cancer Surve
Lung_cancer
here we will read the data set

Out[3]:		GENDER	AGE	SMOKING	YELLOW_FINGERS	ANXIETY	PEER_PRESSURE	CHRONIC DISEASE	FATIGUE	Αl
	0	М	69	1	2	2	1	1	2	
	1	М	74	2	1	1	1	2	2	
	2	F	59	1	1	1	2	1	2	
	3	М	63	2	2	2	1	1	1	
	4	F	63	1	2	1	1	1	1	
	•••									
	304	F	56	1	1	1	2	2	2	
	305	М	70	2	1	1	1	1	2	
	306	М	58	2	1	1	1	1	1	
	307	М	67	2	1	2	1	1	2	
	308	М	62	1	1	1	2	1	2	

309 rows × 16 columns

2. Data Quick Check

In [4]: Lung_cancer.head() # top 5 rows rows

Out[4]:	G	ENDER A	AGE S	MOKING Y	ELLOW_FINGERS	A	NXIETY P	PEER_PRESSURE	CHRONIC DISEASE	FATIGUE	ALLE
	0	М	69	1	2		2	1	1	2	
	1	М	74	2	1		1	1	2	2	
	2	F	59	1	1		1	2	1	2	
	3	М	63	2	2		2	1	1	1	
	4	F	63	1	2		1	1	1	1	
								·		·	
1											
In [5]:	Lung	_cancer	tail() #bottom	n 5 rows						
Out[5]:					V				CHRONI	c	
		GENDER	AGE	SMOKING	YELLOW_FINGER	RS	ANXIETY	PEER_PRESSUR	DISEAS	EATIGH	E AL
	304	F	56	1		1	1	2	2	2	2
	305	М	70	2		1	1		1	1	2
	306	М	58	2		1	1		1	1	1
	307	М	67	2		1	2		1	1	2
	308	М	62	1		1	1		2	1	2
1											
In [6]:	Lung	_cancer	.shape	# check	ing the shape						
Out[6]:	(309	, 16)									
In [7]:	Lung	_cancer	.info() # summ	nary of data s	et					
	Rang	eIndex:	309 e	re.frame.D ntries, 0 al 16 colu			Dtype 				
	0	GENDER			309 non-null		object				
	1 2	AGE SMOKING	3		309 non-null 309 non-null		int64 int64				
	3	YELLOW_		RS	309 non-null		int64				
	4	ANXIETY		_	309 non-null		int64				
	5 6	PEER_PF			309 non-null 309 non-null		int64 int64				
	7	FATIGUE		ASE	309 non-null		int64				
	8	ALLERGY			309 non-null		int64				
	9	WHEEZIN			309 non-null		int64				
	10	ALCOHOL		UMING	309 non-null		int64				
	11 12	COUGHIN		BREATH	309 non-null 309 non-null		int64 int64				
	13			IFFICULTY			int64				
	14	CHEST F			309 non-null		int64				
		LUNG_C			309 non-null		object				
				, object(2	2)						
	memo	ry usage	2: 38.	8+ KR							

n [8]:	<pre>Lung_cancer.isnull() # is ther any null values or not</pre>										
t[8]:	(GENDER	AGE	SMOKING	YELLOW_FINGERS	ANXIETY	PEER_PRESSURE	CHRONIC DISEASE	FATIGUE	A	
	0	False	False	False	False	False	False	False	False		
	1	False	False	False	False	False	False	False	False		
	2	False	False	False	False	False	False	False	False		
	3	False	False	False	False	False	False	False	False		
	4	False	False	False	False	False	False	False	False		
	•••										
	304	False	False	False	False	False	False	False	False		
	305	False	False	False	False	False	False	False	False		
	306	False	False	False	False	False	False	False	False		
	307	False	False	False	False	False	False	False	False		
	308	False	False	False	False	False	False	False	False		
	309 ro	ws × 16	colum	ns							

 $309 \text{ rows} \times 16 \text{ columns}$

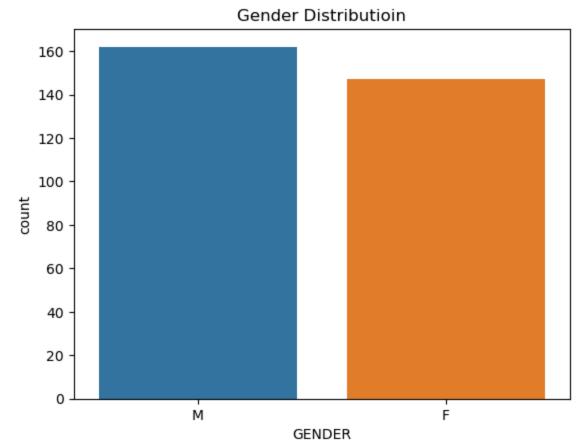
```
In [9]:
        Lung_cancer.isnull().sum() # total null values
        GENDER
Out[9]:
                                  0
        AGE
        SMOKING
                                  0
        YELLOW FINGERS
        ANXIETY
                                  0
        PEER_PRESSURE
                                  0
        CHRONIC DISEASE
        FATIGUE
                                  0
        ALLERGY
        WHEEZING
        ALCOHOL CONSUMING
        COUGHING
        SHORTNESS OF BREATH
                                  0
        SWALLOWING DIFFICULTY
                                  0
        CHEST PAIN
        LUNG_CANCER
        dtype: int64
```

3. Seperating Catgorical and numerical data

```
cat = Lung_cancer.select_dtypes(include = 'object').columns
In [10]:
         # grouping columns having object datatypes in cat variable
         num = Lung_cancer.select_dtypes(exclude ='object').columns
         # grouping columns having numercal datatypes in num variable
         cat, num
```

4. categorical column analysis

```
cat # check cat data
In [11]:
         Index(['GENDER', 'LUNG_CANCER'], dtype='object')
Out[11]:
         # frequency distribution of Gender column
In [12]:
         gender_counts = Lung_cancer['GENDER'].value_counts()
         print('Gender Frequency:\n', gender_counts)
         # ploting the graph
         sns.countplot(x = 'GENDER', data = Lung_cancer)
         plt.title('Gender Distributioin')
         plt.show()
         Gender Frequency:
               162
              147
         Name: GENDER, dtype: int64
```

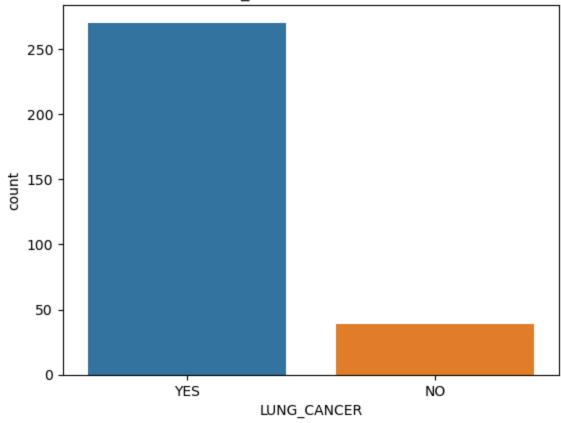


Observations:

- 1. Male (M) count is higher: The number of males in the dataset slightly exceeds the number of females.
- 2. Balanced distribution: Despite the difference, the gender distribution appears relatively balanced, with a small gap between the two groups.

- 1. Gender inclusion: The dataset includes a fairly even representation of males and females, which is good for conducting gender-specific analyses.
- 2. Potential bias: If gender plays a significant role in lung cancer outcomes or characteristics, the slight imbalance should be taken into account during modeling or statistical testing.
- 3. Further analysis: Investigate if gender correlates with any specific patterns, such as the prevalence of lung cancer, severity, or treatment outcomes.

LUNG_CANCER Distributioin

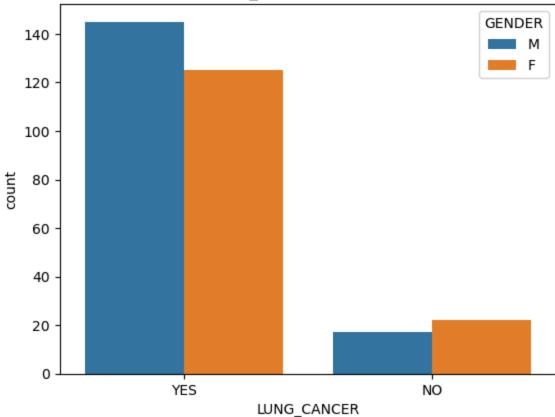


Observation:

The chart shows an imbalance in lung cancer distribution, with most cases in the YES category (over 250) and significantly fewer in the NO category (under 50). This suggests a strong skew towards positive cases.

```
In [14]: # Gender Vs , LUNG_cancer freq
sns.countplot(x = 'LUNG_CANCER', hue = 'GENDER', data = Lung_cancer)
plt.title('Lung_cancer Vs Gender')
plt.show()
```





Observations:

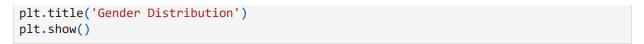
Lung Cancer Diagnosis (YES): Males have the highest count of diagnoses. Females also have a high count but are slightly lower than males.

No Lung Cancer Diagnosis (NO): Both males and females have significantly lower counts compared to the YES category. Females slightly outnumber males in the NO category.

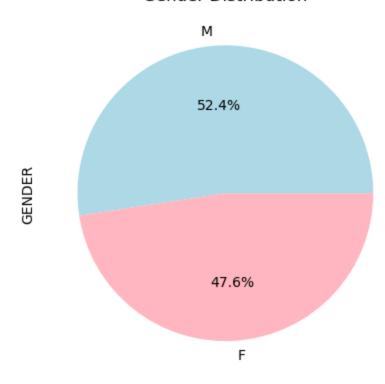
General Observation: The total number of individuals diagnosed with lung cancer (YES) is much greater than those not diagnosed (NO).

- Males are more likely to be diagnosed with lung cancer compared to females, suggesting possible gender-specific risk factors.
- A majority of the population in the chart is diagnosed with lung cancer, which may indicate high exposure to risk factors (e.g., smoking, air pollution, etc.).
- Preventative measures, awareness campaigns, and gender-specific interventions should be prioritized, especially targeting male populations.

```
In [15]: # pie chart for gender distribution
Lung_cancer['GENDER'].value_counts().plot.pie(autopct='%1.1f%%',colors = ['lightblue']
```







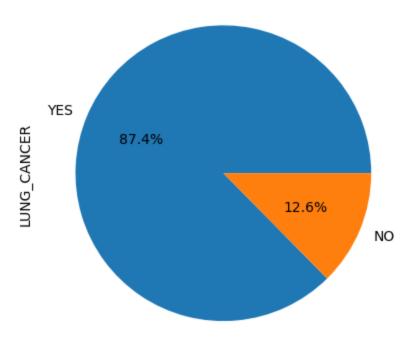
Observations:

- Males (52.4%) slightly outnumber females (47.6%).
- Gender distribution is nearly balanced.

- The balanced gender split ensures fair comparison in lung cancer analysis.
- Slight male majority aligns with their higher lung cancer diagnosis rate.

```
In [16]: # pie chart for Lung_cancer freq
Lung_cancer['LUNG_CANCER'].value_counts().plot.pie(autopct = '%1.1f%%')
plt.title('Lung Cancer frequency')
plt.show()
```

Lung Cancer frequency



Observations:

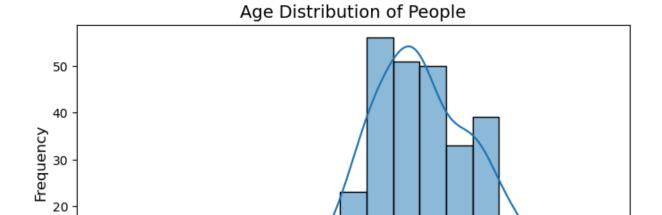
- 87.4% of the population is diagnosed with lung cancer (YES).
- Only **12.6**% of the population is not diagnosed (NO).

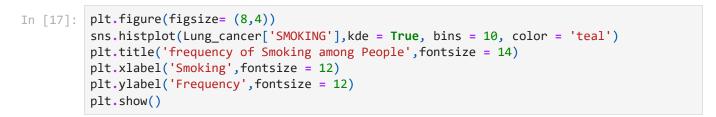
Insights:

- Lung cancer diagnosis is highly prevalent in this dataset.
- Indicates a potential high-risk population or environmental/lifestyle factors at play.

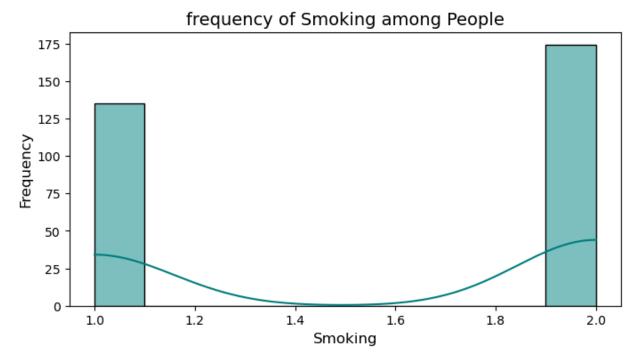
5. numerical column analysis

```
In [19]: plt.figure(figsize= (8,4))
    sns.histplot(Lung_cancer['AGE'],kde = True)
    plt.title('Age Distribution of People',fontsize = 14)
    plt.xlabel('Age',fontsize = 12)
    plt.ylabel('Frequency',fontsize = 12)
    plt.show()
```

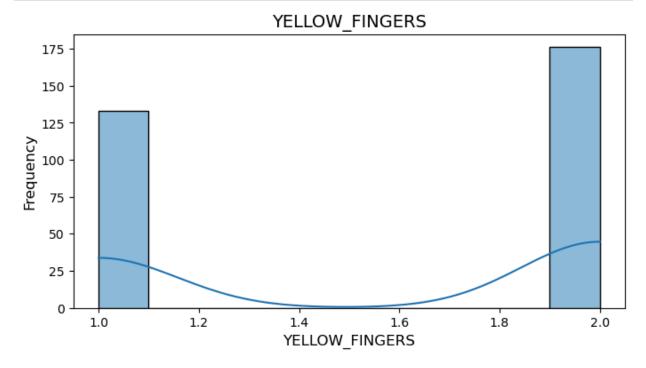




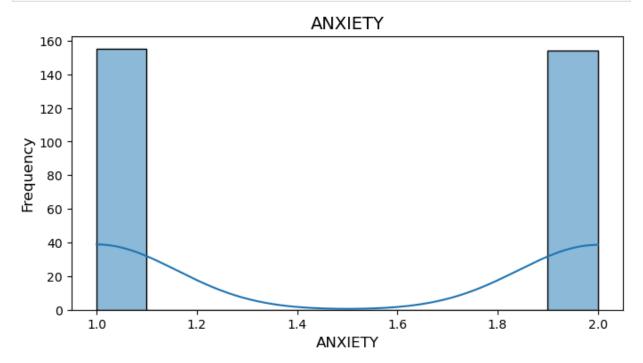
Age



```
In [15]: plt.figure(figsize= (8,4))
    sns.histplot(Lung_cancer['YELLOW_FINGERS'],kde = True)
    plt.title('YELLOW_FINGERS',fontsize = 14)
    plt.xlabel('YELLOW_FINGERS',fontsize = 12)
    plt.ylabel('Frequency',fontsize = 12)
    plt.show()
```



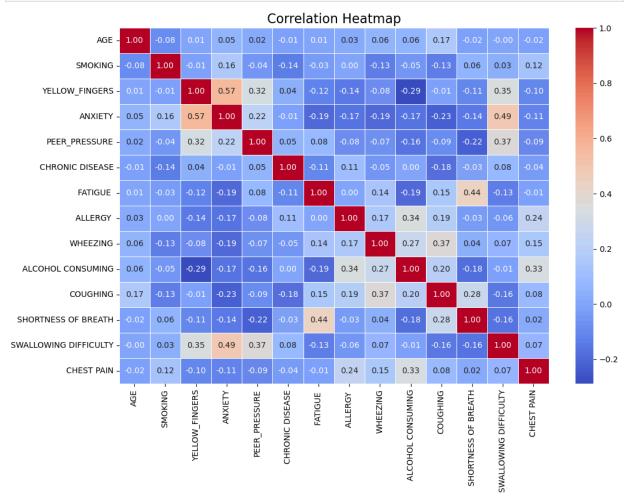
```
In [22]: plt.figure(figsize= (8,4))
    sns.histplot(Lung_cancer['ANXIETY'],kde = True)
    plt.title('ANXIETY',fontsize = 14)
    plt.xlabel('ANXIETY',fontsize = 12)
    plt.ylabel('Frequency',fontsize = 12)
    plt.show()
```



6. Corelation using heat map

```
In [23]: correlation_matrix = Lung_cancer.corr()

plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=.5)
plt.title('Correlation Heatmap', fontsize=16)
plt.show()
```

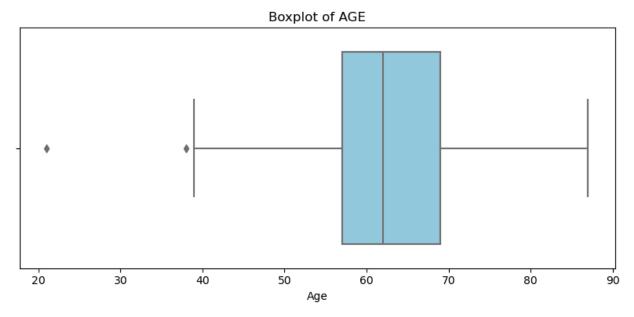


- The heatmap reveals complex relationships between various factors related to lung health and lifestyle.
- Smoking appears to have a strong influence on multiple factors, including anxiety, peer pressure, and yellow fingers.
- Anxiety and alcohol consumption seem to be linked to certain respiratory symptoms.
- Chronic disease might be protective against some respiratory symptoms.

7. Checking outliers

```
In [24]: # Create boxplots for selected numerical column

plt.figure(figsize=(8, 4))
sns.boxplot(x=Lung_cancer['AGE'], color='skyblue')
plt.title(f'Boxplot of AGE', fontsize=12)
plt.xlabel('Age', fontsize=10)
plt.tight_layout()
plt.show()
```



The boxplot of Age shows a right-skewed distribution with a median age of 60 years. The IQR is 10 years, and there are two outliers representing younger individuals. This indicates a dataset primarily consisting of middle-aged individuals with a significant presence of younger individuals.

```
import pandas as pd

# assuming num is athr list of numerica column names in the dataframe

# loop through all numerical columns and remove outliers using IQR

# calculate Q1(25 th percentile) and Q3 (75th percentile)
Q1 = Lung_cancer['AGE'].quantile(0.25)
Q3 = Lung_cancer['AGE'].quantile(0.75)

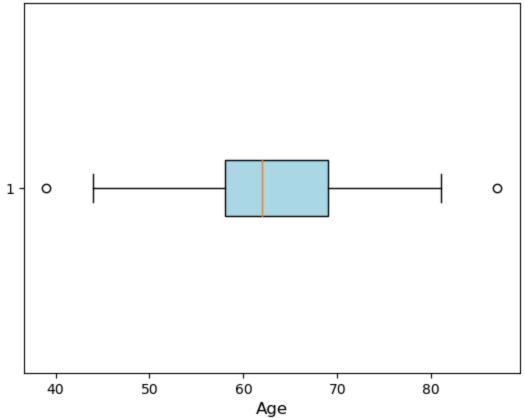
# Calculate IQR (interquartile range)
IQR = Q3 - Q1

#Define outer bounds
lower_bound = Q1 -1.5 * IQR
upper_bound = Q3 +1.5 * IQR
# Remove rows where the column value is an outlier
```

```
Lung_cancer = Lung_cancer[(Lung_cancer['AGE'] >= lower_bound) & (Lung_cancer['AGE'] <=
#verify the data aafter removing thr outliers
Lung_cancer.head()</pre>
```

Out[25]:		GENDER	AGE	SMOKING	YELLOW_FINGERS	ANXIETY	PEER_PRESSURE	CHRONIC DISEASE	FATIGUE	ALLE
	0	М	69	1	2	2	1	1	2	
	1	М	74	2	1	1	1	2	2	
	2	F	59	1	1	1	2	1	2	
	3	М	63	2	2	2	1	1	1	
	4	F	63	1	2	1	1	1	1	

Box Plot of Adjusted Age



Convert cateorical to numerical

Out[29]:		GENDER	AGE	SMOKING	YELLOW_FINGERS	ANXIETY	PEER_PRESSURE	CHRONIC DISEASE	FATIGUE	Αl
	0	1	69	1	2	2	1	1	2	
	1	1	74	2	1	1	1	2	2	
	2	0	59	1	1	1	2	1	2	
	3	1	63	2	2	2	1	1	1	
	4	0	63	1	2	1	1	1	1	
	•••									
	304	0	56	1	1	1	2	2	2	
	305	1	70	2	1	1	1	1	2	
	306	1	58	2	1	1	1	1	1	
	307	1	67	2	1	2	1	1	2	
	308	1	62	1	1	1	2	1	2	

307 rows × 16 columns

Scaling the Data

```
In [31]: from sklearn.preprocessing import MinMaxScaler
    scaler = MinMaxScaler()
    Lung_cancer_scaled = pd.DataFrame(scaler.fit_transform(Lung_cancer), columns=Lung_cancer]
In [32]: Lung_cancer_scaled
```

Out[32]:		GENDER	AGE	SMOKING	YELLOW_FINGERS	ANXIETY	PEER_PRESSURE	CHRONIC DISEASE	FATIGUE
	0	1.0	0.625000	0.0	1.0	1.0	0.0	0.0	1.0
	1	1.0	0.729167	1.0	0.0	0.0	0.0	1.0	1.0
	2	0.0	0.416667	0.0	0.0	0.0	1.0	0.0	1.0
	3	1.0	0.500000	1.0	1.0	1.0	0.0	0.0	0.0
	4	0.0	0.500000	0.0	1.0	0.0	0.0	0.0	0.0
	•••								
	302	0.0	0.354167	0.0	0.0	0.0	1.0	1.0	1.0
	303	1.0	0.645833	1.0	0.0	0.0	0.0	0.0	1.0

0.0

0.0

0.0

0.0

1.0

0.0

0.0

0.0

0.0

0.0

1.0

1.0

0.0

0.0

1.0

307 rows × 16 columns

304

305

306

1.0 0.395833

1.0 0.583333

1.0 0.479167

1.0

1.0

0.0