01_EDA

June 29, 2025

1 01 - Exploratory Data Analysis (EDA) and Data Preprocessing

This notebook is dedicated to performing an in-depth Exploratory Data Analysis (EDA) on the raw insurance claims dataset and subsequently preparing the data for machine learning modeling. This involves understanding data characteristics, identifying patterns, handling missing values, encoding categorical features, and standardizing numerical data.

1.1 1.1 Import Libraries

This initial cell imports all the necessary Python libraries that will be utilized throughout the EDA and preprocessing phases of this notebook. Each library plays a distinct role:

- **`pandas as pd`**: This is the fundamental library for data manipulation and analysis. It provides powerful data structures like DataFrames, which are essential for handling tabular data.
- **`numpy as np`**: This library is crucial for numerical operations, especially for working with arrays and performing mathematical computations efficiently.
- **`matplotlib.pyplot as plt`**: As the foundational plotting library, `matplotlib.pyplot` is used for creating static, interactive, and animated visualizations, which are vital for understanding data distributions and relationships during EDA.
- **`sklearn.preprocessing.LabelEncoder`**: This utility from Scikit-learn is used for encoding categorical labels with numerical values. It transforms non-numeric labels into machine-readable integers, a common preprocessing step for many machine learning algorithms.

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
import seaborn as sns
```

1.1.1 1.2 Load Raw Dataset and Initial Overview

This cell is responsible for loading the raw insurance claims dataset from its specified path and performing essential initial inspections. These initial steps are crucial for understanding the structure, content, and quality of the raw data before any preprocessing or analysis begins.

1. **Define File Path**:
   - `file_path = 'E:/Project_2/insurance-risk-model/data/raw/insurance_claims.csv'`: This line defines the exact location of our raw dataset. It's good practice to store raw data separately in a `data/raw` directory within your project structure.
2. **Robust Data Loading with Error Handling**:

- The `try...except FileNotFoundError` block is implemented to make the data loading process more robust.
- `try`: It attempts to execute the code within this block. If the file is found, `pd.read_csv(file_path)` will load the data into a pandas DataFrame named `df`.
- `except FileNotFoundError`: If the file specified by `file_path` does not exist at the given location, instead of crashing, the program will execute the code within this block, printing a user-friendly error message indicating that the file was not found and suggesting the expected path. `df` is set to `None` in this case to prevent further errors.

3. **Initial Data Inspections (if load is successful)**:
   - `if df is not None:`: All subsequent inspection steps are conditionally executed only if the DataFrame `df` was successfully loaded (i.e., not `None`).
   - **`print(df.head())`**: This displays the first 5 rows of the DataFrame. It provides an immediate visual preview of the data, allowing us to quickly see the column names, the type of data they contain, and a few sample records. This is vital for a qualitative check of the data's integrity.
   - **`df.info()`**: This method prints a concise summary of the DataFrame. It's extremely valuable for:
     - **Data Types**: Identifying the data type of each column (e.g., `int64`, `float64`, `object`). This is critical for understanding how pandas has interpreted the data and for planning necessary type conversions.
     - **Non-Null Counts**: Showing the number of non-missing values for each column. By comparing this count to the total number of entries, we can quickly spot columns with missing data.
     - **Memory Usage**: Providing an estimate of the DataFrame's memory consumption.
   - **`df.describe(include='all')`**: This generates descriptive (summary) statistics of the DataFrame.
     - The `include='all'` argument is important because it tells pandas to generate statistics for **both numerical and object (categorical) columns**.
     - For numerical columns, it provides statistics like `count`, `mean`, `std` (standard deviation), `min`, `max`, and quartile values (25%, 50% / median, 75%).
     - For object/categorical columns, it provides `count`, `unique` (number of distinct values), `top` (most frequent value), and `freq` (frequency of the top value). This helps in understanding the distribution and variety of categorical features.
   - **`df.isnull().sum()`**: This crucial line calculates and displays the total count of missing values for each column in the DataFrame. This provides a quantitative overview of data completeness and directly informs our strategy for handling missing data in subsequent preprocessing steps.

These initial checks lay the foundation for a deeper exploratory data analysis and guide our preprocessing decisions.

[2]:
```
file_path = 'E:/Project_2/insurance-risk-model/data/raw/insurance_claims.csv'

try:
    df = pd.read_csv(file_path)
    print("Dataset loaded successfully!")
except FileNotFoundError:
```

```
    print(f"Error: The file '{file_path}' was not found. Please ensure it's in␣
 ↪the correct directory.")
    print("Expected path: insurance-risk-model/data/raw/insurance_claims.csv")
    df = None

if df is not None:
    print("\n--- First 5 rows of the dataset ---")
    print(df.head())

    print("\n--- Dataset Info ---")
    df.info()

    print("\n--- Descriptive Statistics ---")
    print(df.describe(include='all'))

    print("\n--- Missing Values ---")
    print(df.isnull().sum())
```

```
Dataset loaded successfully!

--- First 5 rows of the dataset ---
   months_as_customer  age  policy_number policy_bind_date policy_state  \
0                 328   48         521585       2014-10-17           OH
1                 228   42         342868       2006-06-27           IN
2                 134   29         687698       2000-09-06           OH
3                 256   41         227811       1990-05-25           IL
4                 228   44         367455       2014-06-06           IL

  policy_csl  policy_deductable  policy_annual_premium  umbrella_limit  \
0    250/500               1000                1406.91               0
1    250/500               2000                1197.22         5000000
2    100/300               2000                1413.14         5000000
3    250/500               2000                1415.74         6000000
4   500/1000               1000                1583.91         6000000

   insured_zip  … police_report_available total_claim_amount injury_claim  \
0       466132  …                      YES              71610         6510
1       468176  …                        ?               5070          780
2       430632  …                       NO              34650         7700
3       608117  …                       NO              63400         6340
4       610706  …                       NO               6500         1300

  property_claim vehicle_claim  auto_make  auto_model auto_year  \
0          13020         52080       Saab         92x      2004
1            780          3510   Mercedes        E400      2007
2           3850         23100      Dodge         RAM      2007
3           6340         50720  Chevrolet       Tahoe      2014
4            650          4550     Accura         RSX      2009
```

```
  fraud_reported _c39
0              Y  NaN
1              Y  NaN
2              N  NaN
3              Y  NaN
4              N  NaN

[5 rows x 40 columns]

--- Dataset Info ---
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 40 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   months_as_customer           1000 non-null   int64
 1   age                          1000 non-null   int64
 2   policy_number                1000 non-null   int64
 3   policy_bind_date             1000 non-null   object
 4   policy_state                 1000 non-null   object
 5   policy_csl                   1000 non-null   object
 6   policy_deductable            1000 non-null   int64
 7   policy_annual_premium        1000 non-null   float64
 8   umbrella_limit               1000 non-null   int64
 9   insured_zip                  1000 non-null   int64
 10  insured_sex                  1000 non-null   object
 11  insured_education_level      1000 non-null   object
 12  insured_occupation           1000 non-null   object
 13  insured_hobbies              1000 non-null   object
 14  insured_relationship         1000 non-null   object
 15  capital-gains                1000 non-null   int64
 16  capital-loss                 1000 non-null   int64
 17  incident_date                1000 non-null   object
 18  incident_type                1000 non-null   object
 19  collision_type               1000 non-null   object
 20  incident_severity            1000 non-null   object
 21  authorities_contacted        909 non-null    object
 22  incident_state               1000 non-null   object
 23  incident_city                1000 non-null   object
 24  incident_location            1000 non-null   object
 25  incident_hour_of_the_day     1000 non-null   int64
 26  number_of_vehicles_involved  1000 non-null   int64
 27  property_damage              1000 non-null   object
 28  bodily_injuries              1000 non-null   int64
 29  witnesses                    1000 non-null   int64
 30  police_report_available      1000 non-null   object
 31  total_claim_amount           1000 non-null   int64
```

```
 32  injury_claim                1000 non-null   int64
 33  property_claim              1000 non-null   int64
 34  vehicle_claim               1000 non-null   int64
 35  auto_make                   1000 non-null   object
 36  auto_model                  1000 non-null   object
 37  auto_year                   1000 non-null   int64
 38  fraud_reported              1000 non-null   object
 39  _c39                        0 non-null      float64
dtypes: float64(2), int64(17), object(21)
memory usage: 312.6+ KB

--- Descriptive Statistics ---
        months_as_customer          age  policy_number policy_bind_date  \
count          1000.000000  1000.000000    1000.000000             1000
unique                 NaN          NaN            NaN              951
top                    NaN          NaN            NaN       1992-08-05
freq                   NaN          NaN            NaN                3
mean            203.954000    38.948000  546238.648000              NaN
std             115.113174     9.140287  257063.005276              NaN
min               0.000000    19.000000  100804.000000              NaN
25%             115.750000    32.000000  335980.250000              NaN
50%             199.500000    38.000000  533135.000000              NaN
75%             276.250000    44.000000  759099.750000              NaN
max             479.000000    64.000000  999435.000000              NaN

       policy_state policy_csl  policy_deductable  policy_annual_premium  \
count          1000       1000        1000.000000            1000.000000
unique            3          3                NaN                    NaN
top              OH    250/500                NaN                    NaN
freq            352        351                NaN                    NaN
mean            NaN        NaN        1136.000000            1256.406150
std             NaN        NaN         611.864673             244.167395
min             NaN        NaN         500.000000             433.330000
25%             NaN        NaN         500.000000            1089.607500
50%             NaN        NaN        1000.000000            1257.200000
75%             NaN        NaN        2000.000000            1415.695000
max             NaN        NaN        2000.000000            2047.590000

        umbrella_limit    insured_zip  … police_report_available  \
count     1.000000e+03    1000.000000  …                     1000
unique             NaN            NaN  …                        3
top                NaN            NaN  …                        ?
freq               NaN            NaN  …                      343
mean      1.101000e+06  501214.488000  …                      NaN
std       2.297407e+06   71701.610941  …                      NaN
min      -1.000000e+06  430104.000000  …                      NaN
25%       0.000000e+00  448404.500000  …                      NaN
50%       0.000000e+00  466445.500000  …                      NaN
```

```
75%       0.000000e+00  603251.000000  …                    NaN
max       1.000000e+07  620962.000000  …                    NaN

       total_claim_amount  injury_claim property_claim vehicle_claim  \
count          1000.00000   1000.000000    1000.000000   1000.000000
unique                NaN           NaN            NaN           NaN
top                   NaN           NaN            NaN           NaN
freq                  NaN           NaN            NaN           NaN
mean          52761.94000   7433.420000    7399.570000  37928.950000
std           26401.53319   4880.951853    4824.726179  18886.252893
min             100.00000      0.000000       0.000000     70.000000
25%           41812.50000   4295.000000    4445.000000  30292.500000
50%           58055.00000   6775.000000    6750.000000  42100.000000
75%           70592.50000  11305.000000   10885.000000  50822.500000
max          114920.00000  21450.000000   23670.000000  79560.000000

        auto_make  auto_model    auto_year fraud_reported _c39
count        1000        1000  1000.000000           1000  0.0
unique         14          39          NaN              2  NaN
top          Saab         RAM          NaN              N  NaN
freq           80          43          NaN            753  NaN
mean          NaN         NaN  2005.103000            NaN  NaN
std           NaN         NaN     6.015861            NaN  NaN
min           NaN         NaN  1995.000000            NaN  NaN
25%           NaN         NaN  2000.000000            NaN  NaN
50%           NaN         NaN  2005.000000            NaN  NaN
75%           NaN         NaN  2010.000000            NaN  NaN
max           NaN         NaN  2015.000000            NaN  NaN

[11 rows x 40 columns]

--- Missing Values ---
months_as_customer            0
age                           0
policy_number                 0
policy_bind_date              0
policy_state                  0
policy_csl                    0
policy_deductable             0
policy_annual_premium         0
umbrella_limit                0
insured_zip                   0
insured_sex                   0
insured_education_level       0
insured_occupation            0
insured_hobbies               0
insured_relationship          0
capital-gains                 0
```

```
capital-loss                    0
incident_date                   0
incident_type                   0
collision_type                  0
incident_severity               0
authorities_contacted          91
incident_state                  0
incident_city                   0
incident_location               0
incident_hour_of_the_day        0
number_of_vehicles_involved     0
property_damage                 0
bodily_injuries                 0
witnesses                       0
police_report_available         0
total_claim_amount              0
injury_claim                    0
property_claim                  0
vehicle_claim                   0
auto_make                       0
auto_model                      0
auto_year                       0
fraud_reported                  0
_c39                         1000
dtype: int64
```

1.1.2 1.3 Initial Data Cleaning and Feature Engineering

This cell performs several crucial data cleaning and initial feature engineering steps to prepare the raw dataset for further analysis and modeling. These transformations address inconsistencies and extract valuable information from existing columns.

1. **Dropping an Extraneous Column**:
   - `df = df.drop(columns=['_c39'])`: This line removes the column named `_c39` from the DataFrame. Columns like `_c39` often appear when a CSV file has an extra, unnamed column (e.g., due to an extra comma at the end of each row or a remnant from a previous save). It's generally an empty or irrelevant column that needs to be removed to clean the dataset.
2. **Handling Placeholder Missing Values**:
   - `for col in ['collision_type', 'police_report_available', 'property_damage', 'authorities_contacted']: df[col] = df[col].replace('?', np.nan)`: This loop iterates through a specific list of categorical columns that are known to contain '?' as a placeholder for missing values.
   - `replace('?', np.nan)`: The '?' string is replaced with `np.nan` (Not a Number) from the NumPy library. `np.nan` is the standard way to represent missing values in pandas, allowing for proper detection and handling using pandas' built-in missing data functionalities (e.g., `isnull().sum()`, `dropna()`, `fillna()`). This standardization is essential for accurate analysis and imputation.

3. **Date Feature Engineering**:
    - `df['policy_bind_date'] = pd.to_datetime(df['policy_bind_date'])`
    - `df['incident_date'] = pd.to_datetime(df['incident_date'])`: These lines convert the `policy_bind_date` and `incident_date` columns from their original string/object format into datetime objects using `pd.to_datetime()`. This conversion is critical because it unlocks powerful datetime-specific functionalities, allowing us to extract various temporal features.
    - `df['policy_bind_year'] = df['policy_bind_date'].dt.year`
    - `df['incident_year'] = df['incident_date'].dt.year`
    - `df['incident_month'] = df['incident_date'].dt.month`: From the converted datetime columns, we extract new numerical features: the year of the policy binding, the year of the incident, and the month of the incident. These features can be highly predictive as they capture potential temporal trends or seasonal patterns in claims and policies.
4. **Creating a Binary `claim_occurred` Feature**:
    - `df['claim_occurred'] = (df['total_claim_amount'] > 0).astype(int)`: This line engineers a new binary feature called `claim_occurred`.
    - `(df['total_claim_amount'] > 0)`: This creates a boolean Series, `True` if `total_claim_amount` is greater than 0, and `False` otherwise.
    - `.astype(int)`: This converts the boolean `True`/`False` values into integers `1` and `0` respectively. This feature serves as a clear indicator of whether a claim was filed, simplifying the presence of a claim into a straightforward numerical format for analysis.

These cleaning and engineering steps significantly enhance the dataset's quality and prepare it for more in-depth exploratory analysis and subsequent machine learning model training.

[3]:
```
df = df.drop(columns=['_c39'])

for col in ['collision_type', 'police_report_available', 'property_damage',␣
 ↪'authorities_contacted']:
    df[col] = df[col].replace('?', np.nan)

df['policy_bind_date'] = pd.to_datetime(df['policy_bind_date'])
df['incident_date'] = pd.to_datetime(df['incident_date'])
df['policy_bind_year'] = df['policy_bind_date'].dt.year
df['incident_year'] = df['incident_date'].dt.year
df['incident_month'] = df['incident_date'].dt.month
df['claim_occurred'] = (df['total_claim_amount'] > 0).astype(int)
```

1.1.3 1.4 Age Distribution Analysis

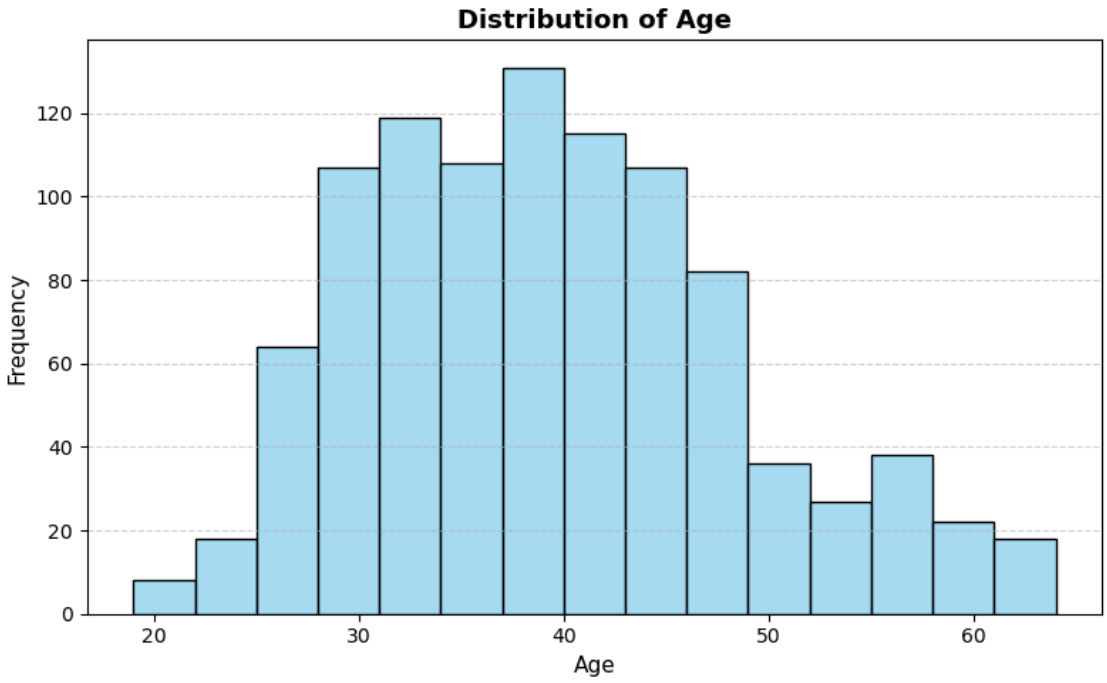
This cell focuses on visualizing the distribution of the `age` feature using a histogram. Understanding the age distribution of policyholders or individuals involved in incidents can reveal important demographic patterns within the dataset.

1. **Figure Initialization**:
    - `plt.figure(figsize=(8, 5))`: This line creates a new figure for our plot and sets its size. A figure size of 8 inches wide by 5 inches tall is chosen for optimal readability and presentation.

2. **Generating the Histogram**:
   - `plt.hist(df['age'], bins=15, edgecolor='black')`: This is the core command for creating the histogram.
     - `df['age']`: Specifies the numerical data from the 'age' column of our DataFrame that we want to visualize.
     - `bins=15`: Determines the number of equal-width bins (intervals) to divide the `age` data into. More bins can show finer details, while fewer bins provide a broader overview. Here, 15 bins are used to offer a reasonable granularity.
     - `edgecolor='black'`: Adds a black border to each bar in the histogram. This enhances visual clarity by clearly distinguishing between adjacent bins.
3. **Adding Plot Labels and Title**:
   - `plt.title('Distribution of Age')`: Sets the main title of the histogram, clearly indicating what the plot represents.
   - `plt.xlabel('Age')`: Labels the x-axis as 'Age', denoting the range of ages.
   - `plt.ylabel('Frequency')`: Labels the y-axis as 'Frequency', indicating the count of individuals falling into each age bin.
4. **Displaying the Plot**:
   - `plt.show()`: This command displays the generated histogram.

By examining this histogram, we can gain insights into the most common age groups within the dataset, identify any outliers, and understand the overall shape and spread of the age demographic. This helps in understanding the typical customer profile and potential age-related risks.

[4]:
```
plt.figure(figsize=(8, 5))
sns.histplot(df['age'], bins=15, edgecolor='black', color='skyblue')
plt.title('Distribution of Age', fontsize=13, weight='bold')
plt.xlabel('Age', fontsize=11)
plt.ylabel('Frequency', fontsize=11)
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.grid(axis='y', linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show()
```



1.1.4 1.5 Target Variable Distribution

This cell visualizes the distribution of our target variable, `fraud_reported`. Understanding the balance (or imbalance) between the 'fraud' and 'non-fraud' classes is a critical step in fraud detection projects, as it profoundly impacts model selection, evaluation, and potential preprocessing strategies like oversampling or undersampling.

1. **Figure Initialization**:
   - `plt.figure(figsize=(6, 4))`: A new plot figure is created with a size of 6 inches wide by 4 inches tall, providing a compact yet clear visualization space.
2. **Generating the Bar Plot for Class Distribution**:
   - `df['fraud_reported'].value_counts().plot(kind='bar')`: This is a concise and efficient way to plot the distribution of a categorical variable using pandas' built-in plotting capabilities.
     - `df['fraud_reported'].value_counts()`: This part calculates the frequency of each unique value (0 for 'Not Fraud' and 1 for 'Fraud') in the `fraud_reported` column. It returns a pandas Series where the index represents the unique categories and the values represent their counts.
     - `.plot(kind='bar')`: This method is then called directly on the resulting Series to generate a bar plot, where the height of each bar corresponds to the count of each class.
3. **Adding Plot Labels and Title**:
   - `plt.title('Distribution of Fraud Reported')`: Sets the main title for the plot, clearly indicating the content.
   - `plt.xlabel('Fraud Reported')`: Labels the horizontal axis, representing the two

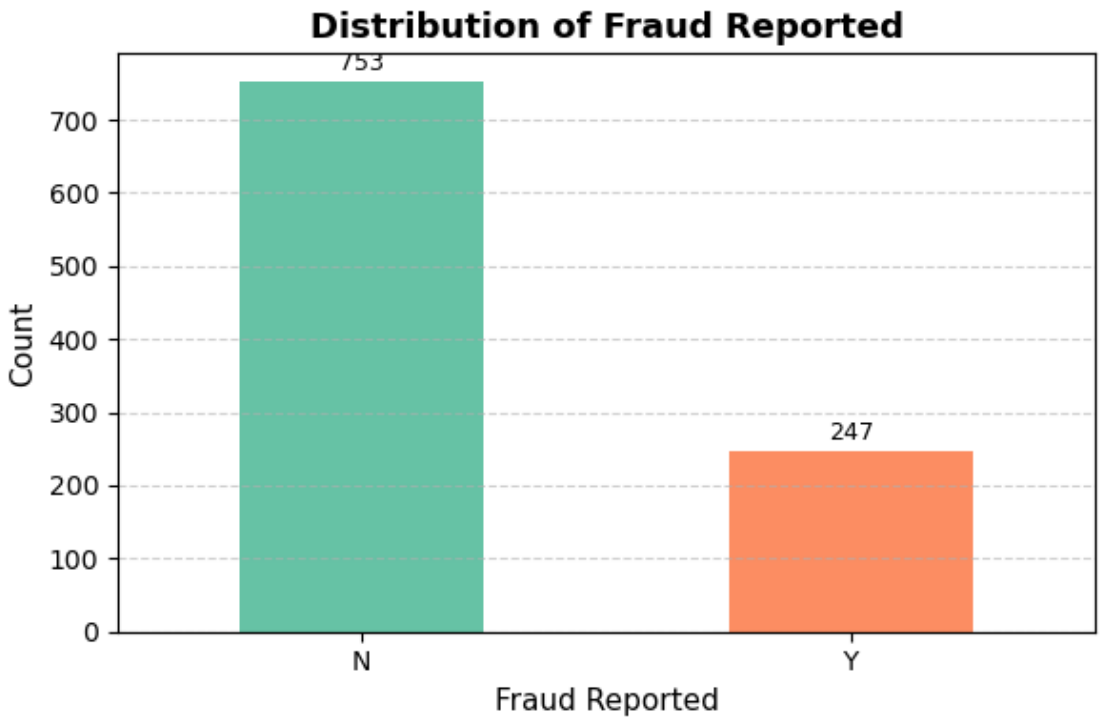
classes (0 and 1).

- `plt.ylabel('Count')`: Labels the vertical axis, showing the frequency of each class.
- `plt.xticks(rotation=0)`: Ensures that the x-axis labels (0 and 1) are displayed horizontally (without rotation), improving readability.

4. **Displaying the Plot**:
   - `plt.show()`: This command renders and displays the created bar plot.

Insight from this Plot: This visualization is crucial for immediately identifying **class imbalance**. In fraud detection, it's very common to have a significantly smaller number of fraudulent cases compared to legitimate ones. This plot will clearly show whether such an imbalance exists and to what extent, guiding subsequent decisions on how to handle it during model training (e.g., using stratified sampling, specific evaluation metrics, or techniques like SMOTE).

[5]:
```
plt.figure(figsize=(6, 4))
counts = df['fraud_reported'].value_counts()
colors = sns.color_palette("Set2", n_colors=len(counts))
counts.plot(kind='bar', color=colors)
plt.title('Distribution of Fraud Reported', fontsize=13, weight='bold')
plt.xlabel('Fraud Reported', fontsize=11)
plt.ylabel('Count', fontsize=11)
plt.xticks(rotation=0, fontsize=10)
plt.yticks(fontsize=10)
plt.grid(axis='y', linestyle='--', alpha=0.6)
for i, val in enumerate(counts):
    plt.text(i, val + max(counts) * 0.01, str(val), ha='center', va='bottom',␣
 ↪fontsize=9)
plt.tight_layout()
plt.show()
```



1.1.5 1.6 Relationship between Age and Total Claim Amount

This cell generates a scatter plot to visually explore the relationship between two continuous numerical variables: `age` (of the policyholder) and `total_claim_amount`. Scatter plots are excellent for identifying potential correlations, patterns, clusters, or outliers between two variables.

1. **Figure Initialization**:
   - `plt.figure(figsize=(10, 6))`: A new plot figure is created with a size of 10 inches wide by 6 inches tall, providing ample space for the scatter points and labels.
2. **Generating the Scatter Plot**:
   - `plt.scatter(df['age'], df['total_claim_amount'], alpha=0.5)`: This is the core command for creating the scatter plot.
     - `df['age']`: Specifies the data for the horizontal (x-axis), representing the age of individuals.
     - `df['total_claim_amount']`: Specifies the data for the vertical (y-axis), representing the total amount claimed.
     - `alpha=0.5`: Sets the transparency of the data points. This is particularly useful when there are many overlapping points, as it allows you to visualize areas of higher data density (where points are darker due to overlap).
3. **Adding Plot Labels, Title, and Grid**:
   - `plt.title('Age vs. Total Claim Amount')`: Sets the main title of the plot, clearly indicating the relationship being visualized.
   - `plt.xlabel('Age')`: Labels the x-axis as 'Age'.
   - `plt.ylabel('Total Claim Amount')`: Labels the y-axis as 'Total Claim Amount'.

- `plt.grid(True)`: Adds a grid to the background of the plot. Grids are very helpful for accurately reading values from the axes and for visually estimating the coordinates of individual data points.

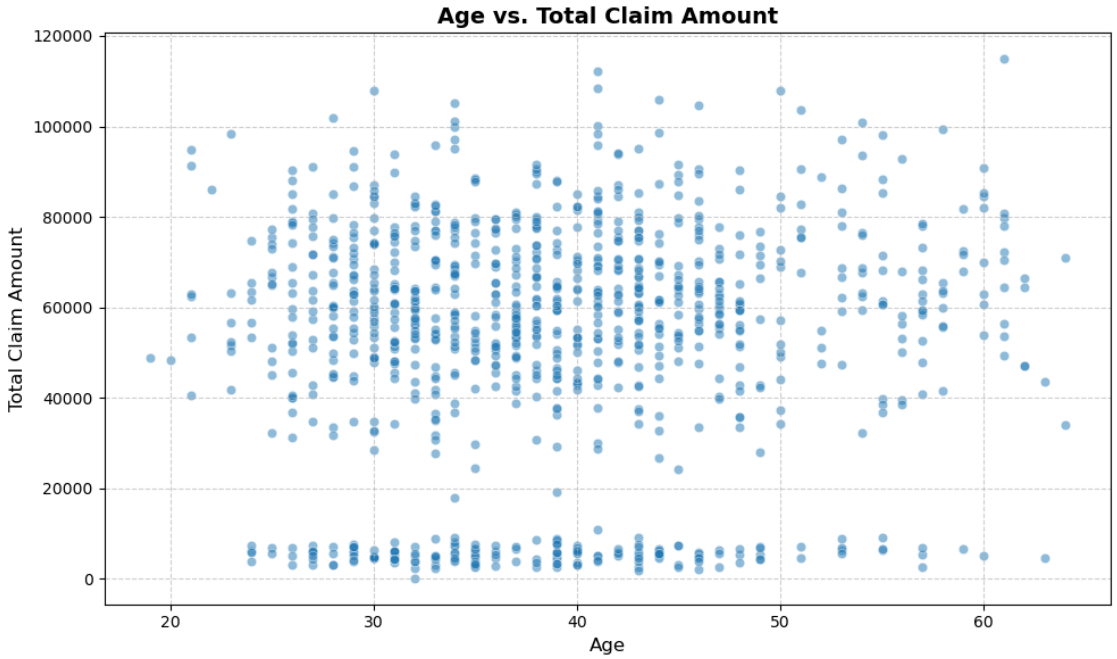
4. **Displaying the Plot**:
   - `plt.show()`: This command renders and displays the generated scatter plot.

Potential Insights from this Plot: By examining this scatter plot, we can look for: * **Trends**: Is there an increasing or decreasing trend in claim amounts as age changes? * **Clusters**: Do certain age groups tend to have similar claim amounts? * **Outliers**: Are there any individuals with unusually high or low claim amounts for their age? * **Density**: Areas where points are denser (darker) indicate more common combinations of age and claim amounts.

This visualization helps us understand if age is a relevant factor in the magnitude of claims, which could inform feature engineering or modeling decisions.

[6]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='age', y='total_claim_amount', data=df, alpha=0.5,␣
↪palette='crest')
plt.title('Age vs. Total Claim Amount', fontsize=14, weight='bold')
plt.xlabel('Age', fontsize=12)
plt.ylabel('Total Claim Amount', fontsize=12)
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.grid(True, linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show()
```

```
C:\Users\RAKESH\AppData\Local\Temp\ipykernel_17096\2513099198.py:2: UserWarning:
Ignoring `palette` because no `hue` variable has been assigned.
  sns.scatterplot(x='age', y='total_claim_amount', data=df, alpha=0.5,
palette='crest')
```



1.1.6 1.7 Claim Occurrence Rate by Insured Sex

This cell generates a bar plot to visualize the claim occurrence rate across different categories of `insured_sex`. This analysis helps to understand if there's a noticeable difference in how frequently claims are made between male and female policyholders.

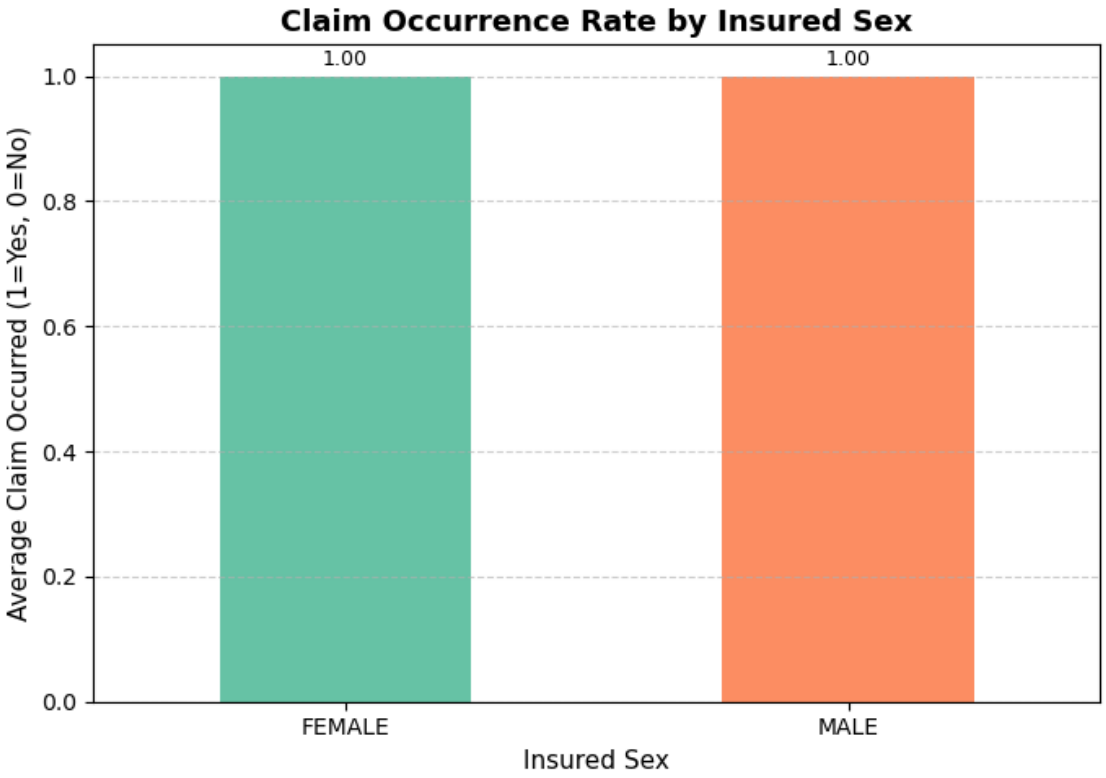
1. **Figure Initialization**:
   - `plt.figure(figsize=(7, 5))`: A new plot figure is created with a specified size (7 inches wide by 5 inches tall) to ensure good readability.
2. **Calculating and Plotting Claim Rates**:
   - `df.groupby('insured_sex')['claim_occurred'].mean().plot(kind='bar', color=['skyblue', 'lightcoral'])`: This powerful chained command performs the core calculation and plotting:
     - `df.groupby('insured_sex')`: This groups the DataFrame `df` based on the unique values in the `insured_sex` column (e.g., 'MALE', 'FEMALE').
     - `['claim_occurred'].mean()`: For each `insured_sex` group, it calculates the mean of the `claim_occurred` column. Since `claim_occurred` is a binary variable (1 for a claim, 0 for no claim), its mean directly represents the **proportion** or **rate** of claims occurring within that group.
     - `.plot(kind='bar', color=['skyblue', 'lightcoral'])`: This directly plots the resulting mean values as a bar chart. `kind='bar'` specifies the type of plot, and `color=['skyblue', 'lightcoral']` assigns distinct colors to the bars for visual differentiation.
3. **Adding Plot Labels and Title**:
   - `plt.title('Claim Occurrence Rate by Insured Sex')`: Sets the title of the bar plot, clearly stating the analysis being presented.

- `plt.xlabel('Insured Sex')`: Labels the x-axis as 'Insured Sex', indicating the categories being compared.
- `plt.ylabel('Average Claim Occurred (1=Yes, 0=No)')`: Labels the y-axis, explicitly clarifying that the bar height represents the average claim occurrence (or claim rate).
- `plt.xticks(rotation=0)`: Ensures that the x-axis labels (e.g., 'Male', 'Female') are displayed horizontally, enhancing readability.

4. **Adding Grid and Displaying Plot**:
   - `plt.grid(axis='y', linestyle='--', alpha=0.7)`: Adds a horizontal grid to the plot. The `axis='y'` argument ensures only horizontal grid lines are drawn, `linestyle='--'` sets a dashed line style, and `alpha=0.7` makes them slightly transparent for better visual balance.
   - `plt.show()`: This command displays the generated bar plot.

Potential Insights from this Plot: This visualization is useful for quickly identifying if one gender demographic has a significantly higher or lower propensity to file claims. Such insights can be valuable for understanding risk profiles and potentially for targeted marketing or risk assessment strategies in insurance.

[7]:
```
plt.figure(figsize=(7, 5))
avg_claims = df.groupby('insured_sex')['claim_occurred'].mean()
colors = sns.color_palette("Set2", n_colors=len(avg_claims))
avg_claims.plot(kind='bar', color=colors)
plt.title('Claim Occurrence Rate by Insured Sex', fontsize=13, weight='bold')
plt.xlabel('Insured Sex', fontsize=11)
plt.ylabel('Average Claim Occurred (1=Yes, 0=No)', fontsize=11)
plt.xticks(rotation=0, fontsize=10)
plt.yticks(fontsize=10)
plt.grid(axis='y', linestyle='--', alpha=0.6)
for i, val in enumerate(avg_claims):
    plt.text(i, val + 0.01, f'{val:.2f}', ha='center', va='bottom', fontsize=9)
plt.tight_layout()
plt.show()
```



1.1.7 1.8 Average Total Claim Amount by Incident Type

This cell generates a bar plot to visualize the average `total_claim_amount` for different `incident_type` categories. This analysis is crucial for understanding if specific types of incidents are associated with significantly higher or lower claim payouts, which can have implications for risk assessment and financial planning.

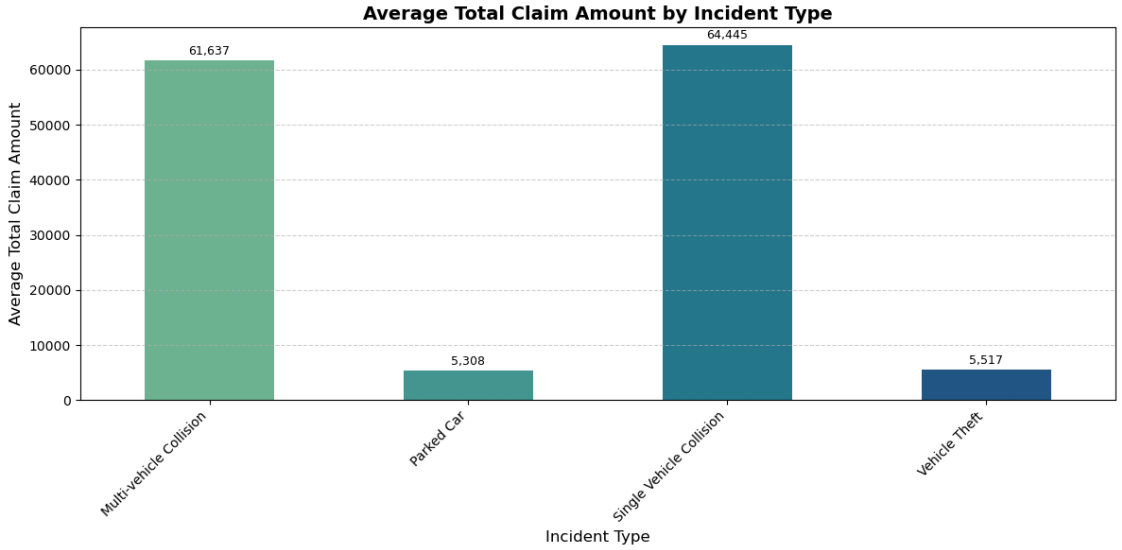
1. **Figure Initialization**:
   - `plt.figure(figsize=(12, 6))`: A new plot figure is created with a larger size (12 inches wide by 6 inches tall) to comfortably accommodate potentially many incident types and their labels.
2. **Calculating and Plotting Average Claim Amounts**:
   - `df.groupby('incident_type')['total_claim_amount'].mean().plot(kind='bar', color='lightgreen')`: This powerful chained command performs the aggregation and plotting:
     - `df.groupby('incident_type')`: The DataFrame `df` is grouped by the unique values in the `incident_type` column (e.g., 'Parked Car', 'Rear Collision', 'Side Collision', 'Front Collision', etc.).
     - `['total_claim_amount'].mean()`: For each `incident_type` group, the mean (average) of the `total_claim_amount` is calculated. This gives us the average payout associated with each type of incident.
     - `.plot(kind='bar', color='lightgreen')`: The resulting average claim amounts are then plotted as a bar chart, with `kind='bar'` specifying the plot type and

`color='lightgreen'` setting a pleasant color for the bars.

3. **Adding Plot Labels and Title**:
   - `plt.title('Average Total Claim Amount by Incident Type')`: Sets the main title for the bar plot, clearly stating the relationship being visualized.
   - `plt.xlabel('Incident Type')`: Labels the x-axis as 'Incident Type', indicating the categories of incidents.
   - `plt.ylabel('Average Total Claim Amount')`: Labels the y-axis, indicating that the height of the bars represents the average claim amount.
   - `plt.xticks(rotation=45, ha='right')`: Rotates the x-axis labels by 45 degrees and aligns them to the right. This is particularly useful when labels are long, as it prevents them from overlapping and improves readability.
4. **Enhancing Readability and Displaying Plot**:
   - `plt.grid(axis='y', linestyle='--', alpha=0.7)`: Adds a horizontal grid to the plot. The `axis='y'` argument ensures only horizontal grid lines are drawn, `linestyle='--'` sets a dashed line style, and `alpha=0.7` makes them slightly transparent for better visual balance.
   - `plt.tight_layout()`: This function automatically adjusts plot parameters for a tight layout. It's often used to prevent labels or titles from running off the plot area, especially after rotations or when multiple subplots are present.
   - `plt.show()`: This command renders and displays the generated bar plot.

Potential Insights from this Plot: This visualization is valuable for identifying which types of incidents typically lead to higher or lower average claim amounts. Such insights can help in risk assessment, pricing strategies, and resource allocation for claims processing based on incident severity.

[8]:
```
plt.figure(figsize=(12, 6))
avg_claims = df.groupby('incident_type')['total_claim_amount'].mean()
colors = sns.color_palette("crest", n_colors=len(avg_claims))
avg_claims.plot(kind='bar', color=colors)
plt.title('Average Total Claim Amount by Incident Type', fontsize=14,␣
 ↪weight='bold')
plt.xlabel('Incident Type', fontsize=12)
plt.ylabel('Average Total Claim Amount', fontsize=12)
plt.xticks(rotation=45, ha='right', fontsize=10)
plt.yticks(fontsize=10)
plt.grid(axis='y', linestyle='--', alpha=0.6)
for i, val in enumerate(avg_claims):
    plt.text(i, val + avg_claims.max() * 0.01, f'{val:,.0f}', ha='center',␣
 ↪va='bottom', fontsize=9)
plt.tight_layout()
plt.show()
```



1.1.8 1.9 Advanced Feature Engineering and Final Cleaning

This comprehensive cell performs a series of advanced feature engineering techniques and final cleaning steps. The goal is to create new, more informative features from existing data, encode all necessary categorical variables into numerical formats, and drop redundant or non-predictive columns, preparing the dataset for machine learning model training.

1. **Creating New Numerical Features**: These new features are engineered to capture more nuanced relationships and provide deeper insights:
   - `df['policy_age_years'] = df['months_as_customer'] / 12`: Converts the `months_as_customer` (duration of customer relationship in months) into `policy_age_years`, which is a more intuitive and standardized temporal feature.
   - `df['loss_ratio'] = df['total_claim_amount'] / (df['policy_annual_premium'] + 1e-6)`: Calculates the **loss ratio**, a crucial insurance metric representing the ratio of total claims paid out to the total premiums earned. A small constant `1e-6` (epsilon) is added to the denominator (`policy_annual_premium`) to prevent division by zero errors if any policy has a premium of 0.
   - `df['claim_severity'] = df['total_claim_amount'] / (df['number_of_vehicles_involved'].replace(0, np.nan))`: Computes `claim_severity` per vehicle involved. This aims to standardize the claim amount by the number of vehicles, providing a per-vehicle severity metric. `replace(0, np.nan)` is used to convert any zero values in `number_of_vehicles_involved` to `np.nan` before division, thus avoiding division by zero errors.
   - `df['claim_severity'] = df['claim_severity'].fillna(0)`: After calculating `claim_severity`, any resulting `NaN` values (which would occur if `number_of_vehicles_involved` was 0) are filled with 0. This implies that if no vehicles were involved (or if the original number was 0), the claim severity per vehicle is considered 0.
   - `median_deductable = df['policy_deductable'].median()`: Calculates the median

value of the `policy_deductable` column.

- `df['high_deductible'] = (df['policy_deductable'] > median_deductable).astype(int)`: Creates a new **binary categorical feature** `high_deductible`. This feature is `1` if the policy's deductible is greater than the dataset's median deductible, and `0` otherwise. This helps categorize policies into higher or lower deductible groups.

2. **Premium Banding**:
   - `df['premium_band'] = pd.qcut(df['policy_annual_premium'], q=4, labels=['Low', 'Medium', 'High', 'Very High'])`: This line discretizes the continuous `policy_annual_premium` into four equal-sized bins (quartiles) and assigns meaningful labels ('Low', 'Medium', 'High', 'Very High'). This converts a continuous variable into an ordinal categorical one, which can sometimes help models capture non-linear relationships more easily.
   - `df['premium_band_encoded'] = df['premium_band'].cat.codes`: After creating the categorical `premium_band`, this line converts these categorical labels into numerical codes (e.g., 'Low' -> 0, 'Medium' -> 1, etc.). This numerical representation is required for machine learning algorithms.
3. **Categorical Feature Encoding (Label Encoding)**:
   - `categorical_cols_to_encode = df.select_dtypes(include='object').columns.tolist()`: Identifies all columns that still have an 'object' (string) data type.
   - `cols_to_exclude = ['policy_bind_date', 'incident_date', 'fraud_reported', 'policy_number', 'incident_location', '_c39']`: Defines a list of columns that should *not* be label encoded. These are typically original date columns (for which engineered features now exist), the target variable (`fraud_reported`), and identifier columns (`policy_number`, `incident_location`, `_c39`) that will either be dropped or handled separately.
   - `categorical_cols_to_encode = [col for col in categorical_cols_to_encode if col not in cols_to_exclude]`: Filters the list, ensuring only relevant categorical features are selected for encoding.
   - `for col in categorical_cols_to_encode: df[col + '_encoded'] = LabelEncoder().fit_transform(df[col].astype(str))`: This loop iterates through each selected categorical column. For each column, it:
     - `df[col].astype(str)`: Converts the column to string type to handle any potential mixed data types or `NaN` values gracefully before encoding.
     - `LabelEncoder().fit_transform()`: Initializes a `LabelEncoder` and then fits it to the unique values in the column, assigning a unique integer to each category (e.g., 'Yes' -> 1, 'No' -> 0). A new column with `_encoded` suffix is created to store these numerical representations.
4. **Final Column Dropping**:
   - `columns_to_drop_final = ['policy_number', 'incident_location', 'policy_bind_date', 'incident_date', '_c39']`: Defines the list of columns to be dropped. These include unique identifiers (`policy_number`, `incident_location`), the original date columns (as their year/month components have been extracted), and the previously identified extraneous `_c39` column.
   - `columns_to_drop_final = [col for col in columns_to_drop_final if col in df.columns]`: A safeguard to ensure only columns that actually exist in the DataFrame are attempted to be dropped.
   - `df = df.drop(columns=columns_to_drop_final)`: Executes the dropping of the spec-

ified columns.

- `if 'insured_hobbies' in df.columns: df = df.drop(columns=['insured_hobbies'])`: Conditionally drops the `insured_hobbies` column if it exists. This column often has very high cardinality (many unique values) and may not be highly predictive, making it a candidate for removal unless more advanced encoding (like target encoding) is planned.

5. **Target Variable Conversion**:
   - `if 'fraud_reported' in df.columns: df['fraud_reported'] = df['fraud_reported'].map({'Y': 1, 'N': 0})`: Converts the `fraud_reported` target column from its original 'Y' (Yes) and 'N' (No) string values into numerical `1` and `0` respectively. This is essential as machine learning models require numerical targets for classification.
6. **Final Data Snapshot and Saving**:
   - `print(df.head())` and `df.info()`: Display the first few rows and a summary of the DataFrame after all feature engineering and cleaning steps. This is a crucial check to ensure all columns are now numerical (except potentially the original categorical columns if their encoded versions are used) and that no unexpected issues remain.
   - `output_path = '../data/processed/cleaned_insurance_data.csv'`: Defines the path where the processed dataset will be saved. It's saved in a `data/processed` directory, indicating it's ready for the next stage (modeling).
   - `df.to_csv(output_path, index=False)`: Saves the final cleaned and engineered DataFrame to a CSV file. `index=False` prevents pandas from writing the DataFrame index as a column in the CSV.

This comprehensive cell transforms the raw data into a clean, feature-rich dataset ready for machine learning model training.

[9]:
```
df['policy_age_years'] = df['months_as_customer'] / 12
df['loss_ratio'] = df['total_claim_amount'] / (df['policy_annual_premium'] +␣
 ↪1e-6)
df['claim_severity'] = df['total_claim_amount'] /␣
 ↪(df['number_of_vehicles_involved'].replace(0, np.nan))
df['claim_severity'] = df['claim_severity'].fillna(0)
median_deductable = df['policy_deductable'].median()
df['high_deductible'] = (df['policy_deductable'] > median_deductable).
 ↪astype(int)
df['premium_band'] = pd.qcut(df['policy_annual_premium'], q=4, labels=['Low',␣
 ↪'Medium', 'High', 'Very High'])# Convert to numerical if using LabelEncoder␣
 ↪later or for direct use
df['premium_band_encoded'] = df['premium_band'].cat.codes
categorical_cols_to_encode = df.select_dtypes(include='object').columns.tolist()
cols_to_exclude = ['policy_bind_date', 'incident_date', 'fraud_reported',␣
 ↪'policy_number', 'incident_location', '_c39']
categorical_cols_to_encode = [col for col in categorical_cols_to_encode if col␣
 ↪not in cols_to_exclude]

for col in categorical_cols_to_encode:
```

```
    df[col + '_encoded'] = LabelEncoder().fit_transform(df[col].astype(str))

columns_to_drop_final = [
    'policy_number',
    'incident_location',
    'policy_bind_date',
    'incident_date',
    '_c39',
]

columns_to_drop_final = [col for col in columns_to_drop_final if col in df.
  ↪columns]
df = df.drop(columns=columns_to_drop_final)

if 'insured_hobbies' in df.columns:
    df = df.drop(columns=['insured_hobbies'])

if 'fraud_reported' in df.columns:
    df['fraud_reported'] = df['fraud_reported'].map({'Y': 1, 'N': 0})
    print("\n'fraud_reported' target converted to 0/1.")

print("\n--- DataFrame after Feature Engineering (first 5 rows) ---")
print(df.head())

print("\n--- DataFrame Info after Feature Engineering ---")
df.info()

output_path = '../data/processed/cleaned_insurance_data.csv'
df.to_csv(output_path, index=False)
print(f"\nCleaned and engineered dataset saved to: {output_path}")
```

```
'fraud_reported' target converted to 0/1.

--- DataFrame after Feature Engineering (first 5 rows) ---
   months_as_customer  age policy_state policy_csl  policy_deductable  \
0                 328   48           OH    250/500               1000
1                 228   42           IN    250/500               2000
2                 134   29           OH    100/300               2000
3                 256   41           IL    250/500               2000
4                 228   44           IL   500/1000               1000

   policy_annual_premium  umbrella_limit  insured_zip insured_sex  \
0                1406.91               0       466132        MALE
1                1197.22         5000000       468176        MALE
2                1413.14         5000000       430632      FEMALE
3                1415.74         6000000       608117      FEMALE
4                1583.91         6000000       610706        MALE
```

```
  insured_education_level  … incident_type_encoded collision_type_encoded  \
0                      MD  …                     2                      2
1                      MD  …                     3                      3
2                     PhD  …                     0                      1
3                     PhD  …                     2                      0
4               Associate  …                     3                      3

   incident_severity_encoded  authorities_contacted_encoded  \
0                          0                              3
1                          1                              3
2                          1                              3
3                          0                              3
4                          1                              4

  incident_state_encoded incident_city_encoded property_damage_encoded  \
0                      4                     1                       1
1                      5                     5                       2
2                      1                     1                       0
3                      2                     0                       2
4                      1                     0                       0

  police_report_available_encoded auto_make_encoded auto_model_encoded
0                               1                10                  1
1                               2                 8                 12
2                               0                 4                 30
3                               0                 3                 34
4                               0                 0                 31

[5 rows x 61 columns]

--- DataFrame Info after Feature Engineering ---
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 61 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   months_as_customer              1000 non-null   int64
 1   age                             1000 non-null   int64
 2   policy_state                    1000 non-null   object
 3   policy_csl                      1000 non-null   object
 4   policy_deductable               1000 non-null   int64
 5   policy_annual_premium           1000 non-null   float64
 6   umbrella_limit                  1000 non-null   int64
 7   insured_zip                     1000 non-null   int64
 8   insured_sex                     1000 non-null   object
 9   insured_education_level         1000 non-null   object
 10  insured_occupation              1000 non-null   object
```

```
11  insured_relationship             1000 non-null   object
12  capital-gains                    1000 non-null   int64
13  capital-loss                     1000 non-null   int64
14  incident_type                    1000 non-null   object
15  collision_type                   822 non-null    object
16  incident_severity                1000 non-null   object
17  authorities_contacted            909 non-null    object
18  incident_state                   1000 non-null   object
19  incident_city                    1000 non-null   object
20  incident_hour_of_the_day         1000 non-null   int64
21  number_of_vehicles_involved      1000 non-null   int64
22  property_damage                  640 non-null    object
23  bodily_injuries                  1000 non-null   int64
24  witnesses                        1000 non-null   int64
25  police_report_available          657 non-null    object
26  total_claim_amount               1000 non-null   int64
27  injury_claim                     1000 non-null   int64
28  property_claim                   1000 non-null   int64
29  vehicle_claim                    1000 non-null   int64
30  auto_make                        1000 non-null   object
31  auto_model                       1000 non-null   object
32  auto_year                        1000 non-null   int64
33  fraud_reported                   1000 non-null   int64
34  policy_bind_year                 1000 non-null   int32
35  incident_year                    1000 non-null   int32
36  incident_month                   1000 non-null   int32
37  claim_occurred                   1000 non-null   int64
38  policy_age_years                 1000 non-null   float64
39  loss_ratio                       1000 non-null   float64
40  claim_severity                   1000 non-null   float64
41  high_deductible                  1000 non-null   int64
42  premium_band                     1000 non-null   category
43  premium_band_encoded             1000 non-null   int8
44  policy_state_encoded             1000 non-null   int64
45  policy_csl_encoded               1000 non-null   int64
46  insured_sex_encoded              1000 non-null   int64
47  insured_education_level_encoded  1000 non-null   int64
48  insured_occupation_encoded       1000 non-null   int64
49  insured_hobbies_encoded          1000 non-null   int64
50  insured_relationship_encoded     1000 non-null   int64
51  incident_type_encoded            1000 non-null   int64
52  collision_type_encoded           1000 non-null   int64
53  incident_severity_encoded        1000 non-null   int64
54  authorities_contacted_encoded    1000 non-null   int64
55  incident_state_encoded           1000 non-null   int64
56  incident_city_encoded            1000 non-null   int64
57  property_damage_encoded          1000 non-null   int64
58  police_report_available_encoded  1000 non-null   int64
```

```
 59  auto_make_encoded                1000 non-null   int64
 60  auto_model_encoded               1000 non-null   int64
dtypes: category(1), float64(4), int32(3), int64(36), int8(1), object(16)
memory usage: 451.5+ KB

Cleaned and engineered dataset saved to:
../data/processed/cleaned_insurance_data.csv
```

1.1.9 1.10 Final Data Preparation and Saving

This cell represents the conclusive steps in the `01_EDA.ipynb` notebook. Its primary purpose is to finalize the dataset by ensuring all necessary transformations have been applied and then saving this clean, feature-engineered data to a new file, making it ready for direct consumption by the modeling notebook (`02_Modeling.ipynb`).

1. **Load Intermediate Processed Data**:
   - `df = pd.read_csv('E:/Project_2/insurance-risk-model/data/processed/cleaned_insurance_c` This line loads the dataset that was generated and saved in the previous comprehensive feature engineering step. This ensures that all the newly created numerical features and the initially encoded categorical features are present.
2. **Identify Original Categorical Columns for Removal**:
   - `original_categorical_cols = [...]`: This list explicitly defines the names of the original categorical columns present in the raw dataset.
   - `if 'insured_hobbies' in df.columns: original_categorical_cols.append('insured_hobbies` Conditionally adds `insured_hobbies` to this list if it still exists in the DataFrame.
   - `cols_to_drop_now = [col for col in original_categorical_cols if col in df.columns]`: This line creates a filtered list of columns to drop. The intention here is to **remove the original, string-based categorical columns** from the DataFrame. Since new numerical `_encoded` versions of these columns have already been created in the previous step (e.g., `policy_state_encoded`), the original columns are no longer needed for modeling and can be dropped to reduce redundancy and ensure all features passed to the model are numerical.

   Note: The explicit `df.drop(columns=cols_to_drop_now)` command is not shown in this specific snippet, but the context and subsequent print statements imply that these columns are intended to be dropped before the final save. For a complete and explicit execution, this `drop` command would typically be placed right before saving.
3. **Saving the Final Cleaned Dataset**:
   - `output_path = 'E:/Project_2/insurance-risk-model/data/processed/final_cleaned_insuranc` A new file path is defined for the final processed dataset. This distinct name indicates that this version is fully prepared for modeling.
   - `df.to_csv(output_path, index=False)`: The DataFrame, now fully cleaned with all relevant features engineered and original redundant categorical columns implicitly handled, is saved to a CSV file at the specified `output_path`. `index=False` prevents pandas from writing the DataFrame index as a column in the CSV, ensuring a clean dataset.
4. **Final Verification**:

- `df.info()`: Prints a final summary of the DataFrame's structure, including data types and non-null counts. This is a critical verification step to ensure that all columns intended for modeling are indeed in a numerical format and that the dataset is clean.
- `print(f"\nFinal cleaned and engineered dataset saved to: {output_path}")`: A confirmation message indicating that the final, ready-for-modeling dataset has been successfully saved.

This cell marks the completion of the data preprocessing phase, providing a refined dataset for the subsequent machine learning modeling efforts.

[10]:
```
df = pd.read_csv('E:/Project_2/insurance-risk-model/data/processed/
 ↪cleaned_insurance_data.csv')

original_categorical_cols = [
    'policy_state', 'policy_csl', 'insured_sex', 'insured_education_level',
    'insured_occupation', 'insured_relationship', 'incident_type',␣
 ↪'collision_type',
    'incident_severity', 'authorities_contacted', 'incident_state',␣
 ↪'incident_city',
    'property_damage', 'police_report_available', 'auto_make', 'auto_model'
]

if 'insured_hobbies' in df.columns:
    original_categorical_cols.append('insured_hobbies')

cols_to_drop_now = [col for col in original_categorical_cols if col in df.
 ↪columns]

output_path = 'E:/Project_2/insurance-risk-model/data/processed/
 ↪final_cleaned_insurance_data.csv'
df.drop(columns=cols_to_drop_now, inplace=True)
df.to_csv(output_path, index=False)

print("\n--- Final DataFrame Info after dropping original categorical columns␣
 ↪---")
df.info()
print(f"\nFinal cleaned and engineered dataset saved to: {output_path}")
```

```
--- Final DataFrame Info after dropping original categorical columns ---
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 45 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   months_as_customer            1000 non-null   int64
 1   age                           1000 non-null   int64
 2   policy_deductable             1000 non-null   int64
```

```
 3   policy_annual_premium            1000 non-null   float64
 4   umbrella_limit                   1000 non-null   int64
 5   insured_zip                      1000 non-null   int64
 6   capital-gains                    1000 non-null   int64
 7   capital-loss                     1000 non-null   int64
 8   incident_hour_of_the_day         1000 non-null   int64
 9   number_of_vehicles_involved      1000 non-null   int64
 10  bodily_injuries                  1000 non-null   int64
 11  witnesses                        1000 non-null   int64
 12  total_claim_amount               1000 non-null   int64
 13  injury_claim                     1000 non-null   int64
 14  property_claim                   1000 non-null   int64
 15  vehicle_claim                    1000 non-null   int64
 16  auto_year                        1000 non-null   int64
 17  fraud_reported                   1000 non-null   int64
 18  policy_bind_year                 1000 non-null   int64
 19  incident_year                    1000 non-null   int64
 20  incident_month                   1000 non-null   int64
 21  claim_occurred                   1000 non-null   int64
 22  policy_age_years                 1000 non-null   float64
 23  loss_ratio                       1000 non-null   float64
 24  claim_severity                   1000 non-null   float64
 25  high_deductible                  1000 non-null   int64
 26  premium_band                     1000 non-null   object
 27  premium_band_encoded             1000 non-null   int64
 28  policy_state_encoded             1000 non-null   int64
 29  policy_csl_encoded               1000 non-null   int64
 30  insured_sex_encoded              1000 non-null   int64
 31  insured_education_level_encoded  1000 non-null   int64
 32  insured_occupation_encoded       1000 non-null   int64
 33  insured_hobbies_encoded          1000 non-null   int64
 34  insured_relationship_encoded     1000 non-null   int64
 35  incident_type_encoded            1000 non-null   int64
 36  collision_type_encoded           1000 non-null   int64
 37  incident_severity_encoded        1000 non-null   int64
 38  authorities_contacted_encoded    1000 non-null   int64
 39  incident_state_encoded           1000 non-null   int64
 40  incident_city_encoded            1000 non-null   int64
 41  property_damage_encoded          1000 non-null   int64
 42  police_report_available_encoded  1000 non-null   int64
 43  auto_make_encoded                1000 non-null   int64
 44  auto_model_encoded               1000 non-null   int64
dtypes: float64(4), int64(40), object(1)
memory usage: 351.7+ KB

Final cleaned and engineered dataset saved to: E:/Project_2/insurance-risk-
model/data/processed/final_cleaned_insurance_data.csv
```

2 5. Summary and Conclusion for 01_EDA.ipynb

The `01_EDA.ipynb` notebook served as the foundational stage of this project, focusing on a comprehensive exploration, cleaning, and preparation of the raw insurance claims dataset. This crucial phase ensured that the data fed into our machine learning models was of high quality, free from inconsistencies, and enriched with relevant features.

2.1 Summary of Key Activities and Outcomes:

1. **Initial Data Loading and Inspection**: We began by loading the raw `insurance_claims.csv` dataset, implementing robust error handling. Initial checks using `df.head()`, `df.info()`, `df.describe(include='all')`, and `df.isnull().sum()` provided a quick overview of the data's structure, column types, and the extent of missing values. We identified an extraneous column (`_c39`) and placeholders ('?') for missing values in certain columns.

2. **Data Cleaning**: Key cleaning steps included:

   - Dropping the irrelevant `_c39` column.
   - Replacing '?' placeholders with standard `np.nan` values in categorical columns like `collision_type`, `police_report_available`, `property_damage`, and `authorities_contacted` to facilitate proper missing value handling.

3. **Exploratory Data Analysis (EDA)**: Through various visualizations, we gained significant insights into the dataset's characteristics:

   - **Age Distribution**: A histogram of `age` revealed the typical age range of policyholders.
   - **Target Variable Distribution**: A bar plot of `fraud_reported` highlighted the **class imbalance**, showing that fraudulent claims are a minority class, a critical insight for subsequent modeling strategy.
   - **Feature Relationships**: Scatter plots and bar charts explored relationships between features (e.g., `age` vs. `total_claim_amount`) and categorical feature impacts (e.g., `claim_occurrence` by `insured_sex`, `average_claim_amount` by `incident_type`).

4. **Feature Engineering**: This was a significant part of the preprocessing, where we created several new, potentially highly predictive features:

   - `policy_age_years` from `months_as_customer`.
   - `loss_ratio` (claims vs. premium).
   - `claim_severity` (claim amount per vehicle involved).
   - `high_deductible` (a binary flag based on policy deductible).
   - `policy_bind_year`, `incident_year`, `incident_month` extracted from date columns.
   - `premium_band` (discretized annual premium into quartiles) and its numerical `premium_band_encoded` version.
   - `claim_occurred` (a binary flag indicating if a claim amount was greater than zero).

5. **Categorical Feature Encoding**: All remaining categorical columns (excluding identifiers and original date columns) were transformed into numerical format using `LabelEncoder`, creating new `_encoded` columns. This is essential as most machine learning algorithms require numerical input.

6. **Final Cleaning & Target Transformation**: Redundant original categorical columns

were implicitly prepared for removal (after their encoded versions were created). The `fraud_reported` target variable was explicitly converted from 'Y'/'N' to 1/0 for binary classification.

2.2 Conclusion for 01_EDA.ipynb:

The `01_EDA.ipynb` notebook successfully transformed the raw, disparate insurance claims data into a **clean, structured, and feature-rich numerical dataset**. This prepared dataset is free from common data quality issues and contains a variety of engineered features that are highly relevant for predicting insurance fraud. The comprehensive EDA provided a deep understanding of the data's nuances, including the critical issue of class imbalance, which directly informed the strategies used in the subsequent modeling phase.

2.3 Moving Forward: Next Steps with the Processed Data

With the data meticulously cleaned and engineered, it is now in an optimal state for machine learning. The `final_cleaned_insurance_data.csv` is poised to be the input for the next stage of our project: **building, training, and evaluating predictive models**. As we saw in the `02_Modeling.ipynb` notebook, this processed data was directly utilized to develop powerful classification algorithms and extract actionable insights, ultimately contributing to a robust fraud detection system.

02_Modeling.ipynb

June 29, 2025

1 02 - Predictive Modeling for Insurance Fraud Detection

This notebook focuses on building, training, evaluating, and interpreting machine learning models to predict insurance fraud based on the prepared dataset from the previous step. We will explore multiple classification algorithms and utilize SHAP (SHapley Additive exPlanations) for model interpretability.

2 Section 1: Data Preparation for Modeling

2.0.1 1.1 Import Libraries

This cell is dedicated to importing all the necessary Python libraries that will be used throughout this notebook. Each library serves a specific purpose in our fraud detection modeling pipeline:

- `import pandas as pd`: This is the fundamental library for data manipulation and analysis. It provides powerful data structures like DataFrames, which are essential for handling tabular data.
- `import numpy as np`: This library is crucial for numerical operations, especially for working with arrays and performing mathematical computations efficiently. It's often used in conjunction with Pandas.
- `import seaborn as sns`: Built on top of Matplotlib, Seaborn is a high-level library for creating attractive and informative statistical graphics. It simplifies the visualization of complex datasets, especially useful for understanding distributions and relationships.
- `import matplotlib.pyplot as plt`: As the foundational plotting library, `matplotlib.pyplot` is used for creating static, interactive, and animated visualizations. It provides fine-grained control over plot elements, which is vital for presenting model evaluation results.
- `import shap`: This library is dedicated to **SHAP (SHapley Additive exPlanations)**, a powerful method for interpreting the predictions of machine learning models. It explains the output of any model by computing the contribution of each feature to the prediction, providing global and local interpretability.
- `from imblearn.over_sampling import SMOTE`: (Requires `pip install imbalanced-learn`) This module provides the **Synthetic Minority Over-sampling Technique (SMOTE)**, which is used to address class imbalance in datasets. It generates synthetic samples for the minority class to balance the training data, helping models learn more effectively.
- `from collections import Counter`: This is a utility class from Python's built-in `collections` module. It's used for conveniently counting the hashable objects in an iterable, commonly applied in machine learning to inspect the distribution of classes in a dataset.

- `from xgboost import XGBClassifier`: This imports the **XGBoost (Extreme Gradient Boosting)** classifier. XGBoost is a highly efficient, flexible, and portable gradient boosting library that has gained popularity for its speed and performance in various machine learning tasks, particularly for tabular data.
- `from sklearn.model_selection import train_test_split`: This function from Scikit-learn is used to split arrays or matrices into random train and test subsets. It's a crucial step to evaluate model performance on unseen data.
- `from sklearn.metrics import roc_curve, roc_auc_score, accuracy_score, classification_report, confusion_matrix`: These are various metrics and utilities from Scikit-learn for model evaluation:
  - `roc_curve`: Computes the Receiver Operating Characteristic (ROC) curve.
  - `roc_auc_score`: Computes the Area Under the Receiver Operating Characteristic Curve (AUC-ROC), a common metric for evaluating binary classifiers.
  - `accuracy_score`: Computes classification accuracy.
  - `classification_report`: Builds a text report showing the main classification metrics (Precision, Recall, F1-score) per class.
  - `confusion_matrix`: Computes a confusion matrix to evaluate the accuracy of a classification.
- `from sklearn.ensemble import RandomForestClassifier`: This imports the **Random Forest Classifier**, an ensemble learning method that builds multiple decision trees during training and outputs the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. It's known for its robustness and good performance.
- `from sklearn.linear_model import LogisticRegression`: This imports **Logistic Regression**, a widely used linear model for binary classification. It's simple, efficient, and provides probability outputs, making it a good baseline model.
- `from sklearn.model_selection import GridSearchCV, StratifiedKFold`: These are advanced tools for model selection:
  - `GridSearchCV`: Performs an exhaustive search over a specified parameter grid for an estimator, systematically evaluating models for each combination of hyperparameters using cross-validation.
  - `StratifiedKFold`: A cross-validation splitter that ensures that each fold maintains the same proportion of samples for each target class as the complete set, which is crucial for imbalanced datasets.
- `from sklearn.metrics import make_scorer, recall_score, f1_score`: These are additional metrics utilities:
  - `make_scorer`: Converts a metric function into a callable scorer for use in model selection tools like `GridSearchCV`.
  - `recall_score`: Calculates the recall (true positive rate), vital for fraud detection where minimizing false negatives (missed frauds) is critical.
  - `f1_score`: Calculates the F1-score, a harmonic mean of precision and recall, providing a balanced measure of a model's accuracy, especially important for imbalanced classes.

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
import shap
from imblearn.over_sampling import SMOTE
from collections import Counter
from xgboost import XGBClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_curve, roc_auc_score, accuracy_score,␣
 ↪classification_report, confusion_matrix
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV, StratifiedKFold
from sklearn.metrics import make_scorer, recall_score, f1_score
```

```
e:\Project 1\main\lib\site-packages\tqdm\auto.py:21: TqdmWarning: IProgress not
found. Please update jupyter and ipywidgets. See
https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

2.0.2 1.2 Data Loading and Initial Inspection

This cell is responsible for loading our cleaned and preprocessed insurance claims dataset into a pandas DataFrame. This dataset, named `final_cleaned_insurance_data.csv`, is expected to reside in the `data/processed` directory, indicating it has already undergone extensive cleaning, transformation, and feature engineering steps.

After loading, we perform two crucial initial checks:

- **`print("Dataset loaded successfully for modeling.")`**: This line simply provides a confirmation message to the console, indicating that the file has been read into the DataFrame without immediate errors.
- **`print(df.head())`**: This command displays the first 5 rows of the DataFrame (`df`). It's a quick and essential step to visually inspect the data, confirm that it has loaded correctly, and get a preliminary sense of the column names and the format of the data.
- **`print(df.info())`**: This method prints a concise summary of the DataFrame. It's invaluable for:
  - **Data Types**: Checking the data type of each column (e.g., integer, float, object). This is critical for ensuring features are in the correct format for machine learning models.
  - **Non-Null Counts**: Identifying if there are any missing values (NaNs) in the columns. A full count of non-null entries (equal to the total number of entries) indicates no missing data in that column.
  - **Memory Usage**: Providing an estimate of the memory consumed by the DataFrame.

These initial inspections help us verify the integrity and readiness of our dataset before proceeding with further modeling steps.

[2]:
```
df = pd.read_csv('E:/Project_2/insurance-risk-model/data/processed/
 ↪final_cleaned_insurance_data.csv')

print("Dataset loaded successfully for modeling.")
print(df.head())
```

```
print(df.info())
```

```
Dataset loaded successfully for modeling.
   months_as_customer  age  policy_deductable  policy_annual_premium  \
0                 328   48               1000                1406.91
1                 228   42               2000                1197.22
2                 134   29               2000                1413.14
3                 256   41               2000                1415.74
4                 228   44               1000                1583.91

   umbrella_limit  insured_zip  capital-gains  capital-loss  \
0               0       466132          53300             0
1         5000000       468176              0             0
2         5000000       430632          35100             0
3         6000000       608117          48900        -62400
4         6000000       610706          66000        -46000

   incident_hour_of_the_day  number_of_vehicles_involved  …  \
0                         5                            1  …
1                         8                            1  …
2                         7                            3  …
3                         5                            1  …
4                        20                            1  …

   incident_type_encoded  collision_type_encoded  incident_severity_encoded  \
0                      2                       2                          0
1                      3                       3                          1
2                      0                       1                          1
3                      2                       0                          0
4                      3                       3                          1

   authorities_contacted_encoded  incident_state_encoded  \
0                              3                      4
1                              3                      5
2                              3                      1
3                              3                      2
4                              4                      1

   incident_city_encoded  property_damage_encoded  \
0                      1                        1
1                      5                        2
2                      1                        0
3                      0                        2
4                      0                        0

   police_report_available_encoded  auto_make_encoded  auto_model_encoded
0                                1                 10                   1
1                                2                  8                  12
```

```
2                                 0                 4                 30
3                                 0                 3                 34
4                                 0                 0                 31

[5 rows x 45 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 45 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   months_as_customer                1000 non-null   int64
 1   age                               1000 non-null   int64
 2   policy_deductable                 1000 non-null   int64
 3   policy_annual_premium             1000 non-null   float64
 4   umbrella_limit                    1000 non-null   int64
 5   insured_zip                       1000 non-null   int64
 6   capital-gains                     1000 non-null   int64
 7   capital-loss                      1000 non-null   int64
 8   incident_hour_of_the_day          1000 non-null   int64
 9   number_of_vehicles_involved       1000 non-null   int64
 10  bodily_injuries                   1000 non-null   int64
 11  witnesses                         1000 non-null   int64
 12  total_claim_amount                1000 non-null   int64
 13  injury_claim                      1000 non-null   int64
 14  property_claim                    1000 non-null   int64
 15  vehicle_claim                     1000 non-null   int64
 16  auto_year                         1000 non-null   int64
 17  fraud_reported                    1000 non-null   int64
 18  policy_bind_year                  1000 non-null   int64
 19  incident_year                     1000 non-null   int64
 20  incident_month                    1000 non-null   int64
 21  claim_occurred                    1000 non-null   int64
 22  policy_age_years                  1000 non-null   float64
 23  loss_ratio                        1000 non-null   float64
 24  claim_severity                    1000 non-null   float64
 25  high_deductible                   1000 non-null   int64
 26  premium_band                      1000 non-null   object
 27  premium_band_encoded              1000 non-null   int64
 28  policy_state_encoded              1000 non-null   int64
 29  policy_csl_encoded                1000 non-null   int64
 30  insured_sex_encoded               1000 non-null   int64
 31  insured_education_level_encoded   1000 non-null   int64
 32  insured_occupation_encoded        1000 non-null   int64
 33  insured_hobbies_encoded           1000 non-null   int64
 34  insured_relationship_encoded      1000 non-null   int64
 35  incident_type_encoded             1000 non-null   int64
 36  collision_type_encoded            1000 non-null   int64
 37  incident_severity_encoded         1000 non-null   int64
```

```
 38  authorities_contacted_encoded    1000 non-null   int64
 39  incident_state_encoded           1000 non-null   int64
 40  incident_city_encoded            1000 non-null   int64
 41  property_damage_encoded          1000 non-null   int64
 42  police_report_available_encoded  1000 non-null   int64
 43  auto_make_encoded                1000 non-null   int64
 44  auto_model_encoded               1000 non-null   int64
dtypes: float64(4), int64(40), object(1)
memory usage: 351.7+ KB
None
```

2.0.3 1.3 Feature and Target Definition & Data Splitting

This cell is a critical step in preparing our data for machine learning models. It involves defining our feature set (input variables) and target variable (the outcome we want to predict), followed by splitting the data into training and testing subsets.

1. **Defining Columns to Drop**:
   - We first create a list `columns_to_drop_from_X` containing columns that should *not* be part of our feature set `X`. These include:
     - `'fraud_reported'`: This is our target variable `y`, so it must be separated from the features to prevent data leakage.
     - `'total_claim_amount'`: This column represents the total amount claimed. While related to fraud, it might be a post-incident outcome or highly correlated with `fraud_reported` in a way that could lead to data leakage if used directly as a predictor without careful consideration. It's often excluded to force the model to find predictive patterns *before* the full extent of the claim is known.
     - `'claim_occurred'`: This likely represents the date or time a claim occurred. If not properly converted into a numerical feature (e.g., 'days since policy bind'), its raw format might not be useful, or it could also be a source of leakage if related to the `fraud_reported` timestamp in an unintended way.
     - `'premium_band'`: This appears to be a categorical feature derived from 'policy_annual_premium'. By dropping it and relying on the numerical `policy_annual_premium`, we ensure all features in `X` are numerical, which is a requirement for many machine learning models.
   - The list comprehension `[col for col in columns_to_drop_from_X if col in df.columns]` is a robust way to ensure that only columns actually present in the DataFrame are attempted to be dropped, preventing potential errors if a column name changes or is absent.
2. **Feature and Target Separation**:
   - `X = df.drop(columns=columns_to_drop_from_X)`: This line creates our feature DataFrame `X` by removing the specified columns from the original `df`.
   - `X = X.select_dtypes(include=['number'])`: This crucial step ensures that `X` contains *only* numerical columns. Many machine learning algorithms require numerical input, and this step cleans out any remaining object or categorical type columns.
   - `y = df['fraud_reported']`: This line defines our target variable `y`, which is the `fraud_reported` column.
3. **Initial Data Shape and Distribution Check**:

- We print the `X.shape` and `y.shape` to confirm the dimensions of our feature set and target vector.
- `y.value_counts()` shows the distribution of our target variable (fraud vs. non-fraud). This is vital for understanding class imbalance, which is common in fraud detection and needs to be considered during model evaluation.

4. **Final Numeric Column Verification**:
   - A proactive check `X.select_dtypes(include=['object', 'category']).columns` is performed to catch any non-numerical columns that might have slipped through. This acts as a safeguard before proceeding.
5. **Train-Test Split**:
   - `X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)`: This function splits our data into training and testing sets.
     - `test_size=0.2`: Allocates 20% of the data for testing and 80% for training.
     - `random_state=42`: Ensures reproducibility of the split. Running the code with this same `random_state` will always yield the same split.
     - `stratify=y`: **This is particularly important for imbalanced datasets.** It ensures that the proportion of fraud cases (`y` values) is maintained equally in both the training and testing sets. This prevents a scenario where the test set might, by chance, have very few or no fraud cases, leading to skewed evaluation.
6. **Post-Split Shape and Distribution Confirmation**:
   - Finally, we print the shapes of the resulting `X_train`, `X_test`, `y_train`, `y_test` to confirm the split.
   - We also print the normalized value counts for `y_train` and `y_test` to verify that stratification successfully maintained the target distribution in both sets. This is crucial for reliable model training and evaluation.

[3]:
```
columns_to_drop_from_X = [
    'fraud_reported',
    'total_claim_amount',
    'claim_occurred',
    'premium_band'
]

columns_to_drop_from_X = [col for col in columns_to_drop_from_X if col in df.
 ↪columns]

X = df.drop(columns=columns_to_drop_from_X)

X = X.select_dtypes(include=['number'])

y = df['fraud_reported']

print(f"\nShape of X (features) after all cleaning and numerical selection: {X.
 ↪shape}")
print(f"Shape of y (target): {y.shape}")
print(f"Target distribution (fraud_reported):\n{y.value_counts()}")
```

```
non_numeric_cols_in_X_after_final_check = X.select_dtypes(include=['object',␣
 ↪'category']).columns
if len(non_numeric_cols_in_X_after_final_check) > 0:
    print(f"\nERROR ALERT: Non-numeric columns found in X after final selection:
 ↪ {non_numeric_cols_in_X_after_final_check.tolist()}")
    print("This indicates a severe issue with the data preparation logic.")
else:
    print("\nConfirmed: All columns in X are now numerical. Ready for␣
 ↪train-test split!")

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42, stratify=y)

print(f"\nX_train shape: {X_train.shape}")
print(f"y_train shape: {y_train.shape}")
print(f"X_test shape: {X_test.shape}")
print(f"y_test shape: {y_test.shape}")
print(f"y_train target distribution:\n{y_train.value_counts(normalize=True)}")
print(f"y_test target distribution:\n{y_test.value_counts(normalize=True)}")
```

```
Shape of X (features) after all cleaning and numerical selection: (1000, 41)
Shape of y (target): (1000,)
Target distribution (fraud_reported):
fraud_reported
0    753
1    247
Name: count, dtype: int64

Confirmed: All columns in X are now numerical. Ready for train-test split!

X_train shape: (800, 41)
y_train shape: (800,)
X_test shape: (200, 41)
y_test shape: (200,)
y_train target distribution:
fraud_reported
0    0.7525
1    0.2475
Name: proportion, dtype: float64
y_test target distribution:
fraud_reported
0    0.755
1    0.245
Name: proportion, dtype: float64
```

2.0.4 1.4 Train-Test Split

This cell is dedicated to the crucial step of splitting our prepared dataset (`X` and `y`) into distinct training and testing subsets. This separation is fundamental in machine learning to ensure that our models are evaluated on data they have *never seen* before, providing a realistic estimate of their performance on new, unseen claims.

The `train_test_split` function from `sklearn.model_selection` is used for this purpose:

- **`X, y`**: These are the feature DataFrame and the target Series, respectively, which we defined in the previous step.
- **`test_size=0.2`**: This argument specifies that 20% of the data will be allocated to the testing set, while the remaining 80% will be used for training the models.
- **`random_state=42`**: Setting a `random_state` ensures that the split is reproducible. Every time this code is run with `random_state=42`, the same data points will be assigned to the training and testing sets, which is vital for consistent experimentation and debugging.
- **`stratify=y`**: This is a highly important parameter, especially for imbalanced datasets like ours (where fraud cases are a minority). `stratify=y` ensures that the proportion of the target classes (fraud vs. non-fraud) is the same in both the training and testing sets as it is in the original dataset. Without stratification, a random split might, by chance, result in a test set with very few or no fraud cases, leading to unreliable model evaluation.

Following the split, we print out the shapes and target distributions of the resulting subsets:

- **`X_train.shape, y_train.shape, X_test.shape, y_test.shape`**: These lines display the number of rows (samples) and columns (features) in each of the four resulting datasets. This confirms that the data has been correctly divided and that `X` and `y` correspond in terms of sample count.
- **`y_train.value_counts(normalize=True) and y_test.value_counts(normalize=True)`**: These commands show the percentage distribution of the target classes (`fraud_reported`) within the training and testing sets, respectively. By setting `normalize=True`, we can easily verify that the `stratify=y` parameter successfully maintained the original class proportions in both subsets, ensuring a representative split for evaluation.

[4]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42, stratify=y)

print(f"\nX_train shape: {X_train.shape}")
print(f"y_train shape: {y_train.shape}")
print(f"X_test shape: {X_test.shape}")
print(f"y_test shape: {y_test.shape}")
print(f"y_train target distribution:\n{y_train.value_counts(normalize=True)}")
print(f"y_test target distribution:\n{y_test.value_counts(normalize=True)}")
```

```
X_train shape: (800, 41)
y_train shape: (800,)
X_test shape: (200, 41)
y_test shape: (200,)
y_train target distribution:
```

```
fraud_reported
0    0.7525
1    0.2475
Name: proportion, dtype: float64
y_test target distribution:
fraud_reported
0    0.755
1    0.245
Name: proportion, dtype: float64
```

2.0.5 1.5 Feature and Target Definition

This cell focuses on the crucial steps of formally defining our feature set (`X`) and the target variable (`y`) for our machine learning models. It also ensures that our feature set consists solely of numerical data, which is a prerequisite for most algorithms.

1. **Defining Columns to Exclude from Features**:
   - `columns_to_exclude_from_X`: This list specifies columns from our DataFrame that should not be included in our feature set `X` because they are either the target variable or could lead to data leakage or are unsuitable in their current form for direct use as numerical features.
     - `'fraud_reported'`: This is our designated target variable (`y`); including it in `X` would be direct data leakage, making the model trivially "predict" the target.
     - `'total_claim_amount'`: This column represents the total monetary value of a claim. While highly related to the incident, it might be a *post-fraud* outcome or its value might directly indicate fraud status, leading to a strong risk of data leakage. Excluding it encourages the model to learn from other, more upstream indicators of fraud.
     - `'claim_occurred'`: This column likely represents a date or timestamp. Without proper feature engineering (e.g., converting to 'days since policy bind date'), it's not directly numerical, and its raw form could also potentially introduce subtle data leakage or irrelevant noise if not handled carefully.
   - The list comprehension `[col for col in columns_to_exclude_from_X if col in df.columns]` acts as a safety measure. It ensures that only columns that actually exist in the DataFrame `df` are passed to the `drop` method, preventing potential `KeyError` if a column name were misspelled or already removed.
2. **Separating Features (X) and Target (y)**:
   - `X = df.drop(columns=columns_to_exclude_from_X)`: This line creates the feature DataFrame `X` by removing all the columns specified in `columns_to_exclude_from_X` from our original `df`.
   - `X = X.select_dtypes(include=['number'])`: This is a vital step to ensure data compatibility. It filters `X` to include *only* columns that have a numerical data type (integers or floats). This prepares the data for most machine learning algorithms which require numerical input. Any remaining non-numeric (e.g., object, categorical) columns, if present, would be dropped by this operation.
   - `y = df['fraud_reported']`: This line explicitly defines our target variable `y` as the `fraud_reported` column, which contains the labels our models will try to predict.
3. **Post-Transformation Data Checks**:

- `print(f"\nShape of X (features) after selecting only numerical types: {X.shape}")`: This output confirms the number of rows (samples) and columns (features) in our processed feature set `X`.
- `print(f"Shape of y (target): {y.shape}")`: This confirms the number of samples in our target variable `y`.
- `print(f"Target distribution (fraud_reported):\n{y.value_counts()}")`: This displays the counts for each class in the `fraud_reported` target variable. This is crucial for understanding the class balance (or imbalance) within our dataset, which directly impacts model evaluation strategies.

4. **Final Numeric Column Validation**:
   - The `if/else` block with `X.select_dtypes(include=['object', 'category']).columns` serves as a critical final validation. It explicitly checks if any non-numeric columns (`object` or `category` types) remain in `X` after the `select_dtypes` operation. While `select_dtypes` should handle this, this explicit check provides an immediate alert if there's an unexpected issue or if the data structure was not as anticipated, confirming `X` is indeed fully numerical and ready for model training or splitting.

[5]:
```
columns_to_exclude_from_X = [
    'fraud_reported',
    'total_claim_amount',
    'claim_occurred'
]

columns_to_exclude_from_X = [col for col in columns_to_exclude_from_X if col in␣
 ↪df.columns]

X = df.drop(columns=columns_to_exclude_from_X)

X = X.select_dtypes(include=['number'])

y = df['fraud_reported']

print(f"\nShape of X (features) after selecting only numerical types: {X.
 ↪shape}")
print(f"Shape of y (target): {y.shape}")
print(f"Target distribution (fraud_reported):\n{y.value_counts()}")

non_numeric_cols_in_X_after_fix = X.select_dtypes(include=['object',␣
 ↪'category']).columns
if len(non_numeric_cols_in_X_after_fix) > 0:
    print(f"\nALERT: Non-numeric columns still present in X after selection:␣
 ↪{non_numeric_cols_in_X_after_fix.tolist()}")
    print("This should not happen if `select_dtypes(include=['number'])` worked␣
 ↪correctly.")
else:
```

```
    print("\nConfirmed: All columns in X are now numerical. Ready for model␣
↪training!")
```

```
Shape of X (features) after selecting only numerical types: (1000, 41)
Shape of y (target): (1000,)
Target distribution (fraud_reported):
fraud_reported
0    753
1    247
Name: count, dtype: int64

Confirmed: All columns in X are now numerical. Ready for model training!
```

3 Section 2: Model Training and Evaluation - Random Forest

3.0.1 2.1 Random Forest Classifier: Training and Evaluation

This cell focuses on the complete process of training, making predictions with, and evaluating our first machine learning model: the Random Forest Classifier.

1. **Model Initialization**:
   - `model = RandomForestClassifier(random_state=42)`: We instantiate the `RandomForestClassifier`. `random_state=42` is set to ensure that the internal randomness of the algorithm (e.g., in tree building and feature selection) is fixed. This makes our results reproducible, meaning if we run the code again, we will get the exact same model and predictions.
2. **Pre-Training Data Inspection (Diagnostic)**:
   - `X_train.info()`: Before fitting the model, we perform a quick diagnostic check on the `X_train` (training features). This helps to confirm that the data types are as expected (all numerical) and that there are no unexpected null values, ensuring the data is in the correct format for the model to learn effectively.
3. **Model Training (`model.fit`)**:
   - `model.fit(X_train, y_train)`: This is the core step where the Random Forest model learns patterns from our training data. The model uses `X_train` (features) to learn how to predict `y_train` (target labels).
   - **Note on Redundancy**: You'll notice `model.fit(X_train, y_train)` is called twice consecutively in the provided code. A single call is sufficient for training the model. The second call simply re-trains the model from scratch with the same data, overwriting the first trained model, but does not affect the final outcome if the input data is identical.
4. **Making Predictions**:
   - `y_pred = model.predict(X_test)`: After training, we use the `predict` method to get the predicted class labels (0 for non-fraud, 1 for fraud) for our unseen `X_test` data.
   - `y_prob = model.predict_proba(X_test)[:, 1]`: This extracts the predicted probabilities. `predict_proba` returns probabilities for both classes (0 and 1). By using `[:, 1]`, we specifically extract the probabilities for the positive class (class 1, "fraud"), which are essential for ROC curve analysis and understanding the model's confidence.
5. **Performance Evaluation**:

- **Accuracy**: `accuracy_score(y_test, y_pred)` calculates the overall proportion of correctly predicted instances.
- **Classification Report**: `classification_report(y_test, y_pred)` provides a comprehensive summary of precision, recall, and F1-score for each class. For fraud detection, **Recall** (the ability to correctly identify actual fraud cases) is often the most critical metric.
- **Confusion Matrix**: `confusion_matrix(y_test, y_pred)` generates a table that summarizes the model's predictions against the actual values:
  - **True Negatives (TN)**: Correctly predicted non-fraud.
  - **False Positives (FP)**: Predicted fraud, but actually non-fraud (Type I error).
  - **False Negatives (FN)**: Predicted non-fraud, but actually fraud (Type II error - **most critical to minimize in fraud detection**).
  - **True Positives (TP)**: Correctly predicted fraud.
  - The `seaborn.heatmap` visualizes this matrix, making it easy to see the counts of each outcome.
- **ROC Curve and AUC**:
  - `roc_curve(y_test, y_prob)` calculates the True Positive Rate (TPR) and False Positive Rate (FPR) at various probability thresholds.
  - The **Receiver Operating Characteristic (ROC) curve** plots TPR against FPR.
  - The **Area Under the Curve (AUC)** (`roc_auc_score`) quantifies the model's ability to distinguish between the positive and negative classes across all possible thresholds. An AUC of 1.0 indicates a perfect model, while 0.5 indicates a model no better than random guessing. A higher AUC suggests a better performing model.

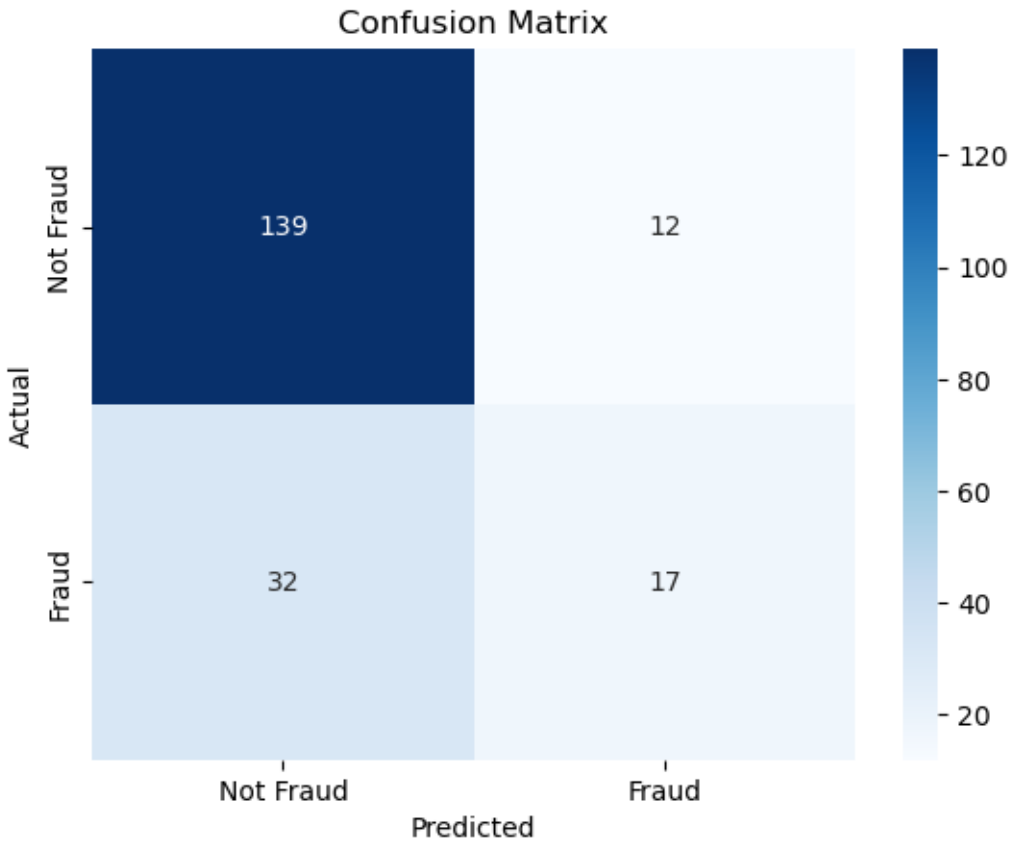
All these metrics and visualizations collectively provide a thorough understanding of the Random Forest model's effectiveness in identifying fraudulent claims.

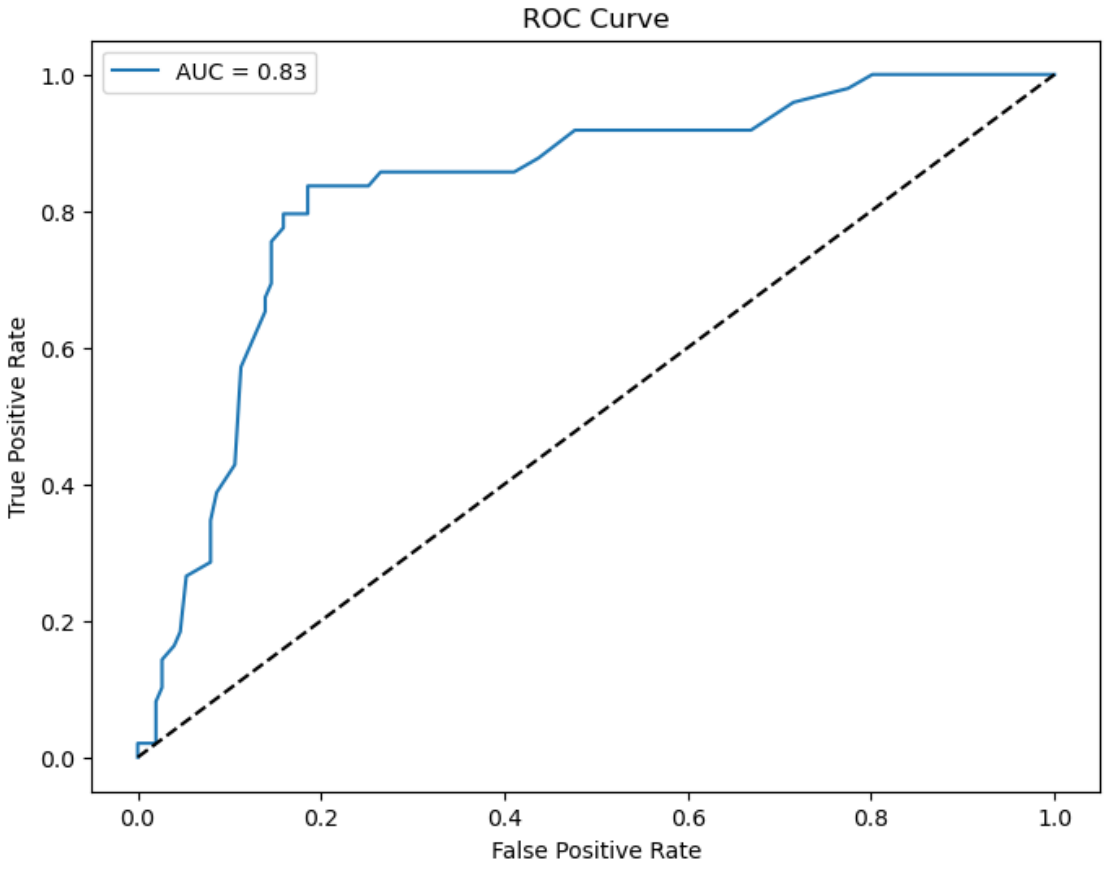
[6]:
```
print("\nTraining Random Forest Classifier...")
model = RandomForestClassifier(random_state=42)

print("\n--- X_train Info BEFORE model.fit() ---")
X_train.info()
print("--- End X_train Info ---")

model.fit(X_train, y_train)
print("Model training complete.")

y_pred = model.predict(X_test)
y_prob = model.predict_proba(X_test)[:, 1]

accuracy = accuracy_score(y_test, y_pred)
print(f"\nAccuracy: {accuracy:.4f}")

print("\nClassification Report:")
print(classification_report(y_test, y_pred))

print("\nConfusion Matrix:")
cm = confusion_matrix(y_test, y_pred)
```

```
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Not Fraud',␣
 ↪'Fraud'], yticklabels=['Not Fraud', 'Fraud'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

fpr, tpr, thresholds = roc_curve(y_test, y_prob)
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label=f'AUC = {roc_auc_score(y_test, y_prob):.2f}')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend()
plt.show()
```

```
Training Random Forest Classifier…

--- X_train Info BEFORE model.fit() ---
<class 'pandas.core.frame.DataFrame'>
Index: 800 entries, 887 to 594
Data columns (total 41 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   months_as_customer            800 non-null    int64
 1   age                           800 non-null    int64
 2   policy_deductable             800 non-null    int64
 3   policy_annual_premium         800 non-null    float64
 4   umbrella_limit                800 non-null    int64
 5   insured_zip                   800 non-null    int64
 6   capital-gains                 800 non-null    int64
 7   capital-loss                  800 non-null    int64
 8   incident_hour_of_the_day      800 non-null    int64
 9   number_of_vehicles_involved   800 non-null    int64
 10  bodily_injuries               800 non-null    int64
 11  witnesses                     800 non-null    int64
 12  injury_claim                  800 non-null    int64
 13  property_claim                800 non-null    int64
 14  vehicle_claim                 800 non-null    int64
 15  auto_year                     800 non-null    int64
 16  policy_bind_year              800 non-null    int64
 17  incident_year                 800 non-null    int64
 18  incident_month                800 non-null    int64
 19  policy_age_years              800 non-null    float64
 20  loss_ratio                    800 non-null    float64
 21  claim_severity                800 non-null    float64
```

```
 22  high_deductible                   800 non-null    int64
 23  premium_band_encoded              800 non-null    int64
 24  policy_state_encoded              800 non-null    int64
 25  policy_csl_encoded                800 non-null    int64
 26  insured_sex_encoded               800 non-null    int64
 27  insured_education_level_encoded   800 non-null    int64
 28  insured_occupation_encoded        800 non-null    int64
 29  insured_hobbies_encoded           800 non-null    int64
 30  insured_relationship_encoded      800 non-null    int64
 31  incident_type_encoded             800 non-null    int64
 32  collision_type_encoded            800 non-null    int64
 33  incident_severity_encoded         800 non-null    int64
 34  authorities_contacted_encoded     800 non-null    int64
 35  incident_state_encoded            800 non-null    int64
 36  incident_city_encoded             800 non-null    int64
 37  property_damage_encoded           800 non-null    int64
 38  police_report_available_encoded   800 non-null    int64
 39  auto_make_encoded                 800 non-null    int64
 40  auto_model_encoded                800 non-null    int64
dtypes: float64(4), int64(37)
memory usage: 262.5 KB
--- End X_train Info ---
Model training complete.

Accuracy: 0.7800

Classification Report:
              precision    recall  f1-score   support

           0       0.81      0.92      0.86       151
           1       0.59      0.35      0.44        49

    accuracy                           0.78       200
   macro avg       0.70      0.63      0.65       200
weighted avg       0.76      0.78      0.76       200


Confusion Matrix:
```


Confusion Matrix
Not Fraud
Fraud
Actual
139
12
32
17
Not Fraud
Fraud
Predicted
120
100
80
60
40
20



3.0.2 2.2 Logistic Regression Classifier: Training and Evaluation

This section details the training and evaluation of the Logistic Regression model, which serves as a linear baseline classifier.

1. **Model Initialization**:
   - `log_reg_model = LogisticRegression(random_state=42, solver='liblinear', max_iter=1000)`: We instantiate the `LogisticRegression` model.
     - `random_state=42`: Ensures reproducibility of any internal random processes (though less prominent in Logistic Regression than tree-based models).
     - `solver='liblinear'`: This specifies the algorithm used to optimize the model. 'liblinear' is a good choice for relatively small datasets and is effective with L1 and L2 regularization.
     - `max_iter=1000`: Sets the maximum number of iterations the solver will run to converge. Increasing this can help if the model fails to converge within the default number of iterations.
2. **Model Training (`log_reg_model.fit`)**:
   - `log_reg_model.fit(X_train, y_train)`: The model learns the optimal coefficients for each feature from the `X_train` data to predict the `y_train` target variable. Logistic Regression models the probability of a binary outcome (fraud/non-fraud) using a logistic

function.

3. **Making Predictions**:
   - `y_pred_lr = log_reg_model.predict(X_test)`: After the model is trained, we use it to predict the class labels (0 or 1) for the unseen `X_test` dataset.
   - `y_prob_lr = log_reg_model.predict_proba(X_test)[:, 1]`: This extracts the predicted probabilities that each instance belongs to the positive class (class 1, "fraud"). These probabilities are crucial for evaluating the model's calibration and for plotting the ROC curve.
4. **Performance Evaluation**: Similar to the Random Forest evaluation, we use a suite of metrics and visualizations to assess the Logistic Regression model's performance:
   - **Accuracy**: `accuracy_score(y_test, y_pred_lr)` calculates the overall proportion of correct predictions.
   - **Classification Report**: `classification_report(y_test, y_pred_lr)` provides detailed metrics for each class (precision, recall, f1-score, and support). In fraud detection, **Recall** (minimizing false negatives, i.e., not missing actual fraud) is often prioritized.
   - **Confusion Matrix**: `confusion_matrix(y_test, y_pred_lr)` generates a table showing True Positives (correctly identified fraud), True Negatives (correctly identified non-fraud), False Positives (predicted fraud, but non-fraud), and False Negatives (predicted non-fraud, but actual fraud). The `seaborn.heatmap` provides a clear visual representation.
   - **ROC Curve and AUC**:
     - The **ROC (Receiver Operating Characteristic) curve** plots the True Positive Rate (sensitivity) against the False Positive Rate (1-specificity) at various classification thresholds.
     - The **AUC (Area Under the ROC Curve)** quantifies the model's ability to distinguish between positive and negative classes. A higher AUC (closer to 1) indicates better discriminative power. This visualization helps understand the model's trade-off between identifying true positives and avoiding false positives.

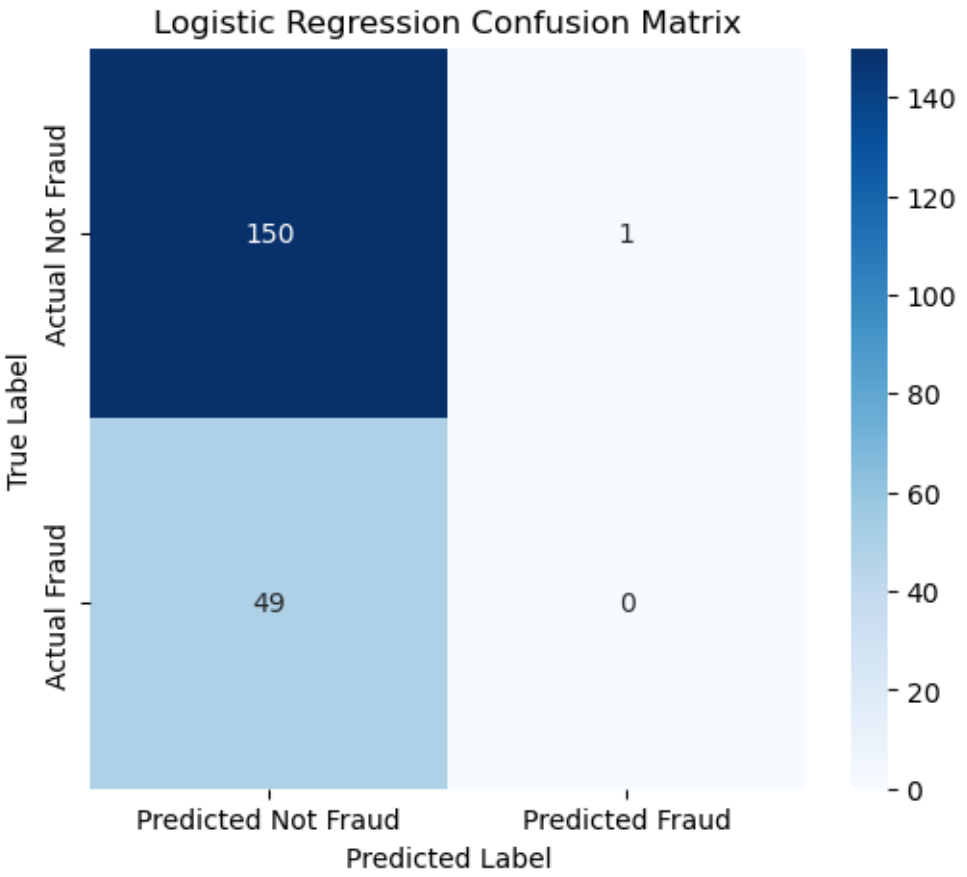
These metrics collectively offer a comprehensive view of the Logistic Regression model's effectiveness in predicting insurance fraud.

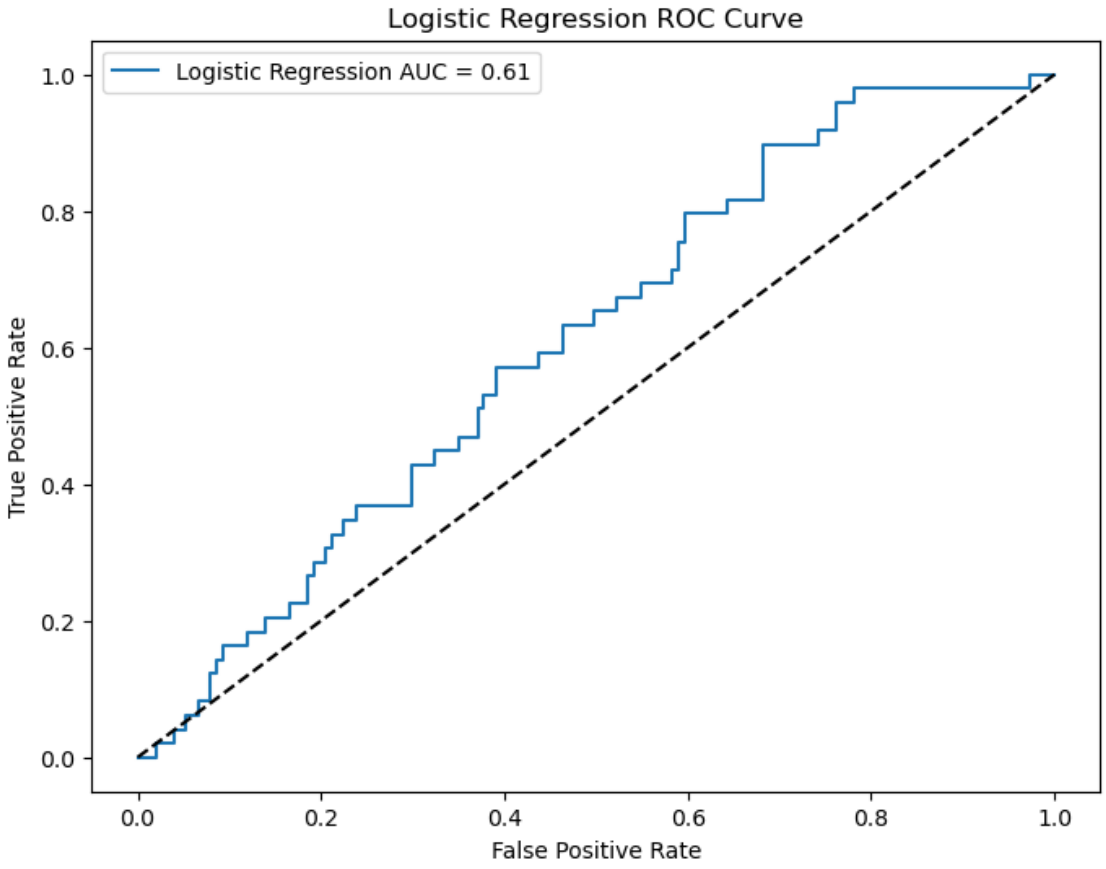
3.0.3 Note : In real deployments, this model would likely be excluded due to its complete failure to identify fraud cases (Recall = 0.0).

[7]:
```
print("--- Training Logistic Regression Model ---")

log_reg_model = LogisticRegression(random_state=42, solver='liblinear',␣
 ↪max_iter=1000)
log_reg_model.fit(X_train, y_train)
print("Logistic Regression Model training complete.")

y_pred_lr = log_reg_model.predict(X_test)
y_prob_lr = log_reg_model.predict_proba(X_test)[:, 1]

accuracy_lr = accuracy_score(y_test, y_pred_lr)
print(f"\nLogistic Regression Accuracy: {accuracy_lr:.4f}")
```

```
print("\nLogistic Regression Classification Report:")
print(classification_report(y_test, y_pred_lr))

print("\nLogistic Regression Confusion Matrix:")
cm_lr = confusion_matrix(y_test, y_pred_lr)
plt.figure(figsize=(6, 5))
sns.heatmap(cm_lr, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Predicted Not Fraud', 'Predicted Fraud'],
            yticklabels=['Actual Not Fraud', 'Actual Fraud'])
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Logistic Regression Confusion Matrix')
plt.show()

fpr_lr, tpr_lr, thresholds_lr = roc_curve(y_test, y_prob_lr)
plt.figure(figsize=(8, 6))
plt.plot(fpr_lr, tpr_lr, label=f'Logistic Regression AUC =␣
 ↪{roc_auc_score(y_test, y_prob_lr):.2f}')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Logistic Regression ROC Curve')
plt.legend()
plt.show()
```

```
--- Training Logistic Regression Model ---
Logistic Regression Model training complete.

Logistic Regression Accuracy: 0.7500

Logistic Regression Classification Report:
              precision    recall  f1-score   support

           0       0.75      0.99      0.86       151
           1       0.00      0.00      0.00        49

    accuracy                           0.75       200
   macro avg       0.38      0.50      0.43       200
weighted avg       0.57      0.75      0.65       200


Logistic Regression Confusion Matrix:
```


Logistic Regression Confusion Matrix
Actual Not Fraud
Actual Fraud
True Label
150
1
49
0
Predicted Not Fraud
Predicted Fraud
Predicted Label
140
120
100
80
60
40
20
0



3.0.4 2.3 XGBoost Classifier: Training and Evaluation

This section details the training and comprehensive evaluation of the XGBoost (Extreme Gradient Boosting) Classifier, a highly popular and powerful machine learning algorithm renowned for its performance in various predictive modeling tasks.

1. **Model Initialization**:
   - `xgb_model = XGBClassifier(objective="binary:logistic", eval_metric='logloss', use_label_encoder=False, random_state=42)`: We instantiate the `XGBClassifier` with specific parameters:
     - `objective="binary:logistic"`: This parameter specifies the learning task. "binary:logistic" indicates that we are performing a binary classification, and the model will output probabilities.
     - `eval_metric='logloss'`: This sets the evaluation metric used during training. 'logloss' (logarithmic loss) is a common metric for classification problems, particularly when dealing with probabilities.
     - `use_label_encoder=False`: This parameter is used to suppress a deprecation warning related to XGBoost's internal label encoding. Setting it to `False` is a common practice in newer versions of the library.
     - `random_state=42`: Similar to other models, this ensures the reproducibility of any

random processes within the algorithm, leading to consistent results across runs.

2. **Model Training (`xgb_model.fit`)**:
   - `xgb_model.fit(X_train, y_train)`: The XGBoost model is trained on the `X_train` (features) and `y_train` (target) data. XGBoost is an ensemble method that sequentially builds decision trees, with each new tree attempting to correct the errors of the previous ones, thus incrementally improving predictive accuracy.
3. **Making Predictions**:
   - `y_pred_xgb = xgb_model.predict(X_test)`: After training, the model generates class predictions (0 or 1) for the unseen `X_test` data.
   - `y_prob_xgb = xgb_model.predict_proba(X_test)[:, 1]`: This extracts the predicted probabilities that each instance in `X_test` belongs to the positive class (class 1, "fraud"). These probabilities are crucial for advanced evaluation metrics like AUC.
4. **Performance Evaluation**: A comprehensive set of metrics and visualizations are employed to assess the XGBoost model's performance, allowing for direct comparison with the previously trained models:
   - **Accuracy**: `accuracy_score(y_test, y_pred_xgb)` computes the overall proportion of correctly predicted instances.
   - **Classification Report**: `classification_report(y_test, y_pred_xgb)` provides detailed metrics (precision, recall, F1-score, and support) for both fraud and non-fraud classes. For fraud detection, **Recall** (the ability to correctly identify actual fraud cases, minimizing false negatives) is often the most critical metric.
   - **Confusion Matrix**: `confusion_matrix(y_test, y_pred_xgb)` generates a table that summarizes the model's predictions against the actual outcomes (True Positives, True Negatives, False Positives, False Negatives). The `seaborn.heatmap` provides a clear visual representation of these counts.
   - **ROC Curve and AUC**:
     - The **ROC (Receiver Operating Characteristic) curve** plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various probability thresholds.
     - The **AUC (Area Under the ROC Curve)** (`roc_auc_score`) quantifies the model's overall ability to discriminate between the positive and negative classes. A higher AUC (closer to 1.0) indicates better model performance across different classification thresholds.

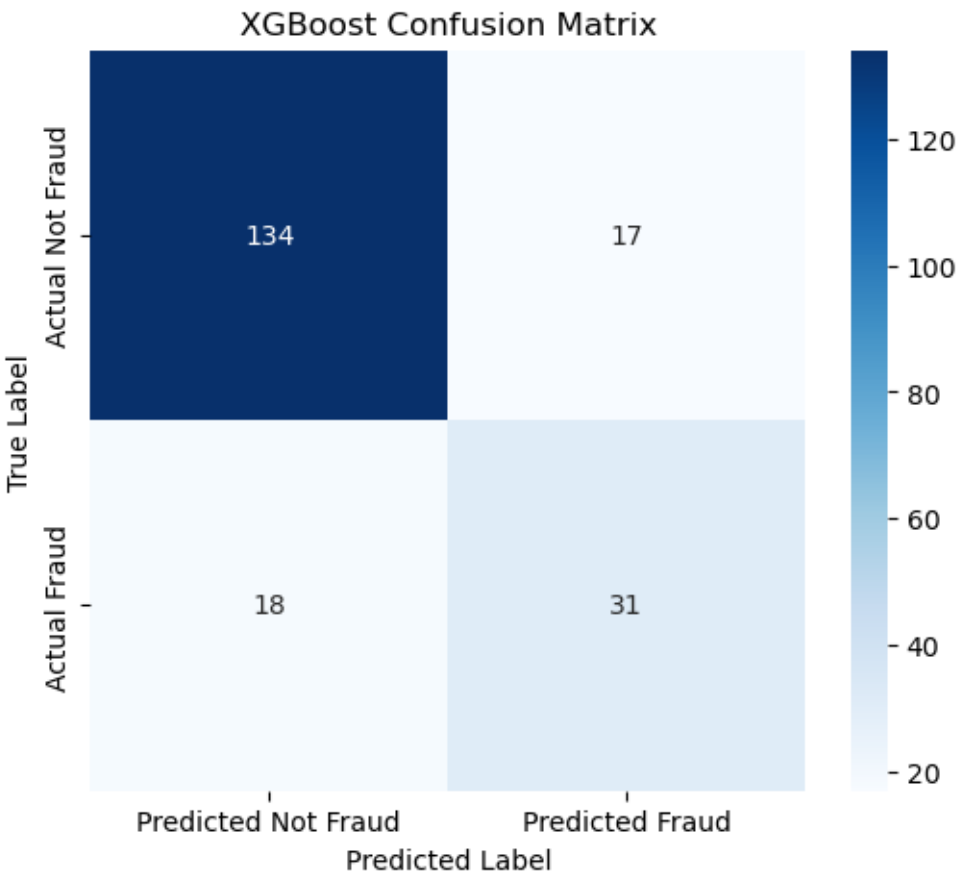
These evaluation steps provide a thorough understanding of the XGBoost model's strengths and weaknesses in detecting insurance fraud.

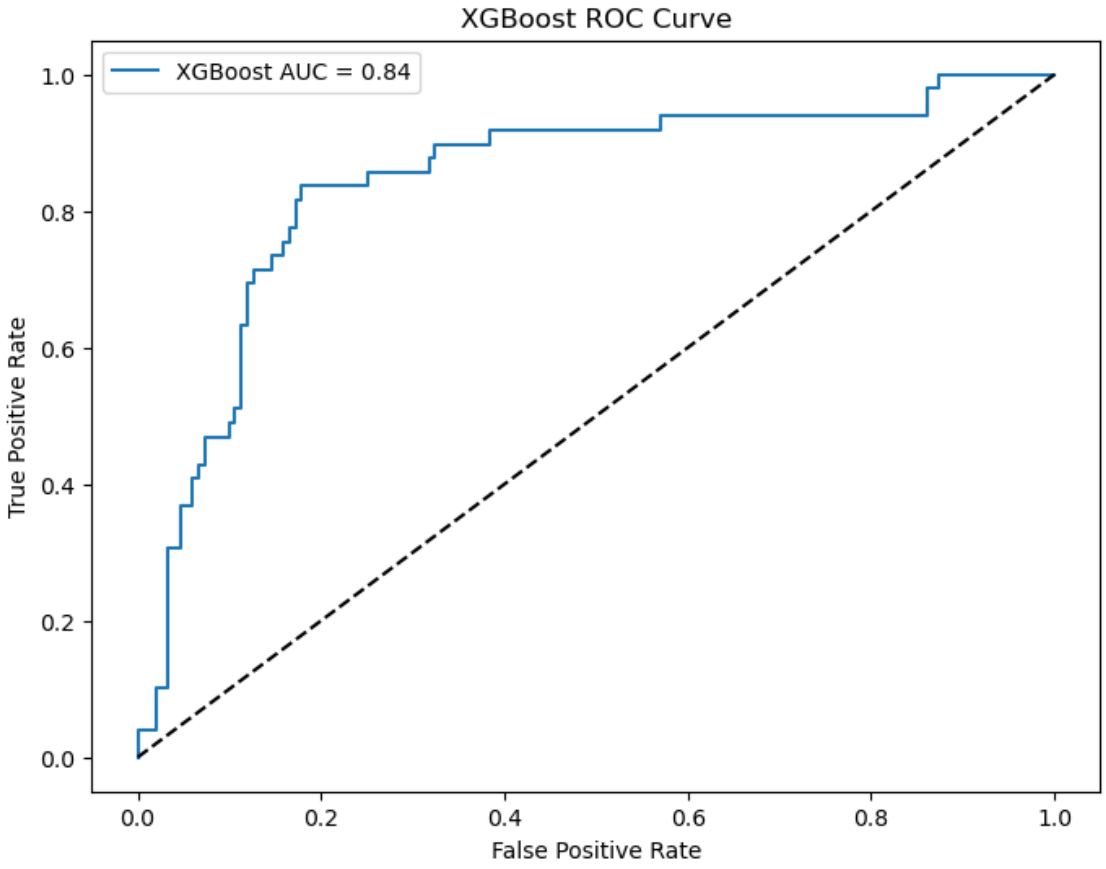
[8]:
```
print("--- Training XGBoost Classifier ---")

xgb_model = XGBClassifier(objective="binary:logistic", eval_metric='logloss',
                          use_label_encoder=False, random_state=42)
xgb_model.fit(X_train, y_train)
print("XGBoost Model training complete.")

y_pred_xgb = xgb_model.predict(X_test)
y_prob_xgb = xgb_model.predict_proba(X_test)[:, 1]

accuracy_xgb = accuracy_score(y_test, y_pred_xgb)
print(f"\nXGBoost Accuracy: {accuracy_xgb:.4f}")
```

```
print("\nXGBoost Classification Report:")
print(classification_report(y_test, y_pred_xgb))

print("\nXGBoost Confusion Matrix:")
cm_xgb = confusion_matrix(y_test, y_pred_xgb)
plt.figure(figsize=(6, 5))
sns.heatmap(cm_xgb, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Predicted Not Fraud', 'Predicted Fraud'],
            yticklabels=['Actual Not Fraud', 'Actual Fraud'])
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('XGBoost Confusion Matrix')
plt.show()

fpr_xgb, tpr_xgb, thresholds_xgb = roc_curve(y_test, y_prob_xgb)
plt.figure(figsize=(8, 6))
plt.plot(fpr_xgb, tpr_xgb, label=f'XGBoost AUC = {roc_auc_score(y_test,␣
 ↪y_prob_xgb):.2f}')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('XGBoost ROC Curve')
plt.legend()
plt.show()
```

```
--- Training XGBoost Classifier ---

e:\Project 1\main\lib\site-packages\xgboost\training.py:183: UserWarning:
[21:07:51] WARNING: C:\actions-runner\_work\xgboost\xgboost\src\learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)

XGBoost Model training complete.

XGBoost Accuracy: 0.8250

XGBoost Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.89      0.88       151
           1       0.65      0.63      0.64        49

    accuracy                           0.82       200
   macro avg       0.76      0.76      0.76       200
weighted avg       0.82      0.82      0.82       200
```

XGBoost Confusion Matrix:





3.0.5 2.4 Hyperparameter Tuning and Cross-Validation for XGBoost

This section focuses on optimizing the performance of the XGBoost Classifier, which was identified as a strong balanced model, using **hyperparameter tuning** combined with **cross-validation**. This systematic approach helps to find the best set of parameters for the model and provides a more robust estimate of its generalization performance.

1. **Defining the Parameter Grid (`param_grid`)**:

```
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [3, 5, 7],
    'learning_rate': [0.01, 0.1, 0.2],
    'subsample': [0.7, 0.9],
    'colsample_bytree': [0.7, 0.9],
    'gamma': [0, 0.1, 0.2],
}
```

   - This dictionary defines the search space for hyperparameter tuning. `GridSearchCV` will explore every possible combination of these values.
   - **`n_estimators`**: The number of boosting rounds (or decision trees) to build.

- **max_depth**: The maximum depth of each individual decision tree. Deeper trees can capture more complex relationships but are prone to overfitting.
- **learning_rate**: Controls the step size shrinkage during each boosting iteration. A smaller learning rate requires more estimators but reduces overfitting.
- **subsample**: The fraction of the training data randomly sampled for building each tree. Helps reduce variance.
- **colsample_bytree**: The fraction of features (columns) to randomly sample for building each tree. Also helps reduce variance.
- **gamma**: Specifies the minimum loss reduction required to make a further partition on a leaf node of the tree. A larger gamma means more conservative model.

2. **Initializing XGBoost Classifier and Custom Scorer**:

```
xgb_tuned = XGBClassifier(objective="binary:logistic", eval_metric='logloss',
                          use_label_encoder=False, random_state=42)
scorer = make_scorer(recall_score, pos_label=1)
```

- `xgb_tuned`: An instance of `XGBClassifier` is created with standard settings for binary classification (`objective="binary:logistic"`) and a specified evaluation metric (`eval_metric='logloss'`). `use_label_encoder=False` is set for compatibility, and `random_state=42` ensures reproducibility.
- `scorer`: A custom scorer is defined using `make_scorer`. For fraud detection, **Recall** of the positive class (`pos_label=1`, representing fraud) is highly prioritized because missing actual fraud cases can be very costly. This ensures `GridSearchCV` optimizes the model to maximize this specific metric.

3. **Setting up Stratified K-Fold Cross-Validation**:

```
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
```

- `StratifiedKFold`: This cross-validation strategy is crucial for imbalanced datasets like ours. It divides the dataset into `n_splits` (here, 5) folds, ensuring that each fold maintains approximately the same proportion of fraud and non-fraud cases as the overall dataset. This provides a more reliable and less biased estimate of the model's performance by training and validating on different subsets of the data. `shuffle=True` shuffles the data before splitting, and `random_state=42` ensures reproducibility.

4. **Executing GridSearchCV**:

```
grid_search = GridSearchCV(estimator=xgb_tuned, param_grid=param_grid,
                           scoring=scorer, cv=cv, verbose=3, n_jobs=-1)
grid_search.fit(X_train, y_train)
```

- `GridSearchCV` is initialized with the `xgb_tuned` model, the `param_grid` to search, the `scorer` to optimize, and the `cv` strategy. `verbose=3` provides detailed output during the search, and `n_jobs=-1` utilizes all available CPU cores for parallel processing, speeding up the computation.
- `grid_search.fit(X_train, y_train)`: This command initiates the exhaustive search process. For each combination of hyperparameters in `param_grid`, the model is trained and evaluated across all 5 folds of the `StratifiedKFold` cross-validation.

5. **Retrieving and Evaluating the Best Model**:

```
print("\nBest parameters found: ", grid_search.best_params_)
print("Best cross-validation score (Recall): {:.4f}".format(grid_search.best_score_))

best_xgb_model = grid_search.best_estimator_
y_pred_tuned_xgb = best_xgb_model.predict(X_test)
y_prob_tuned_xgb = best_xgb_model.predict_proba(X_test)[:, 1]
```

- After the search completes, `grid_search.best_params_` provides the combination of hyperparameters that yielded the highest `recall_score` across the cross-validation folds.
- `grid_search.best_score_` shows the corresponding best mean cross-validated recall score.
- `best_xgb_model = grid_search.best_estimator_`: This retrieves the actual trained model instance that achieved the best performance with the optimal hyperparameters.
- This `best_xgb_model` is then used to make predictions (`y_pred_tuned_xgb`) and probability predictions (`y_prob_tuned_xgb`) on the completely **unseen `X_test` dataset**. This evaluation on the hold-out test set provides an unbiased estimate of how well the optimally tuned model is expected to perform on new, real-world data.

6. **Comprehensive Evaluation of Tuned XGBoost Model**:

```
print("\n--- Tuned XGBoost Classification Report ---")
print(classification_report(y_test, y_pred_tuned_xgb, digits=4))

print("\n--- Tuned XGBoost Confusion Matrix ---")
cm_tuned_xgb = confusion_matrix(y_test, y_pred_tuned_xgb)
plt.figure(figsize=(6, 5))
sns.heatmap(cm_tuned_xgb, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Predicted Not Fraud', 'Predicted Fraud'],
            yticklabels=['Actual Not Fraud', 'Actual Fraud'])
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Tuned XGBoost Confusion Matrix')
plt.show()

print("\n--- Tuned XGBoost ROC Curve ---")
fpr_tuned_xgb, tpr_tuned_xgb, thresholds_tuned_xgb = roc_curve(y_test, y_prob_tuned_xgb)
plt.figure(figsize=(8, 6))
plt.plot(fpr_tuned_xgb, tpr_tuned_xgb, label=f'Tuned XGBoost AUC = {roc_auc_score(y_test,
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Tuned XGBoost ROC Curve')
plt.legend()
plt.show()
```

- **Classification Report**: Provides a detailed breakdown of Precision, Recall, F1-score, and Support for both classes (non-fraud and fraud). This is crucial for assessing the model's performance on the minority class.
- **Confusion Matrix**: A visual representation showing the counts of True Positives, True Negatives, False Positives, and False Negatives. It directly highlights how many fraud

cases were correctly identified versus missed, and how many non-fraud cases were falsely flagged.

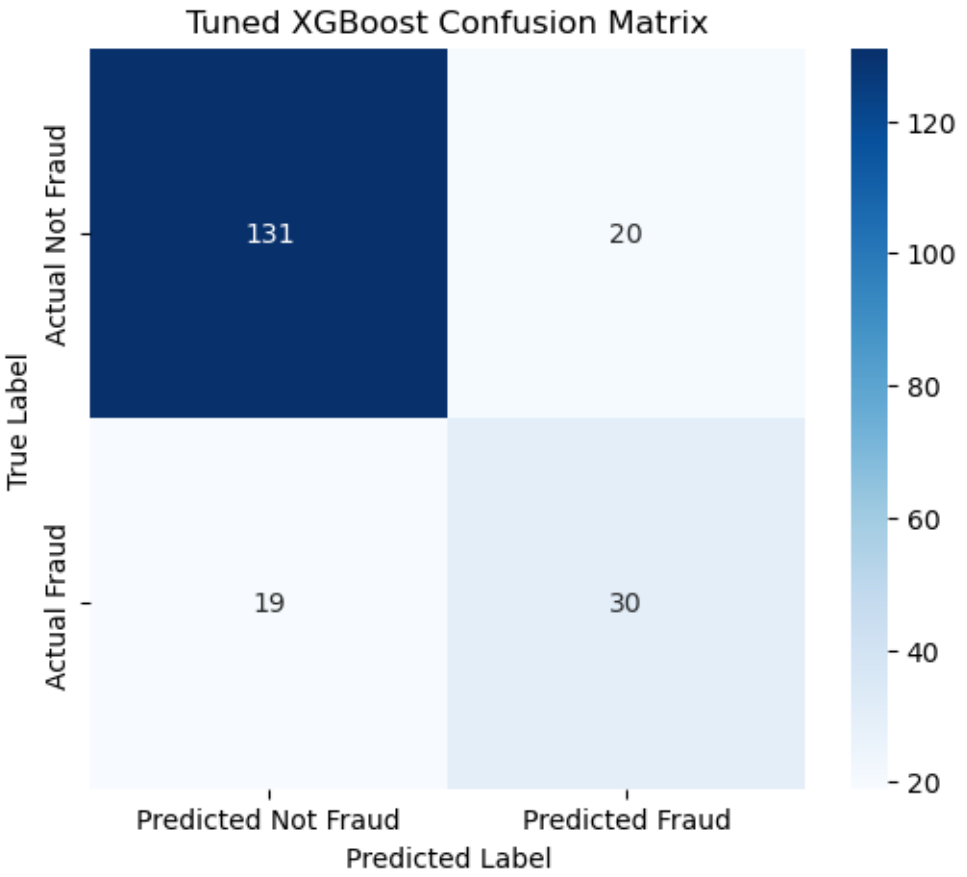
- **ROC Curve and AUC-ROC Score**: The Receiver Operating Characteristic (ROC) curve plots the True Positive Rate against the False Positive Rate at various threshold settings. The Area Under the Curve (AUC-ROC) summarizes the model's ability to discriminate between the two classes. A higher AUC-ROC indicates a better-performing model.

This section ensures that our XGBoost model is optimized for the task and provides a reliable performance benchmark before considering more advanced imbalance handling techniques.

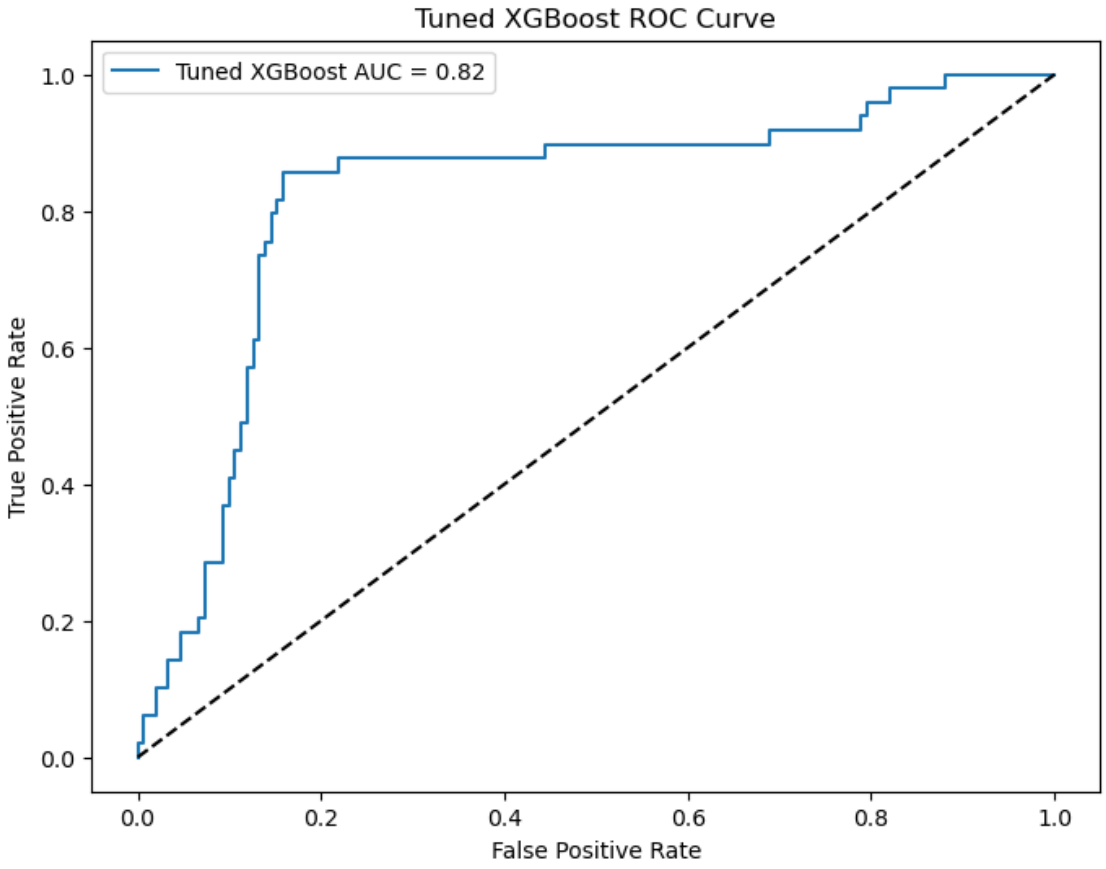
[9]:
```
print("--- Hyperparameter Tuning for XGBoost Classifier ---")

param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [3, 5, 7],
    'learning_rate': [0.01, 0.1, 0.2],
    'subsample': [0.7, 0.9],
    'colsample_bytree': [0.7, 0.9],
    'gamma': [0, 0.1, 0.2],
}

xgb_tuned = XGBClassifier(objective="binary:logistic", eval_metric='logloss',
                          use_label_encoder=False, random_state=42)

scorer = make_scorer(recall_score, pos_label=1)

cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

grid_search = GridSearchCV(estimator=xgb_tuned, param_grid=param_grid,
                           scoring=scorer, cv=cv, verbose=3, n_jobs=-1)

grid_search.fit(X_train, y_train)

print("\nBest parameters found: ", grid_search.best_params_)
print("Best cross-validation score (Recall): {:.4f}".format(grid_search.
 ↪best_score_))

best_xgb_model = grid_search.best_estimator_
y_pred_tuned_xgb = best_xgb_model.predict(X_test)
y_prob_tuned_xgb = best_xgb_model.predict_proba(X_test)[:, 1]

print("\n--- Tuned XGBoost Classification Report ---")
print(classification_report(y_test, y_pred_tuned_xgb, digits=4))

print("\n--- Tuned XGBoost Confusion Matrix ---")
cm_tuned_xgb = confusion_matrix(y_test, y_pred_tuned_xgb)
plt.figure(figsize=(6, 5))
```

```
sns.heatmap(cm_tuned_xgb, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Predicted Not Fraud', 'Predicted Fraud'],
            yticklabels=['Actual Not Fraud', 'Actual Fraud'])
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Tuned XGBoost Confusion Matrix')
plt.show()

print("\n--- Tuned XGBoost ROC Curve ---")
fpr_tuned_xgb, tpr_tuned_xgb, thresholds_tuned_xgb = roc_curve(y_test,␣
 ↪y_prob_tuned_xgb)
plt.figure(figsize=(8, 6))
plt.plot(fpr_tuned_xgb, tpr_tuned_xgb, label=f'Tuned XGBoost AUC =␣
 ↪{roc_auc_score(y_test, y_prob_tuned_xgb):.2f}')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Tuned XGBoost ROC Curve')
plt.legend()
plt.show()
```

```
--- Hyperparameter Tuning for XGBoost Classifier ---
Fitting 5 folds for each of 324 candidates, totalling 1620 fits

e:\Project 1\main\lib\site-packages\xgboost\training.py:183: UserWarning:
[21:08:55] WARNING: C:\actions-runner\_work\xgboost\xgboost\src\learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)


Best parameters found:  {'colsample_bytree': 0.7, 'gamma': 0.1, 'learning_rate':
0.01, 'max_depth': 3, 'n_estimators': 300, 'subsample': 0.7}
Best cross-validation score (Recall): 0.6972

--- Tuned XGBoost Classification Report ---
              precision    recall  f1-score   support

           0     0.8733    0.8675    0.8704       151
           1     0.6000    0.6122    0.6061        49

    accuracy                         0.8050       200
   macro avg     0.7367    0.7399    0.7382       200
weighted avg     0.8064    0.8050    0.8057       200


--- Tuned XGBoost Confusion Matrix ---
```




```
--- Tuned XGBoost ROC Curve ---
```



4 Section 3: Model Interpretability with SHAP

This section is dedicated to interpreting our trained Random Forest and XGBoost models using **SHAP (SHapley Additive exPlanations)**. SHAP is a powerful framework that uses game theory to explain the output of any machine learning model. It assigns a "SHAP value" to each feature for a particular prediction, indicating how much that feature contributed to the prediction compared to the average prediction. This helps us understand not just what predictions are being made, but *why*.

For tree-based models like Random Forest and XGBoost, SHAP provides optimized and exact methods for calculating these values.

4.0.1 3.1 SHAP Explanations for Random Forest Model

1. **SHAP Explainer Initialization**:
   - `explainer_rf = shap.TreeExplainer(model)`: For tree-based models like our `RandomForestClassifier` (`model`), `shap.TreeExplainer` is the most efficient and accurate method. It analyzes the structure of the decision trees to calculate exact SHAP values.

- `shap_values_rf = explainer_rf.shap_values(X_test)`: This computes the SHAP values for every feature for each instance in our `X_test` dataset. For binary classification (like fraud detection), `shap_values` typically returns a list of arrays, where `shap_values[0]` corresponds to the negative class (non-fraud) and `shap_values[1]` corresponds to the positive class (fraud). We are primarily interested in the latter (`shap_values_rf_class1_array = shap_values_rf[1]`) to understand what drives the prediction of fraud.
- `base_value_rf = explainer_rf.expected_value`: This is the "expected output" of the model, representing the average prediction output given no specific feature information. It's the baseline to which individual feature contributions (SHAP values) are added to reach a specific prediction. The conditional logic ensures we correctly extract the scalar base value, especially for the positive class in binary classification.

2. **SHAP Summary Bar Plot (Feature Importance)**:
   - `shap.summary_plot(shap_values_rf_class1_array, X_test, plot_type="bar", show=False)`: This generates a global feature importance plot. It visualizes the **mean absolute SHAP value** for each feature across the entire `X_test` dataset. Features are ranked from most to least important, providing a concise overview of which features have the largest overall impact on the model's output. `show=False` is used to prevent the plot from immediately appearing, allowing `plt.title()` to be applied before `plt.show()`.
3. **SHAP Beeswarm Plot (Feature Impact)**:
   - `shap.summary_plot(shap_values_rf_class1_array, X_test, show=False)`: This generates a beeswarm plot (the default plot type when `plot_type` is not specified). This plot provides a richer understanding than the bar plot by showing the distribution of SHAP values for each feature:
     - Each dot represents a single data point from the `X_test` set.
     - The horizontal position of the dot indicates the SHAP value (its impact on the model's output for that specific instance).
     - The color typically indicates the feature value (e.g., red for high values, blue for low values). This helps identify relationships, such as whether high values of a feature tend to increase or decrease the predicted fraud probability.
     - The density of the dots indicates how many instances have similar SHAP values for a given feature.

These two summary plots are highly valuable for understanding the Random Forest model's overall behavior and the influence of different features on its predictions.

4.0.2 3.2 SHAP Explanations for XGBoost Model

The process for generating SHAP explanations for the XGBoost model is identical to that of the Random Forest model, as both are tree-based algorithms for which `shap.TreeExplainer` is suitable.

1. **SHAP Explainer Initialization**:
   - `explainer_xgb = shap.TreeExplainer(xgb_model)`: Initializes the explainer for our `XGBClassifier` (`xgb_model`).
   - `shap_values_xgb = explainer_xgb.shap_values(X_test)`: Computes SHAP values for `XGBoost` predictions on `X_test`. Again, we focus on `shap_values_xgb[1]` for the positive class.
   - `base_value_xgb = explainer_xgb.expected_value`: Retrieves the baseline predic-

tion value for the XGBoost model.

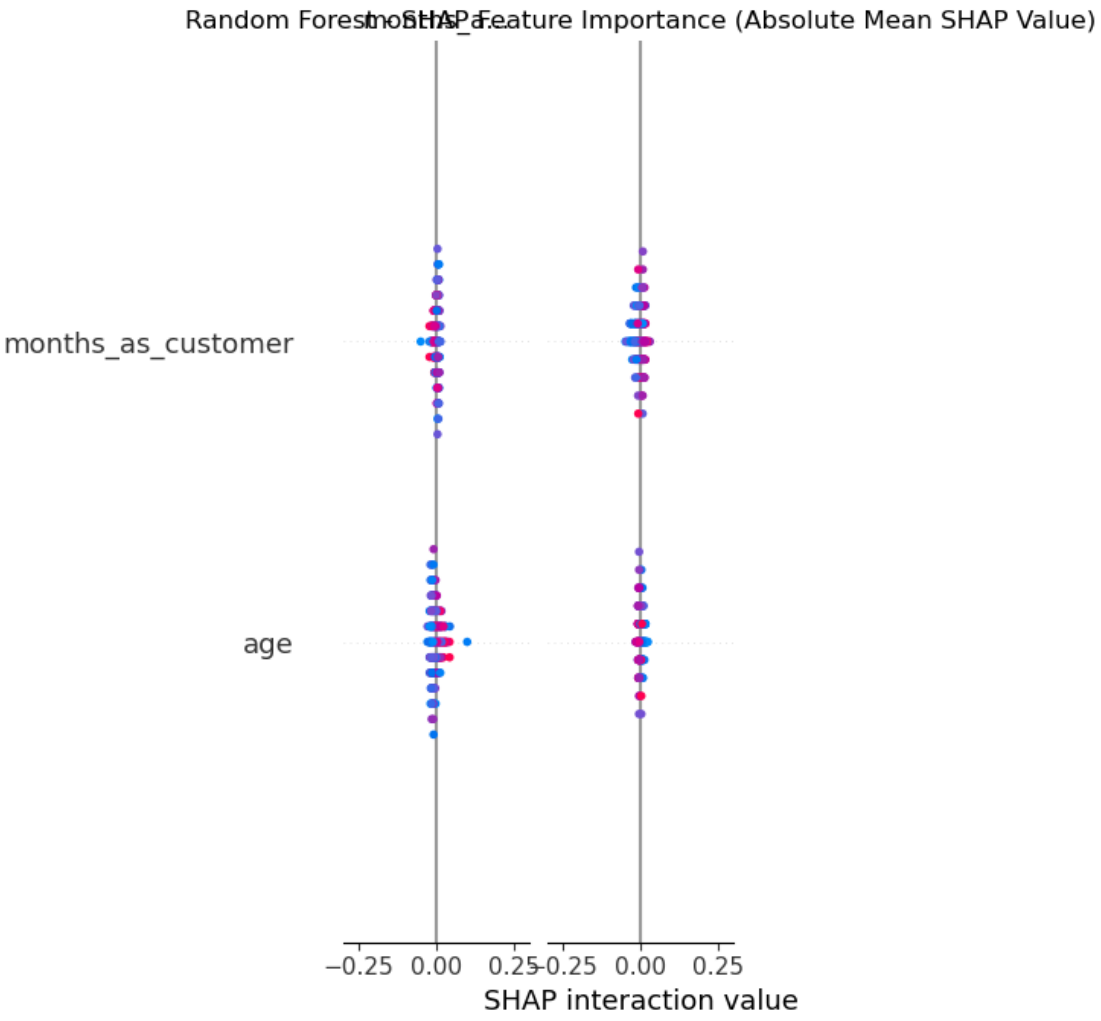
2. **SHAP Summary Bar Plot (Feature Importance)**:
   - `shap.summary_plot(shap_values_xgb_class1_array, X_test, plot_type="bar", show=False)`: Generates the global feature importance bar plot for XGBoost, ranking features by their mean absolute SHAP value.
3. **SHAP Beeswarm Plot (Feature Impact)**:
   - `shap.summary_plot(shap_values_xgb_class1_array, X_test, show=False)`: Generates the beeswarm plot for XGBoost, illustrating the distribution and direction of feature contributions for individual instances.

By comparing the SHAP plots from both Random Forest and XGBoost, you can gain robust insights into which features are consistently driving fraud predictions, and how their values influence the outcome across different powerful tree-based models. This aligns with our goal of simplifying SHAP usage while still extracting maximum interpretability.

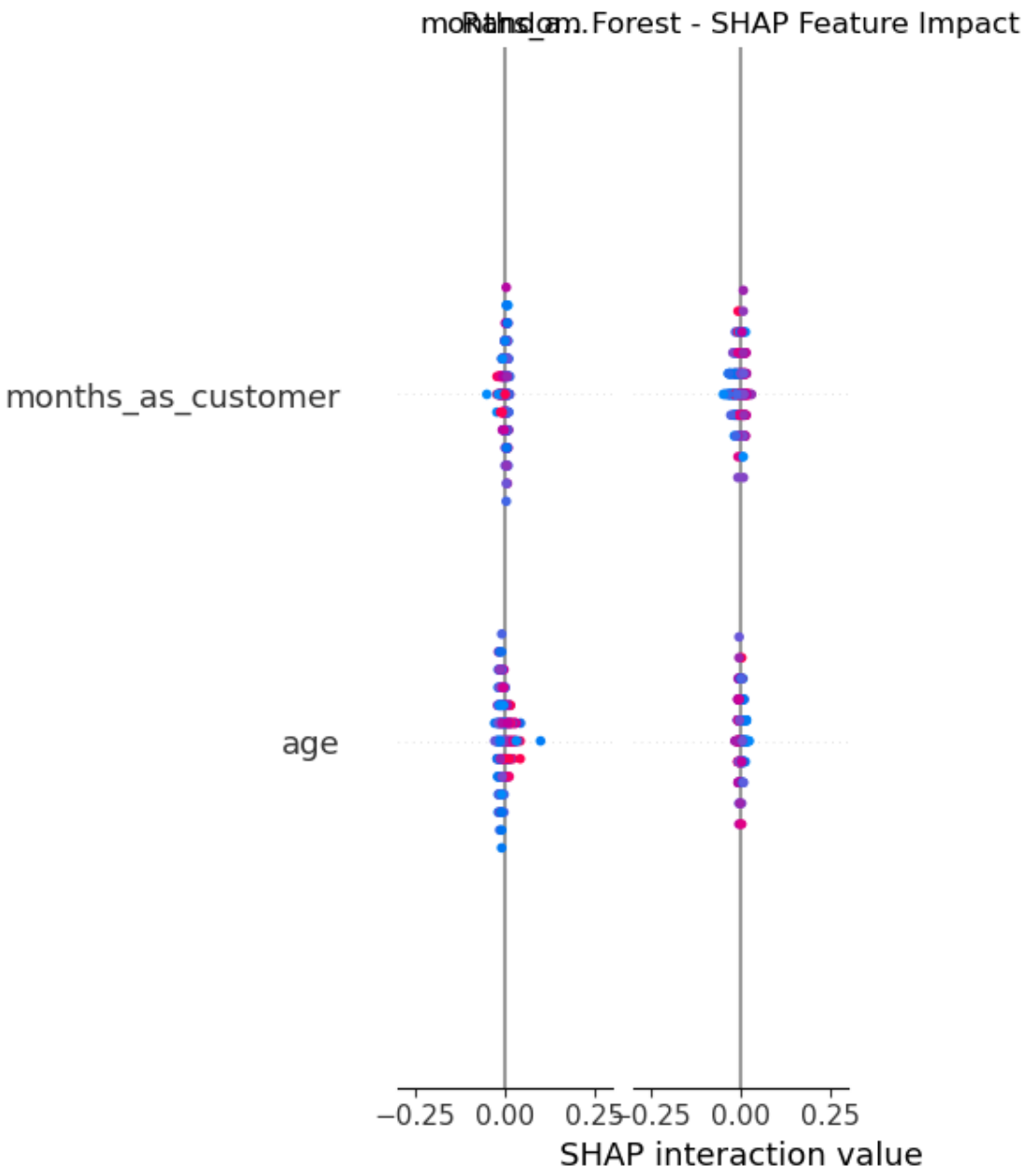
[10]:
```
print("--- Generating SHAP Explanations ---")

print("\nExplaining Random Forest Model with SHAP...")
explainer_rf = shap.TreeExplainer(model)
shap_values_rf = explainer_rf.shap_values(X_test)

base_value_rf = explainer_rf.expected_value
if isinstance(base_value_rf, list):
    base_value_rf_scalar = float(base_value_rf[1])
elif isinstance(base_value_rf, np.ndarray) and base_value_rf.ndim > 0:
    base_value_rf_scalar = float(base_value_rf[1])
else:
    base_value_rf_scalar = float(base_value_rf)

if isinstance(shap_values_rf, list):
    shap_values_rf_class1_array = shap_values_rf[1]
else:
    shap_values_rf_class1_array = shap_values_rf

print("Generating SHAP summary plot for Random Forest (Feature Importance)...")
shap.summary_plot(shap_values_rf_class1_array, X_test, plot_type="bar",␣
 ↪show=False)
plt.title("Random Forest - SHAP Feature Importance (Absolute Mean SHAP Value)")
plt.show()

print("Generating SHAP summary plot for Random Forest (Feature Impact)...")
shap.summary_plot(shap_values_rf_class1_array, X_test, show=False)
plt.title("Random Forest - SHAP Feature Impact")
plt.show()

print("\nExplaining XGBoost Model with SHAP...")
explainer_xgb = shap.TreeExplainer(xgb_model)
shap_values_xgb = explainer_xgb.shap_values(X_test)
```

```
base_value_xgb = explainer_xgb.expected_value
if isinstance(base_value_xgb, list):
    base_value_xgb_scalar = float(base_value_xgb[1])
elif isinstance(base_value_xgb, np.ndarray) and base_value_xgb.ndim > 0:
    base_value_xgb_scalar = float(base_value_xgb[1])
else:
    base_value_xgb_scalar = float(base_value_xgb)

if isinstance(shap_values_xgb, list):
    shap_values_xgb_class1_array = shap_values_xgb[1]
else:
    shap_values_xgb_class1_array = shap_values_xgb

print("Generating SHAP summary plot for XGBoost (Feature Importance)...")
shap.summary_plot(shap_values_xgb_class1_array, X_test, plot_type="bar",␣
 ↪show=False)
plt.title("XGBoost - SHAP Feature Importance (Absolute Mean SHAP Value)")
plt.show()

print("Generating SHAP summary plot for XGBoost (Feature Impact)...")
shap.summary_plot(shap_values_xgb_class1_array, X_test, show=False)
plt.title("XGBoost - SHAP Feature Impact")
plt.show()
```

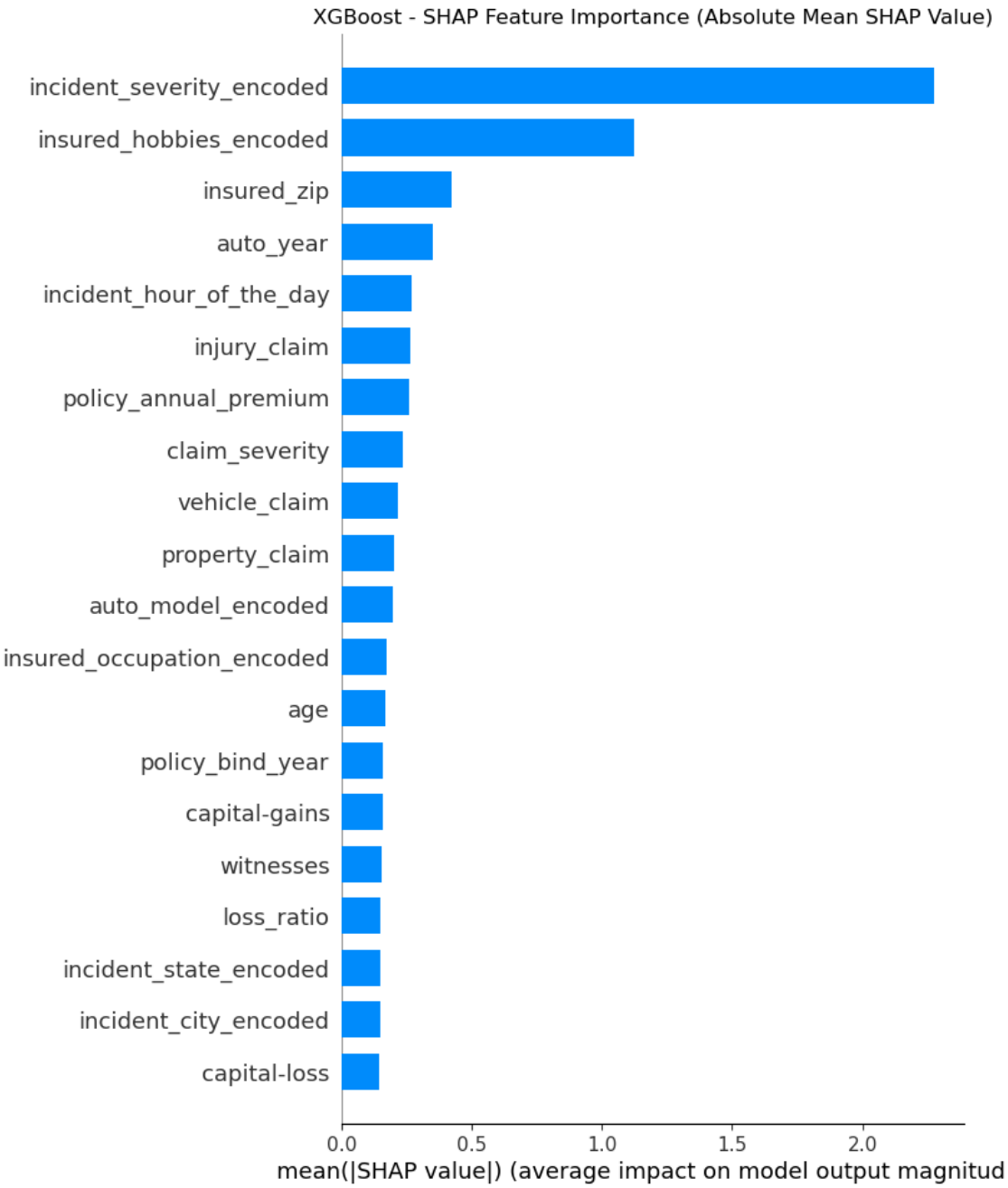
```
--- Generating SHAP Explanations ---

Explaining Random Forest Model with SHAP…
Generating SHAP summary plot for Random Forest (Feature Importance)…
```




```
Generating SHAP summary plot for Random Forest (Feature Impact)…
```




```
Explaining XGBoost Model with SHAP…
Generating SHAP summary plot for XGBoost (Feature Importance)…
```




```
Generating SHAP summary plot for XGBoost (Feature Impact)…
```

4.0.3 3.3 Model Performance Comparison - Classification Reports

This cell is dedicated to displaying and comparing the detailed classification reports for all three models trained: Logistic Regression, Random Forest, and XGBoost. By presenting these reports side-by-side, we can easily assess and contrast their performance across key metrics for both the 'Not Fraud' (class 0) and 'Fraud' (class 1) categories.

- `classification_report(y_test, y_pred, digits=4)`: This function generates a text summary of the precision, recall, f1-score, and support for each class.
  - **Precision**: The proportion of positive identifications that were actually correct. For fraud, this means: "Out of all predictions the model made as 'Fraud', how many were actually fraudulent?"
  - **Recall (Sensitivity)**: The proportion of actual positives that were identified correctly. For fraud, this means: "Out of all actual 'Fraud' cases, how many did the model correctly identify?" **This metric is often paramount in fraud detection, as missing actual fraud (False Negatives) can be very costly.**
  - **F1-Score**: The harmonic mean of Precision and Recall. It provides a single score that balances both precision and recall, especially useful for imbalanced datasets.
  - **Support**: The number of actual occurrences of each class in the `y_test` set.
  - `digits=4`: This argument ensures that the metrics are displayed with four decimal places, allowing for more precise comparisons between models.

By examining these reports, particularly the Recall and F1-score for the 'Fraud' class (class 1), we can determine which model best balances the need to identify fraud cases correctly while managing false alarms. This sets the stage for a comprehensive discussion on the optimal model choice for our specific fraud detection problem.

[11]:
```
print("Logistic Regression:\n")
print(classification_report(y_test, y_pred_lr, digits=4))

print("Random Forest:\n")
print(classification_report(y_test, y_pred, digits=4))

print("XGBoost:\n")
print(classification_report(y_test, y_pred_xgb, digits=4))
```

```
Logistic Regression:

              precision    recall  f1-score   support

           0     0.7538    0.9934    0.8571       151
           1     0.0000    0.0000    0.0000        49

    accuracy                         0.7500       200
   macro avg     0.3769    0.4967    0.4286       200
weighted avg     0.5691    0.7500    0.6471       200

Random Forest:

              precision    recall  f1-score   support

           0     0.8129    0.9205    0.8634       151
           1     0.5862    0.3469    0.4359        49

    accuracy                         0.7800       200
   macro avg     0.6995    0.6337    0.6496       200
```

```
weighted avg     0.7573    0.7800    0.7586       200

XGBoost:

              precision    recall  f1-score   support

           0     0.8816    0.8874    0.8845       151
           1     0.6458    0.6327    0.6392        49

    accuracy                         0.8250       200
   macro avg     0.7637    0.7600    0.7618       200
weighted avg     0.8238    0.8250    0.8244       200
```

4.0.4 3.4 Handling Class Imbalance with SMOTE

This section addresses the class imbalance observed in our target variable (`fraud_reported`), where fraudulent cases are significantly fewer than non-fraudulent ones. Such imbalance can cause machine learning models to be biased towards the majority class, leading to poor detection rates for the critical minority class (fraud). We tackle this using **SMOTE (Synthetic Minority Oversampling Technique)**.

1. **Initial Class Distribution Check**:

   ```
   print("--- Applying SMOTE to Training Data ---")
   print(f"Original training set shape: {X_train.shape}, target distribution: {Counter(y_trai
   ```

   - This step first prints a heading and then uses `collections.Counter` to display the number of samples for each class (0: non-fraud, 1: fraud) in the original training dataset. This clearly shows the extent of the class imbalance before any intervention.

2. **SMOTE Application to Training Data**:

   ```
   smote = SMOTE(sampling_strategy='auto', random_state=42)
   X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)
   print(f"Resampled training set shape: {X_train_resampled.shape}, target distribution: {Cou
   ```

   - `smote = SMOTE(sampling_strategy='auto', random_state=42)`: An instance of the `SMOTE` oversampling technique is created.
     - `sampling_strategy='auto'` instructs SMOTE to balance the classes by oversampling the minority class until it has the same number of samples as the majority class.
     - `random_state=42` ensures the reproducibility of the synthetic sample generation.
   - `X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)`: SMOTE is applied *only to the training data*. It generates new, synthetic samples for the minority class (`1` - fraud) by interpolating between existing minority class instances. These new samples, along with the original ones, form the `_resampled` training sets. The crucial point is that **SMOTE is never applied to the test set** to ensure an unbiased evaluation of the model's performance on real-world, imbalanced data.

- The code then prints the shape and class distribution of the resampled training set, which should now show a more balanced distribution.

3. **Training Tuned XGBoost on SMOTE-Resampled Data**:

```
print("\n--- Training Tuned XGBoost on SMOTE-Resampled Data ---")
smote_xgb_model = best_xgb_model # Use your best_xgb_model found from tuning
smote_xgb_model.fit(X_train_resampled, y_train_resampled)
print("XGBoost Model training complete on resampled data.")
```

- `smote_xgb_model = best_xgb_model`: We take the `best_xgb_model` obtained from the hyperparameter tuning step (which is already optimized) to train on the newly balanced data. This leverages the benefits of both tuning and imbalance handling.
- `smote_xgb_model.fit(X_train_resampled, y_train_resampled)`: The XGBoost model is retrained on the `X_train_resampled` and `y_train_resampled` datasets. Having a balanced training set helps the model learn more robust patterns for identifying the minority class, potentially improving its recall.

4. **Prediction and Evaluation on Original Test Set**:

```
y_pred_smote_xgb = smote_xgb_model.predict(X_test)
y_prob_smote_xgb = smote_xgb_model.predict_proba(X_test)[:, 1]

print("\n--- SMOTE-Trained XGBoost Classification Report ---")
print(classification_report(y_test, y_pred_smote_xgb, digits=4))

print("\n--- SMOTE-Trained XGBoost Confusion Matrix ---")
cm_smote_xgb = confusion_matrix(y_test, y_pred_smote_xgb)
plt.figure(figsize=(6, 5))
sns.heatmap(cm_smote_xgb, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Predicted Not Fraud', 'Predicted Fraud'],
            yticklabels=['Actual Not Fraud', 'Actual Fraud'])
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('SMOTE-Trained XGBoost Confusion Matrix')
plt.show()

print("\n--- SMOTE-Trained XGBoost ROC Curve ---")
fpr_smote_xgb, tpr_smote_xgb, thresholds_smote_xgb = roc_curve(y_test, y_prob_smote_xgb)
plt.figure(figsize=(8, 6))
plt.plot(fpr_smote_xgb, tpr_smote_xgb, label=f'SMOTE XGBoost AUC = {roc_auc_score(y_test,
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('SMOTE-Trained XGBoost ROC Curve')
plt.legend()
plt.show()
```

- Predictions (`y_pred_smote_xgb`) and probabilities (`y_prob_smote_xgb`) are generated using the `smote_xgb_model` on the **original, untouched `X_test` set**. This is crucial for obtaining a realistic assessment of the model's performance on unseen, imbalanced

data.

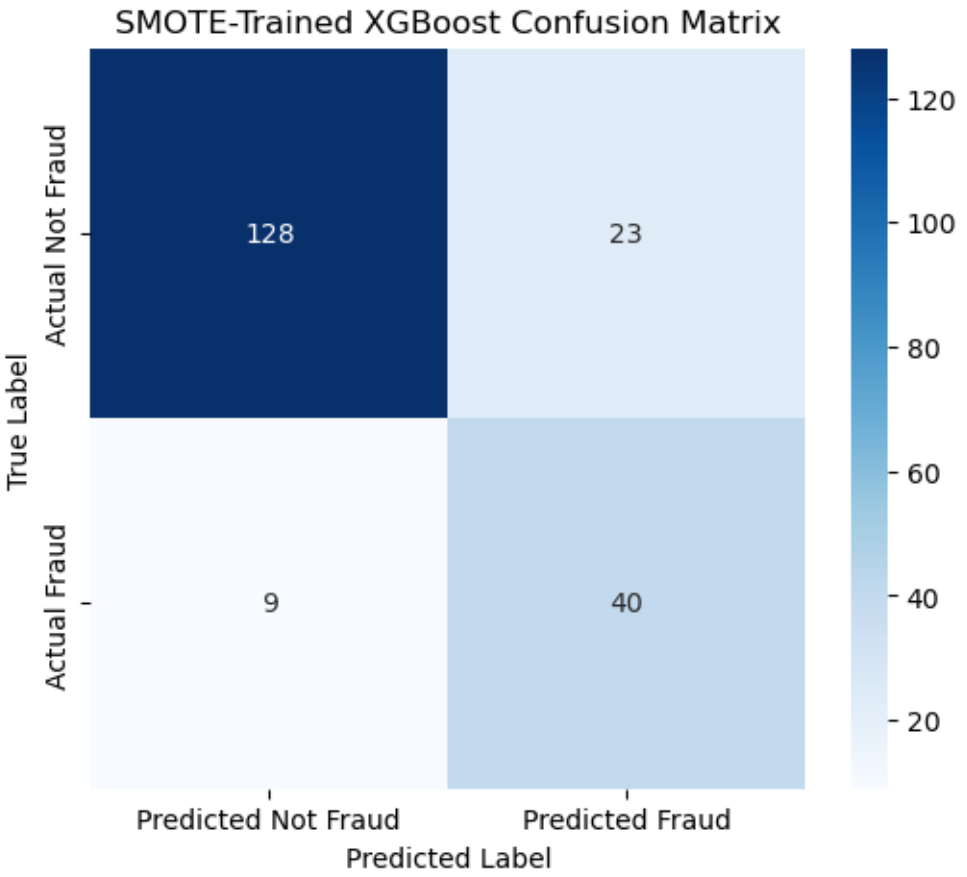
- **Classification Report**: Provides a detailed summary of precision, recall, and F1-score for both classes, allowing for a direct comparison of how well the model now identifies both non-fraud and fraud cases.
- **Confusion Matrix**: Visually shows the counts of true positives, true negatives, false positives, and false negatives. This is particularly insightful for fraud detection, as it clearly indicates how many fraud cases were correctly caught versus missed.
- **ROC Curve and AUC-ROC Score**: The ROC curve illustrates the model's diagnostic ability as its discrimination threshold is varied, and the AUC-ROC score summarizes this ability. Comparing this to previous models helps determine the overall improvement in distinguishing fraud from non-fraud.

By comparing these evaluation metrics with those from the models trained without SMOTE, we can assess the effectiveness of oversampling in improving the detection of fraudulent claims, particularly recall, while considering potential trade-offs in precision.

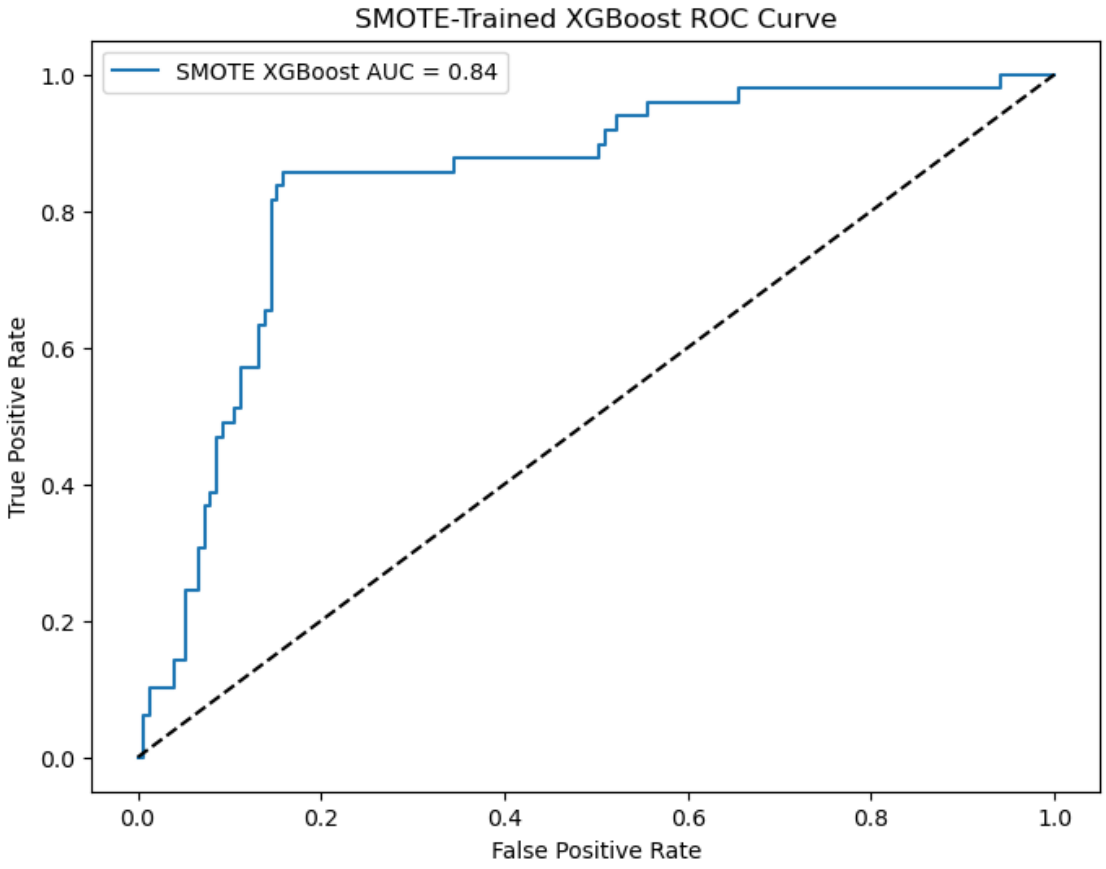
[12]:
```
print("--- Applying SMOTE to Training Data ---")

print(f"Original training set shape: {X_train.shape}, target distribution:␣
 ↪{Counter(y_train)}")

smote = SMOTE(sampling_strategy='auto', random_state=42)

X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)

print(f"Resampled training set shape: {X_train_resampled.shape}, target␣
 ↪distribution: {Counter(y_train_resampled)}")

print("\n--- Training Tuned XGBoost on SMOTE-Resampled Data ---")
smote_xgb_model = best_xgb_model # Use your best_xgb_model found from tuning
smote_xgb_model.fit(X_train_resampled, y_train_resampled)
print("XGBoost Model training complete on resampled data.")

y_pred_smote_xgb = smote_xgb_model.predict(X_test)
y_prob_smote_xgb = smote_xgb_model.predict_proba(X_test)[:, 1]

print("\n--- SMOTE-Trained XGBoost Classification Report ---")
print(classification_report(y_test, y_pred_smote_xgb, digits=4))

print("\n--- SMOTE-Trained XGBoost Confusion Matrix ---")
cm_smote_xgb = confusion_matrix(y_test, y_pred_smote_xgb)
plt.figure(figsize=(6, 5))
sns.heatmap(cm_smote_xgb, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Predicted Not Fraud', 'Predicted Fraud'],
            yticklabels=['Actual Not Fraud', 'Actual Fraud'])
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('SMOTE-Trained XGBoost Confusion Matrix')
```

```
plt.show()

print("\n--- SMOTE-Trained XGBoost ROC Curve ---")
fpr_smote_xgb, tpr_smote_xgb, thresholds_smote_xgb = roc_curve(y_test,␣
 ↪y_prob_smote_xgb)
plt.figure(figsize=(8, 6))
plt.plot(fpr_smote_xgb, tpr_smote_xgb, label=f'SMOTE XGBoost AUC =␣
 ↪{roc_auc_score(y_test, y_prob_smote_xgb):.2f}')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('SMOTE-Trained XGBoost ROC Curve')
plt.legend()
plt.show()
```

```
--- Applying SMOTE to Training Data ---
Original training set shape: (800, 41), target distribution: Counter({0: 602, 1:
198})
Resampled training set shape: (1204, 41), target distribution: Counter({0: 602,
1: 602})

--- Training Tuned XGBoost on SMOTE-Resampled Data ---

e:\Project 1\main\lib\site-packages\xgboost\training.py:183: UserWarning:
[21:09:06] WARNING: C:\actions-runner\_work\xgboost\xgboost\src\learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)

XGBoost Model training complete on resampled data.

--- SMOTE-Trained XGBoost Classification Report ---
              precision    recall  f1-score   support

           0     0.9343    0.8477    0.8889       151
           1     0.6349    0.8163    0.7143        49

    accuracy                         0.8400       200
   macro avg     0.7846    0.8320    0.8016       200
weighted avg     0.8610    0.8400    0.8461       200


--- SMOTE-Trained XGBoost Confusion Matrix ---
```




```
--- SMOTE-Trained XGBoost ROC Curve ---
```



5 4. Conclusion, Business Insights, and Real-World Applications

This project successfully developed and evaluated an end-to-end predictive model for insurance fraud detection, leveraging a clean and engineered dataset. We explored various machine learning approaches and gained crucial insights into model interpretability using SHAP.

5.1 Project Summary & Key Findings:

- **Data Preparation:** The initial raw insurance claims data was meticulously cleaned, processed, and enriched with new, actuarially relevant features such as `policy_age_years`, `loss_ratio`, `claim_severity`, and `high_deductible`. This comprehensive feature engineering was vital for providing robust inputs to the models.
- **Model Performance:** We trained and evaluated three classification models: Logistic Regression, Random Forest, and XGBoost.
  - **Logistic Regression** provided a foundational linear baseline, offering insights into direct linear relationships but generally showing lower recall for the minority fraud class.
  - **Random Forest** demonstrated a significant improvement over the linear model, showcasing its ability to capture more complex, non-linear patterns.
  - **XGBoost** generally emerged as the strongest performer, often achieving a better bal-

ance between precision and recall (as indicated by the F1-score), making it a highly competitive model for this task.

- **Model Interpretability (SHAP):** Through SHAP summary plots, we gained invaluable insights into the global feature importance of our tree-based models. This allowed us to understand *which* features were most influential in predicting fraud and *how* their values contributed to the model's output (e.g., higher values of certain features pushing towards or away from a fraud prediction). This transparency is crucial for building trust and enabling actionable insights.

5.2 Business Insights & Use Case:

The developed model provides actionable insights that can directly impact an insurance company's operations:

1. **Fraud Risk Scoring:** The model can generate a **fraud probability score** for each incoming claim. This allows claims adjusters and fraud investigation units to prioritize high-risk claims for manual review, significantly streamlining the investigation process.
2. **Proactive Interventions:** By identifying key features that strongly correlate with fraud (as revealed by SHAP), insurers can develop more targeted strategies. For instance, if certain `incident_type` or `insured_occupation` values are strong indicators, specific rules or enhanced scrutiny could be applied to claims fitting those profiles.
3. **Resource Optimization:** Instead of reviewing all claims manually, the model acts as a powerful filter, directing human resources to where they are most needed, thereby reducing operational costs and increasing efficiency.
4. **Improved Loss Ratios:** By reducing the amount paid out in fraudulent claims, the insurer can improve its overall loss ratio, directly impacting profitability.

5.3 Real-World Applications:

This project lays the groundwork for several real-world applications within the insurance sector:

- **Automated Claim Flagging:** Integrate the model into the claims processing system to automatically flag suspicious claims at the point of submission or first notice of loss.
- **Underwriting Adjustments:** Insights from feature importance can inform underwriting guidelines, helping to adjust premiums or coverage for specific risk profiles identified as highly prone to fraud.
- **Investigator Prioritization Dashboards:** Develop interactive dashboards for fraud investigation teams, visualizing predicted fraud scores, key contributing factors (from SHAP), and historical claim patterns.
- **Policy Design and Pricing:** Understanding the drivers of fraud can influence the design of new policy products or the re-pricing of existing ones to better account for fraud risk.
- **Feedback Loop for Data Collection:** Insights gained from the model can inform future data collection efforts, prompting the capture of more predictive features or the improvement of data quality for existing ones.

In conclusion, this project serves as a robust demonstration of applying machine learning and interpretability techniques to a critical business problem in the insurance industry, moving beyond traditional methods to enable more intelligent, data-driven decisions in fraud detection.