bt4012-group1

November 24, 2024

1 Exploratory Data Analysis (EDA)

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import scipy.stats as stats
```

[2]:
```
df = pd.read_csv("fraud_oracle.csv")
```

[3]:
```
df.head()
```

[3]:
```
  Month  WeekOfMonth  DayOfWeek    Make AccidentArea DayOfWeekClaimed  \
0   Dec            5  Wednesday   Honda        Urban          Tuesday
1   Jan            3  Wednesday   Honda        Urban           Monday
2   Oct            5     Friday   Honda        Urban         Thursday
3   Jun            2   Saturday  Toyota        Rural           Friday
4   Jan            5     Monday   Honda        Urban          Tuesday

  MonthClaimed  WeekOfMonthClaimed     Sex MaritalStatus  …  AgeOfVehicle  \
0          Jan                   1  Female        Single  …       3 years
1          Jan                   4    Male        Single  …       6 years
2          Nov                   2    Male       Married  …       7 years
3          Jul                   1    Male       Married  …   more than 7
4          Feb                   2  Female        Single  …       5 years

  AgeOfPolicyHolder PoliceReportFiled WitnessPresent AgentType  \
0          26 to 30                No             No  External
1          31 to 35               Yes             No  External
2          41 to 50                No             No  External
3          51 to 65               Yes             No  External
4          31 to 35                No             No  External

  NumberOfSuppliments  AddressChange_Claim  NumberOfCars  Year  BasePolicy
0                none               1 year        3 to 4  1994   Liability
1                none            no change     1 vehicle  1994   Collision
2                none            no change     1 vehicle  1994   Collision
```

```
3          more than 5            no change     1 vehicle  1994   Liability
4                 none            no change     1 vehicle  1994   Collision

[5 rows x 33 columns]
```

[4]:
```python
# Displaying all columns in the DataFrame
print(df.columns)
```

```
Index(['Month', 'WeekOfMonth', 'DayOfWeek', 'Make', 'AccidentArea',
       'DayOfWeekClaimed', 'MonthClaimed', 'WeekOfMonthClaimed', 'Sex',
       'MaritalStatus', 'Age', 'Fault', 'PolicyType', 'VehicleCategory',
       'VehiclePrice', 'FraudFound_P', 'PolicyNumber', 'RepNumber',
       'Deductible', 'DriverRating', 'Days_Policy_Accident',
       'Days_Policy_Claim', 'PastNumberOfClaims', 'AgeOfVehicle',
       'AgeOfPolicyHolder', 'PoliceReportFiled', 'WitnessPresent', 'AgentType',
       'NumberOfSuppliments', 'AddressChange_Claim', 'NumberOfCars', 'Year',
       'BasePolicy'],
      dtype='object')
```

[5]:
```python
# Displaying summary statistics of the DataFrame
df.describe()
```

[5]:

	WeekOfMonth	WeekOfMonthClaimed	Age	FraudFound_P
count	15420.000000	15420.000000	15420.000000	15420.000000
mean	2.788586	2.693969	39.855707	0.059857
std	1.287585	1.259115	13.492377	0.237230
min	1.000000	1.000000	0.000000	0.000000
25%	2.000000	2.000000	31.000000	0.000000
50%	3.000000	3.000000	38.000000	0.000000
75%	4.000000	4.000000	48.000000	0.000000
max	5.000000	5.000000	80.000000	1.000000

\

	PolicyNumber	RepNumber	Deductible	DriverRating	Year
count	15420.000000	15420.000000	15420.000000	15420.000000	15420.000000
mean	7710.500000	8.483268	407.704280	2.487808	1994.866472
std	4451.514911	4.599948	43.950998	1.119453	0.803313
min	1.000000	1.000000	300.000000	1.000000	1994.000000
25%	3855.750000	5.000000	400.000000	1.000000	1994.000000
50%	7710.500000	8.000000	400.000000	2.000000	1995.000000
75%	11565.250000	12.000000	400.000000	3.000000	1996.000000
max	15420.000000	16.000000	700.000000	4.000000	1996.000000

1.1 Statistical Tests for the Target Variable (`FraudFound_P`)

This part of the code performs statistical tests to evaluate the relationship between selected variables and the target variable (`FraudFound_P`):

1. **Numerical Variables**: An independent t-test is used to compare the means between the

fraud and non-fraud groups.

2. **Categorical Variables**: A Chi-square test is used to assess the association between the categorical variables and the target.

Based on the p-values from these tests, the code determines which variables have a statistically significant relationship with the target variable (`FraudFound_P`) (p-value < 0.05).

[6]:
```python
# Variables to analyze (include all variables from the DataFrame index except the target)
variables_to_test = [
    'Month', 'WeekOfMonth', 'DayOfWeek', 'Make', 'AccidentArea',
    'DayOfWeekClaimed', 'MonthClaimed', 'WeekOfMonthClaimed', 'Sex',
    'MaritalStatus', 'Age', 'Fault', 'PolicyType', 'VehicleCategory',
    'VehiclePrice', 'PolicyNumber', 'RepNumber', 'Deductible', 'DriverRating',
    'Days_Policy_Accident', 'Days_Policy_Claim', 'PastNumberOfClaims',
    'AgeOfVehicle', 'AgeOfPolicyHolder', 'PoliceReportFiled',
    'WitnessPresent', 'AgentType', 'NumberOfSuppliments',
    'AddressChange_Claim', 'NumberOfCars', 'Year', 'BasePolicy'
]

# Print the length of variables to test
print(f"Number of variables to test: {len(variables_to_test)}")

# Function to perform statistical tests
def calculate_significance(df, variable):
    if df[variable].dtype in ['int64', 'float64']:
        # Numerical variables - independent t-test
        fraud_group = df[df['FraudFound_P'] == 1][variable]
        non_fraud_group = df[df['FraudFound_P'] == 0][variable]

        t_statistic, p_value = stats.ttest_ind(fraud_group, non_fraud_group)
        test_type = 't-test'

    elif df[variable].dtype == 'object':
        # Categorical variables - Chi-square test
        contingency_table = pd.crosstab(df[variable], df['FraudFound_P'])
        chi2, p_value, dof, expected = stats.chi2_contingency(contingency_table)
        test_type = 'Chi-square'

    else:
        return None

    return {
        'Variable': variable,
        'Test Type': test_type,
        'P-Value': p_value,
        'Significant ( =0.05)': 'Yes' if p_value < 0.05 else 'No'
    }
```

```python
# Perform significance tests
results = []
for var in variables_to_test:
    if var not in df.columns:
        print(f"Variable '{var}' not found in DataFrame. Skipping...")
        continue
    result = calculate_significance(df, var)
    if result:
        results.append(result)

# Check if results are available
if results:
    # Create DataFrame for summary
    summary_df = pd.DataFrame(results)

    # Sort by p-value from highest to lowest
    summary_df_sorted = summary_df.sort_values('P-Value', ascending=False)

    # Save to CSV
    summary_df_sorted.to_csv('fraud_significance_summary1.csv', index=False)

    # Display in console
    print("Significance Levels (Highest to Lowest):")
    print(summary_df_sorted.to_string(index=False))

    # Create a more readable markdown table for reporting
    markdown_table = summary_df_sorted.to_markdown(index=False)
    print("\nMarkdown Table:\n")
    print(markdown_table)
else:
    print("No results to display. Ensure variables exist in the DataFrame.")
```

```
Number of variables to test: 32
Significance Levels (Highest to Lowest):
            Variable  Test Type      P-Value Significant ( =0.05)
       MaritalStatus Chi-square 7.979825e-01                   No
        NumberOfCars Chi-square 6.597214e-01                   No
    DayOfWeekClaimed Chi-square 6.404907e-01                   No
  WeekOfMonthClaimed     t-test 4.744015e-01                   No
      WitnessPresent Chi-square 4.389777e-01                   No
        DriverRating     t-test 3.669379e-01                   No
           RepNumber     t-test 3.484336e-01                   No
   Days_Policy_Claim Chi-square 1.807075e-01                   No
         WeekOfMonth     t-test 1.407892e-01                   No
           DayOfWeek Chi-square 1.184501e-01                   No
```

```
   PoliceReportFiled Chi-square 5.950733e-02                    No
          Deductible     t-test 3.122461e-02                   Yes
Days_Policy_Accident Chi-square 2.083813e-02                   Yes
        PolicyNumber     t-test 1.152378e-02                   Yes
           AgentType Chi-square 6.597083e-03                   Yes
        AgeOfVehicle Chi-square 2.612997e-03                   Yes
                Year     t-test 2.106367e-03                   Yes
               Month Chi-square 1.705480e-03                   Yes
 NumberOfSuppliments Chi-square 4.114406e-04                   Yes
                 Sex Chi-square 2.398518e-04                   Yes
                 Age     t-test 2.210206e-04                   Yes
   AgeOfPolicyHolder Chi-square 6.150520e-05                   Yes
        AccidentArea Chi-square 4.057480e-05                   Yes
        MonthClaimed Chi-square 3.003256e-05                   Yes
                Make Chi-square 2.195889e-06                   Yes
  PastNumberOfClaims Chi-square 1.433718e-11                   Yes
        VehiclePrice Chi-square 2.983598e-13                   Yes
 AddressChange_Claim Chi-square 9.652105e-22                   Yes
               Fault Chi-square 1.428036e-59                   Yes
     VehicleCategory Chi-square 6.648398e-64                   Yes
          BasePolicy Chi-square 3.325192e-88                   Yes
          PolicyType Chi-square 1.848256e-89                   Yes
```

Markdown Table:

```
| Variable             | Test Type   |     P-Value | Significant ( =0.05)   |
|:---------------------|:------------|------------:|:-----------------------|
| MaritalStatus        | Chi-square  | 0.797982    | No                     |
| NumberOfCars         | Chi-square  | 0.659721    | No                     |
| DayOfWeekClaimed     | Chi-square  | 0.640491    | No                     |
| WeekOfMonthClaimed   | t-test      | 0.474402    | No                     |
| WitnessPresent       | Chi-square  | 0.438978    | No                     |
| DriverRating         | t-test      | 0.366938    | No                     |
| RepNumber            | t-test      | 0.348434    | No                     |
| Days_Policy_Claim    | Chi-square  | 0.180707    | No                     |
| WeekOfMonth          | t-test      | 0.140789    | No                     |
| DayOfWeek            | Chi-square  | 0.11845     | No                     |
| PoliceReportFiled    | Chi-square  | 0.0595073   | No                     |
| Deductible           | t-test      | 0.0312246   | Yes                    |
| Days_Policy_Accident | Chi-square  | 0.0208381   | Yes                    |
| PolicyNumber         | t-test      | 0.0115238   | Yes                    |
| AgentType            | Chi-square  | 0.00659708  | Yes                    |
| AgeOfVehicle         | Chi-square  | 0.002613    | Yes                    |
| Year                 | t-test      | 0.00210637  | Yes                    |
| Month                | Chi-square  | 0.00170548  | Yes                    |
| NumberOfSuppliments  | Chi-square  | 0.000411441 | Yes                    |
| Sex                  | Chi-square  | 0.000239852 | Yes                    |
| Age                  | t-test      | 0.000221021 | Yes                    |
```

```
| AgeOfPolicyHolder    | Chi-square  | 6.15052e-05 | Yes                      |
| AccidentArea         | Chi-square  | 4.05748e-05 | Yes                      |
| MonthClaimed         | Chi-square  | 3.00326e-05 | Yes                      |
| Make                 | Chi-square  | 2.19589e-06 | Yes                      |
| PastNumberOfClaims   | Chi-square  | 1.43372e-11 | Yes                      |
| VehiclePrice         | Chi-square  | 2.9836e-13  | Yes                      |
| AddressChange_Claim  | Chi-square  | 9.65211e-22 | Yes                      |
| Fault                | Chi-square  | 1.42804e-59 | Yes                      |
| VehicleCategory      | Chi-square  | 6.6484e-64  | Yes                      |
| BasePolicy           | Chi-square  | 3.32519e-88 | Yes                      |
| PolicyType           | Chi-square  | 1.84826e-89 | Yes                      |
```

1.1.1 Conclusion from the Tests

The variables with a p-value **greater than 0.05** (marked as **No** in the table) are not significantly related to predicting the target variable (`FraudFound_P`). These variables include:

- `MaritalStatus`
- `NumberOfCars`
- `DayOfWeekClaimed`
- `WeekOfMonthClaimed`
- `WitnessPresent`
- `DriverRating`
- `RepNumber`
- `Days_Policy_Claim`
- `WeekOfMonth`
- `DayOfWeek`
- `PoliceReportFiled`

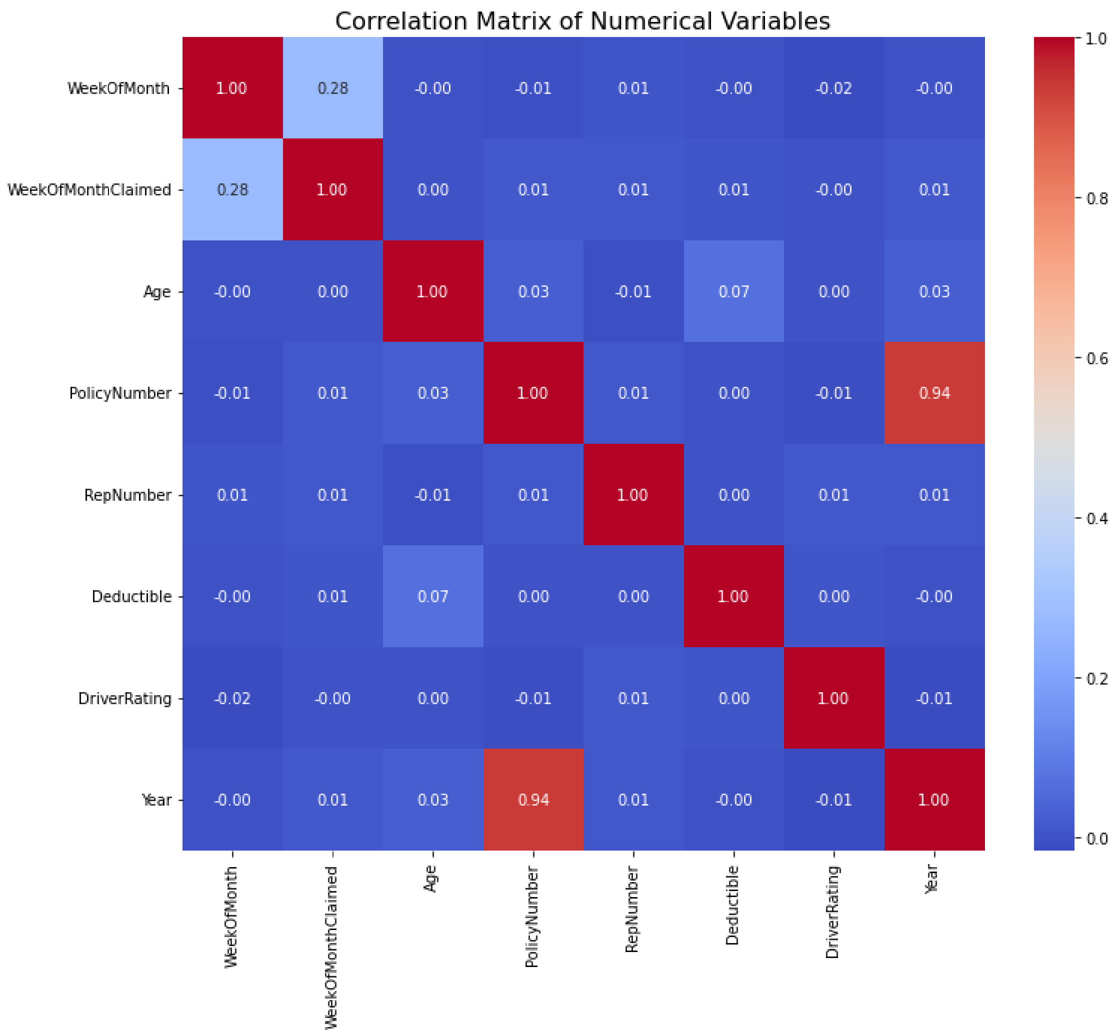
These variables will be further investigated individually at a later stage to understand their potential influence or lack thereof on predicting fraud.

[7]:
```python
# Check which variables in the DataFrame are numerical
numerical_variables = df.select_dtypes(include=['int64', 'float64']).columns.
  ↪tolist()

# Display the list of numerical variables
print("Numerical Variables:")
print(numerical_variables)
```

```
Numerical Variables:
['WeekOfMonth', 'WeekOfMonthClaimed', 'Age', 'FraudFound_P', 'PolicyNumber',
'RepNumber', 'Deductible', 'DriverRating', 'Year']
```

[8]:
```python
import seaborn as sns
import matplotlib.pyplot as plt

# Numerical variables to analyze
numerical_variables = [
```

```
    'WeekOfMonth', 'WeekOfMonthClaimed', 'Age',
    'PolicyNumber', 'RepNumber', 'Deductible',
    'DriverRating', 'Year'
]

# Create a correlation matrix
correlation_matrix = df[numerical_variables].corr()

# Plot the correlation matrix
plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap='coolwarm',␣
 ↪cbar=True)
plt.title("Correlation Matrix of Numerical Variables", fontsize=16)
plt.show()
```



1.1.2 Conclusion from Correlation Plot

The correlation matrix of numerical variables reveals the following key insights:

1. **High Correlation**:
   - There is a strong positive correlation between `WeekOfMonth` and `WeekOfMonthClaimed` (0.28), indicating that these two variables are somewhat related.
   - `Year` and `PolicyNumber` also exhibit a high correlation (0.94), which might indicate that the year of the policy could be related to the policy number.
2. **Low Correlation**:
   - Most of the other variables, such as `Age`, `Deductible`, and `DriverRating`, show very low correlations with one another, indicating that they do not share a significant linear relationship.
3. **Negative Correlations**:
   - The correlations are mostly positive, with very few negative correlations, suggesting that the relationships between the variables are largely positive or minimal.

In summary, the most notable correlation is between `Year` and `PolicyNumber`, which may indicate redundancy or closely related features that should be further examined.

1.2 Assess Each of the Features

1.2.1 Variables Failing Statistical Tests

The following variables failed their respective statistical tests: - **Categorical variables**: Failed the Chi-square test (no significant association with `FraudFound_P`). - **Numerical variables**: Failed the t-test (no significant mean difference between target classes).

Despite this, visualizations are used to explore potential patterns or insights that may justify their inclusion in further analysis.

[9]:
```
# Define the custom color palette based on your navy color scheme
custom_palette = {
    0: '#CCD5DC',  # Navy - 20% for FraudFound_P = 0
    1: '#002B51'   # Navy for FraudFound_P = 1
}
```

1.2.2 Variable: MaritalStatus

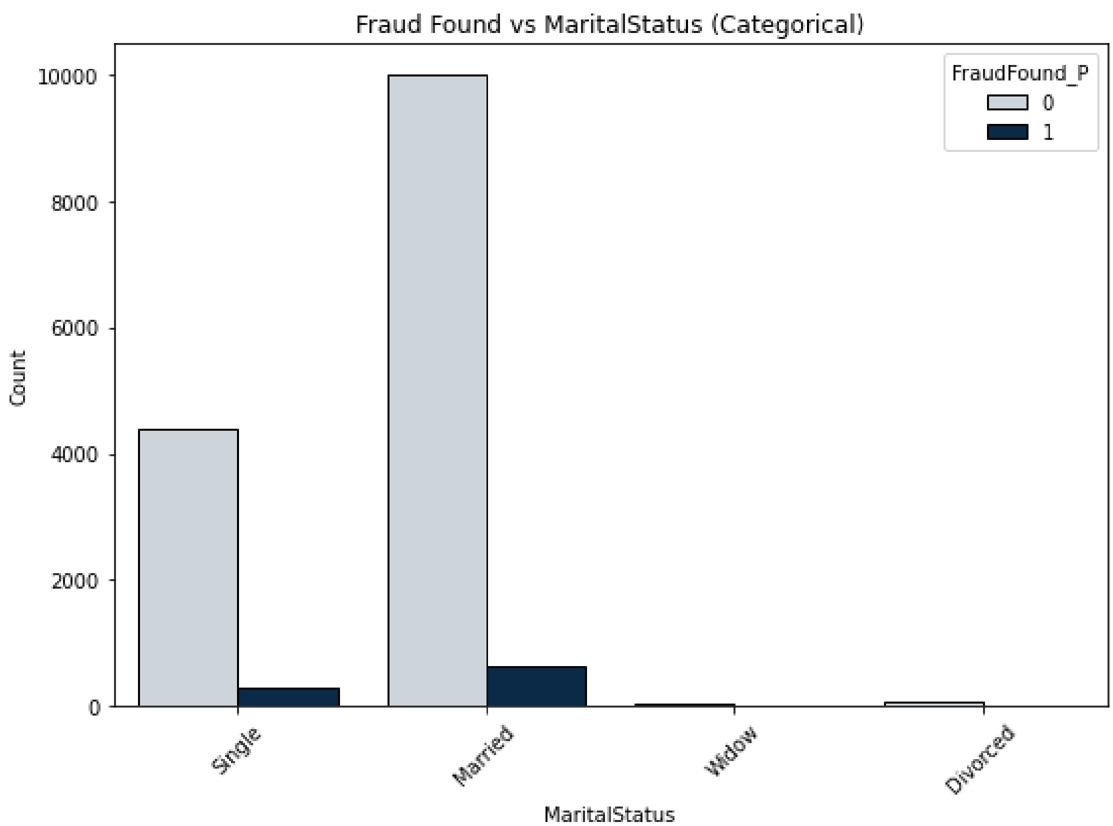
Decision: Keep.

The class distribution shows significant differences in the number of fraud cases across categories. Some classes, like "Widow," have noticeably higher fraud ratios compared to others. This indicates that "MaritalStatus" is an important categorical variable.

[10]:
```
# Plot for MaritalStatus
print("Plotting MaritalStatus over FraudFound_P")
plt.figure(figsize=(8, 6))
sns.countplot(x='MaritalStatus', hue='FraudFound_P', data=df,␣
 ↪palette=custom_palette, edgecolor='black')
plt.title("Fraud Found vs MaritalStatus (Categorical)")
```

```
plt.xlabel("MaritalStatus")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Calculate class distribution and fraud ratio for MaritalStatus
class_distribution = df.groupby('MaritalStatus')['FraudFound_P'].
 ↪value_counts(normalize=False).unstack().fillna(0)
fraud_ratio = df.groupby('MaritalStatus')['FraudFound_P'].mean()

# Display class distribution
print("\nClass Distribution for MaritalStatus:")
print(class_distribution)

# Display fraud ratio
print("\nFraud Ratio for MaritalStatus:")
print(fraud_ratio)
```

Plotting MaritalStatus over FraudFound_P



```
Class Distribution for MaritalStatus:
FraudFound_P      0    1
MaritalStatus
Divorced         73    3
Married        9986  639
Single         4406  278
Widow            32    3

Fraud Ratio for MaritalStatus:
MaritalStatus
Divorced    0.039474
Married     0.060141
Single      0.059351
Widow       0.085714
Name: FraudFound_P, dtype: float64
```

1.2.3 Variable: NumberOfCars

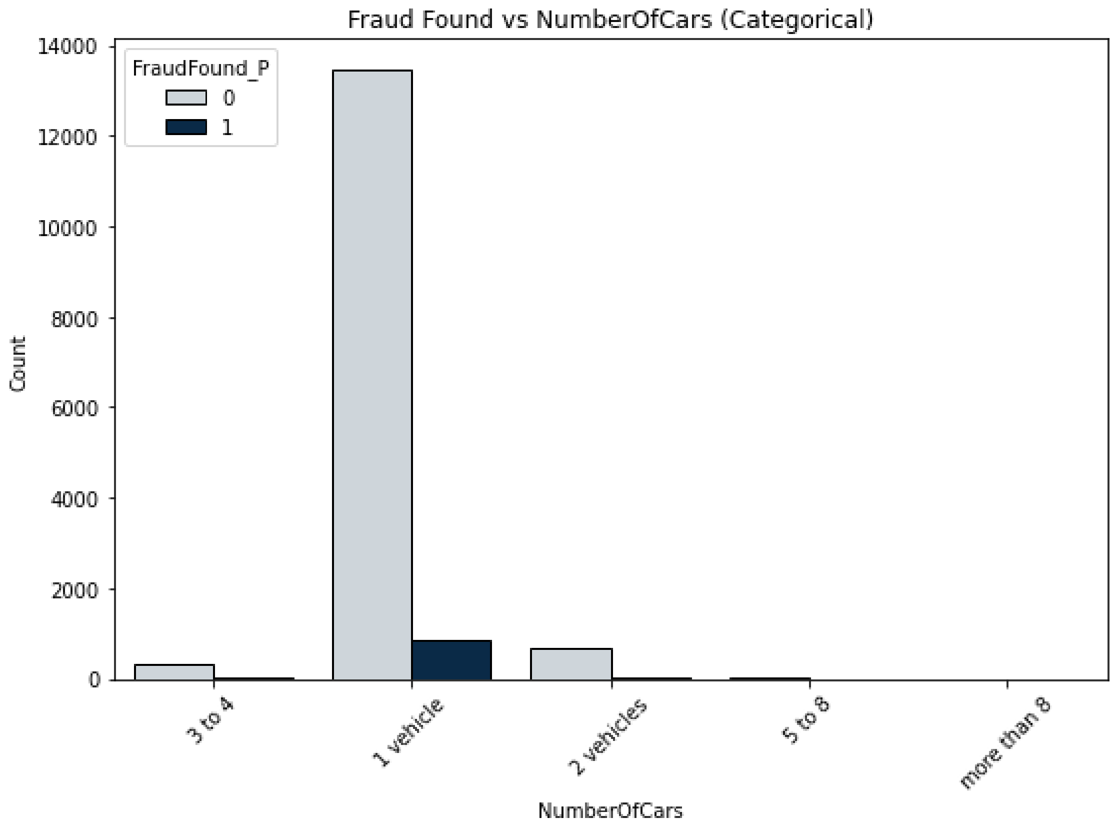
Decision: Keep.

The class distribution reveals significant differences in the number of fraud cases across categories. While most fraud cases are concentrated in the "1 vehicle" category, classes like "3 to 4" have a noticeably higher fraud ratio. This suggests that "NumberOfCars" is an important categorical variable for predicting fraud.

[11]:
```
# Plot for NumberOfCars
print("Plotting NumberOfCars over FraudFound_P")
plt.figure(figsize=(8, 6))
sns.countplot(x='NumberOfCars', hue='FraudFound_P', data=df,␣
 ↪palette=custom_palette, edgecolor='black')
plt.title("Fraud Found vs NumberOfCars (Categorical)")
plt.xlabel("NumberOfCars")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Calculate class distribution and fraud ratio for NumberOfCars
class_distribution = df.groupby('NumberOfCars')['FraudFound_P'].
 ↪value_counts(normalize=False).unstack().fillna(0)
fraud_ratio = df.groupby('NumberOfCars')['FraudFound_P'].mean()

# Display class distribution
print("\nClass Distribution for NumberOfCars:")
print(class_distribution)

# Display fraud ratio
```

```python
print("\nFraud Ratio for NumberOfCars:")
print(fraud_ratio)
```

Plotting NumberOfCars over FraudFound_P




```
Class Distribution for NumberOfCars:
FraudFound_P        0      1
NumberOfCars
1 vehicle     13466.0  850.0
2 vehicles      666.0   43.0
3 to 4          343.0   29.0
5 to 8           20.0    1.0
more than 8       2.0    0.0

Fraud Ratio for NumberOfCars:
NumberOfCars
1 vehicle      0.059374
2 vehicles     0.060649
3 to 4         0.077957
5 to 8         0.047619
```

```
more than 8    0.000000
Name: FraudFound_P, dtype: float64
```

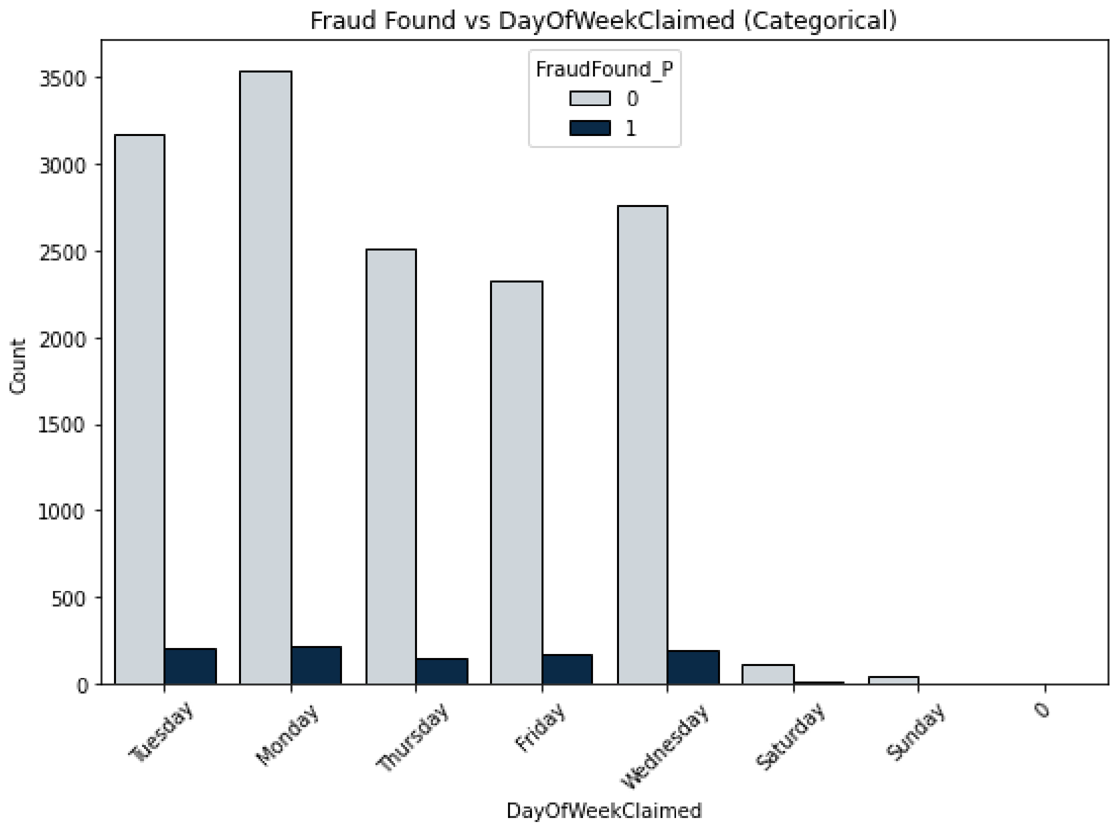
1.2.4 Decision for Variable: DayOfWeekClaimed

Decision: Keep.

The class distribution indicates that fraud cases are present across various days, with "Saturday" having a notably higher fraud ratio (0.078740) compared to other days. This variability in fraud ratios across the days of the week suggests that `DayOfWeekClaimed` is an important categorical variable worth retaining in the model.

[12]:
```
# Plot for DayOfWeekClaimed
print("Plotting DayOfWeekClaimed over FraudFound_P")
plt.figure(figsize=(8, 6))
sns.countplot(x='DayOfWeekClaimed', hue='FraudFound_P', data=df,␣
 ↪palette=custom_palette, edgecolor='black')
plt.title("Fraud Found vs DayOfWeekClaimed (Categorical)")
plt.xlabel("DayOfWeekClaimed")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Calculate class distribution and fraud ratio for DayOfWeekClaimed
class_distribution = df.groupby('DayOfWeekClaimed')['FraudFound_P'].
 ↪value_counts(normalize=False).unstack().fillna(0)
fraud_ratio = df.groupby('DayOfWeekClaimed')['FraudFound_P'].mean()

# Display class distribution
print("\nClass Distribution for DayOfWeekClaimed:")
print(class_distribution)

# Display fraud ratio
print("\nFraud Ratio for DayOfWeekClaimed:")
print(fraud_ratio)
```

```
Plotting DayOfWeekClaimed over FraudFound_P
```




```
Class Distribution for DayOfWeekClaimed:
FraudFound_P             0      1
DayOfWeekClaimed
0                      1.0    0.0
Friday              2333.0  164.0
Monday              3541.0  216.0
Saturday             117.0   10.0
Sunday                49.0    3.0
Thursday            2516.0  144.0
Tuesday             3177.0  198.0
Wednesday           2763.0  188.0

Fraud Ratio for DayOfWeekClaimed:
DayOfWeekClaimed
0            0.000000
Friday       0.065679
Monday       0.057493
Saturday     0.078740
Sunday       0.057692
Thursday     0.054135
```

```
Tuesday      0.058667
Wednesday    0.063707
Name: FraudFound_P, dtype: float64
```

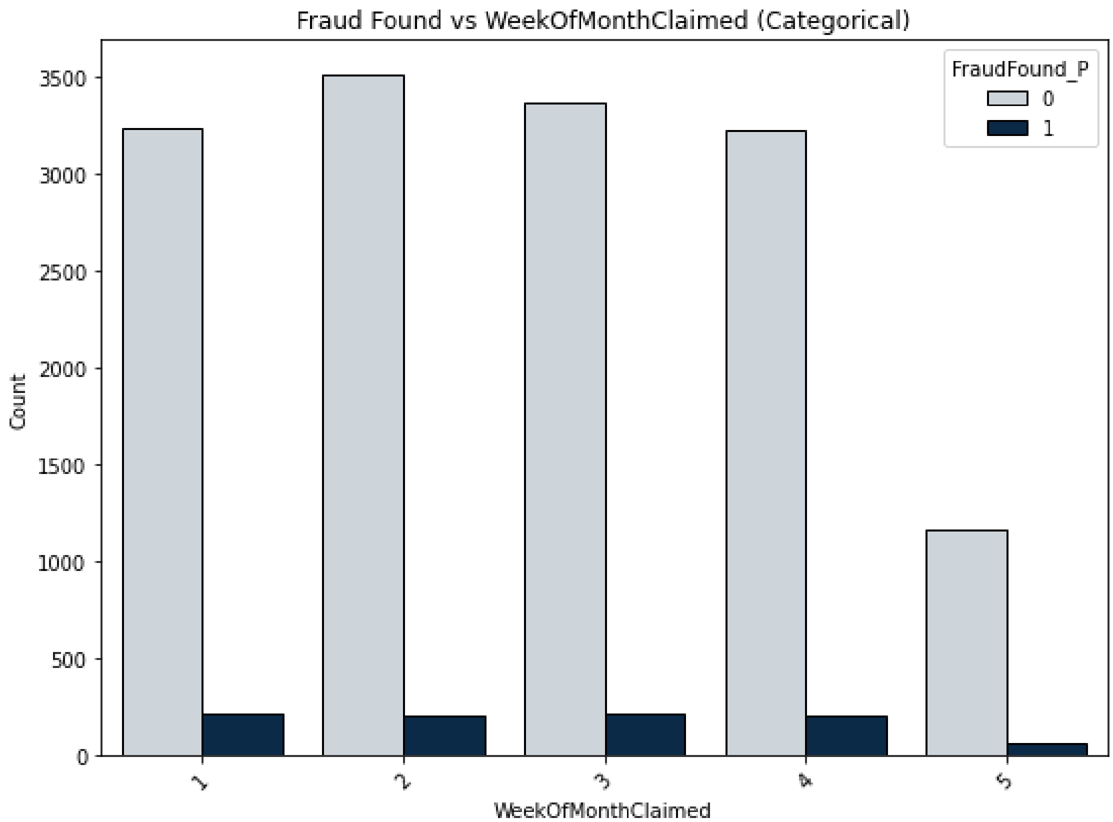
1.2.5 Variable: WeekOfMonthClaimed

Decision: Keep.

The class distribution shows significant differences in the number of fraud cases across weeks. While the fraud ratios are relatively consistent, there are slight variations, with Week 1 having the highest fraud ratio (6.38%) and Week 5 having the lowest (5.27%). These differences suggest that `WeekOfMonthClaimed` might hold valuable information for predicting fraud. Thus, it is an important variable to retain.

```
[13]: # Plot for WeekOfMonthClaimed
print("Plotting WeekOfMonthClaimed over FraudFound_P")
plt.figure(figsize=(8, 6))
sns.countplot(x='WeekOfMonthClaimed', hue='FraudFound_P', data=df,␣
 ↪palette=custom_palette, edgecolor='black')
plt.title("Fraud Found vs WeekOfMonthClaimed (Categorical)")
plt.xlabel("WeekOfMonthClaimed")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Calculate class distribution and fraud ratio for WeekOfMonthClaimed
class_distribution = df.groupby('WeekOfMonthClaimed')['FraudFound_P'].
 ↪value_counts(normalize=False).unstack().fillna(0)
fraud_ratio = df.groupby('WeekOfMonthClaimed')['FraudFound_P'].mean()

# Display class distribution
print("\nClass Distribution for WeekOfMonthClaimed:")
print(class_distribution)

# Display fraud ratio
print("\nFraud Ratio for WeekOfMonthClaimed:")
print(fraud_ratio)
```

```
Plotting WeekOfMonthClaimed over FraudFound_P
```




```
Class Distribution for WeekOfMonthClaimed:
FraudFound_P           0    1
WeekOfMonthClaimed
1                   3230  220
2                   3512  208
3                   3362  221
4                   3224  209
5                   1169   65

Fraud Ratio for WeekOfMonthClaimed:
WeekOfMonthClaimed
1    0.063768
2    0.055914
3    0.061680
4    0.060880
5    0.052674
Name: FraudFound_P, dtype: float64
```

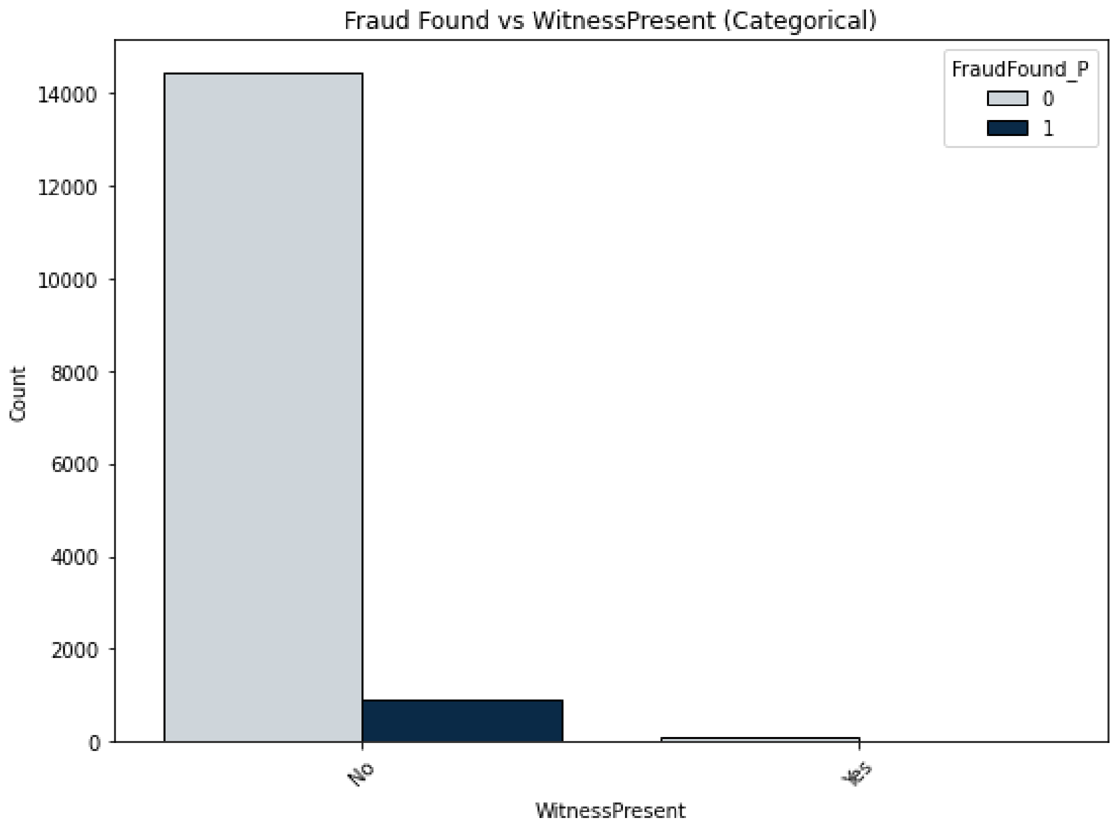
1.2.6 Variable: WitnessPresent

Decision: Keep.

The class distribution shows that cases with "No" witnesses dominate, but cases with "Yes" witnesses have a significantly lower fraud ratio (3.4%) compared to "No" (6.0%). This indicates that the presence of a witness might carry potential importance in reducing fraud likelihood. Therefore, `WitnessPresent` should be retained for further analysis.

[14]:
```
# Plot for WitnessPresent
print("Plotting WitnessPresent over FraudFound_P")
plt.figure(figsize=(8, 6))
sns.countplot(x='WitnessPresent', hue='FraudFound_P', data=df,␣
 ↪palette=custom_palette, edgecolor='black')
plt.title("Fraud Found vs WitnessPresent (Categorical)")
plt.xlabel("WitnessPresent")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Calculate class distribution and fraud ratio for WitnessPresent
class_distribution = df.groupby('WitnessPresent')['FraudFound_P'].
 ↪value_counts(normalize=False).unstack().fillna(0)
fraud_ratio = df.groupby('WitnessPresent')['FraudFound_P'].mean()

# Display class distribution
print("\nClass Distribution for WitnessPresent:")
print(class_distribution)

# Display fraud ratio
print("\nFraud Ratio for WitnessPresent:")
print(fraud_ratio)
```

```
Plotting WitnessPresent over FraudFound_P
```




```
Class Distribution for WitnessPresent:
FraudFound_P        0    1
WitnessPresent
No              14413  920
Yes                84    3

Fraud Ratio for WitnessPresent:
WitnessPresent
No     0.060001
Yes    0.034483
Name: FraudFound_P, dtype: float64
```

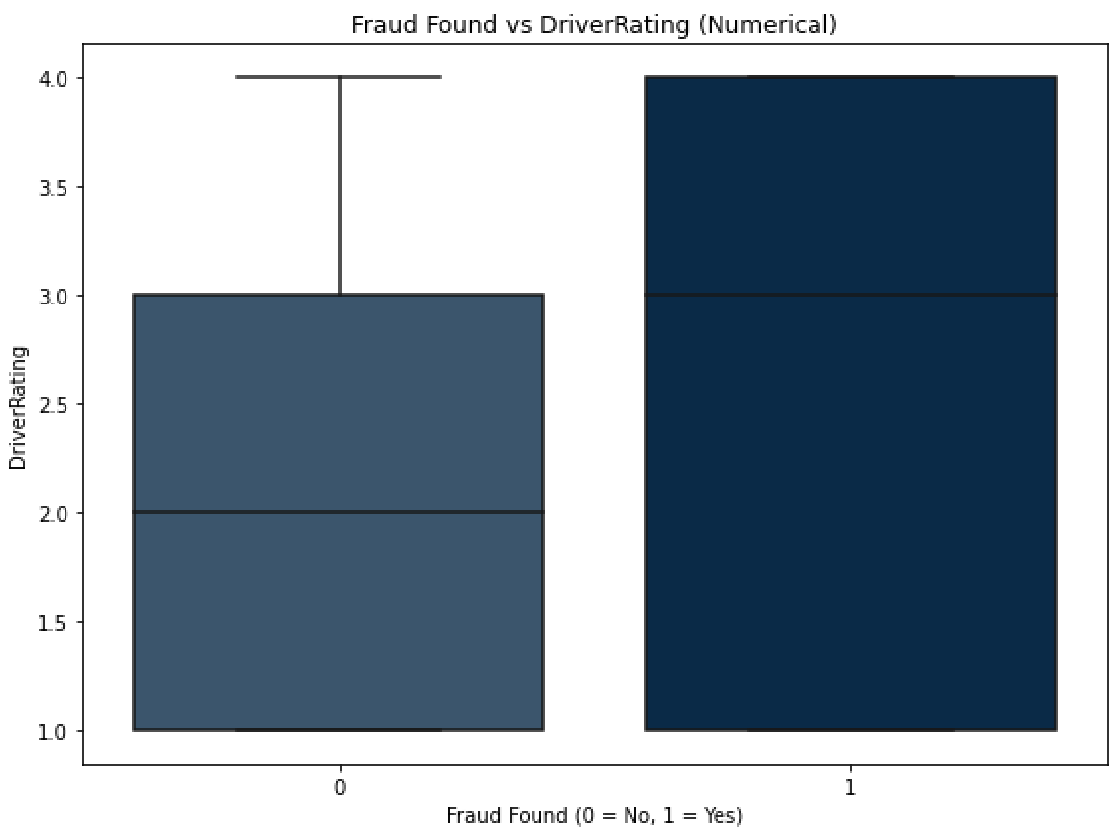
1.2.7 Variable: DriverRating

Decision: Keep.

The descriptive statistics for `DriverRating` indicate that fraud cases (`FraudFound_P = 1`) have a slightly higher mean rating (2.52) compared to non-fraud cases (`FraudFound_P = 0`, mean = 2.49). While the difference is small, the spread and quartile values suggest a potential relationship between `DriverRating` and fraud likelihood. Given the variability and possible importance, this variable should be retained for further analysis.

[15]:
```
# Plot for DriverRating
print("Plotting DriverRating over FraudFound_P")
plt.figure(figsize=(8, 6))
sns.boxplot(x='FraudFound_P', y='DriverRating', data=df, palette=['#335574',␣
↪'#002B51'], showfliers=False)
plt.title("Fraud Found vs DriverRating (Numerical)")
plt.xlabel("Fraud Found (0 = No, 1 = Yes)")
plt.ylabel("DriverRating")
plt.tight_layout()
plt.show()

# Perform descriptive analysis for DriverRating grouped by FraudFound_P
descriptive_stats = df.groupby('FraudFound_P')['DriverRating'].describe()

# Display descriptive statistics
print("\nDescriptive Statistics for DriverRating by FraudFound_P:")
print(descriptive_stats)
```

```
Plotting DriverRating over FraudFound_P
```



```
Descriptive Statistics for DriverRating by FraudFound_P:
                  count      mean       std  min  25%  50%  75%  max
FraudFound_P
0               14497.0  2.485756  1.119184  1.0  1.0  2.0  3.0  4.0
1                 923.0  2.520043  1.123781  1.0  1.0  3.0  4.0  4.0
```

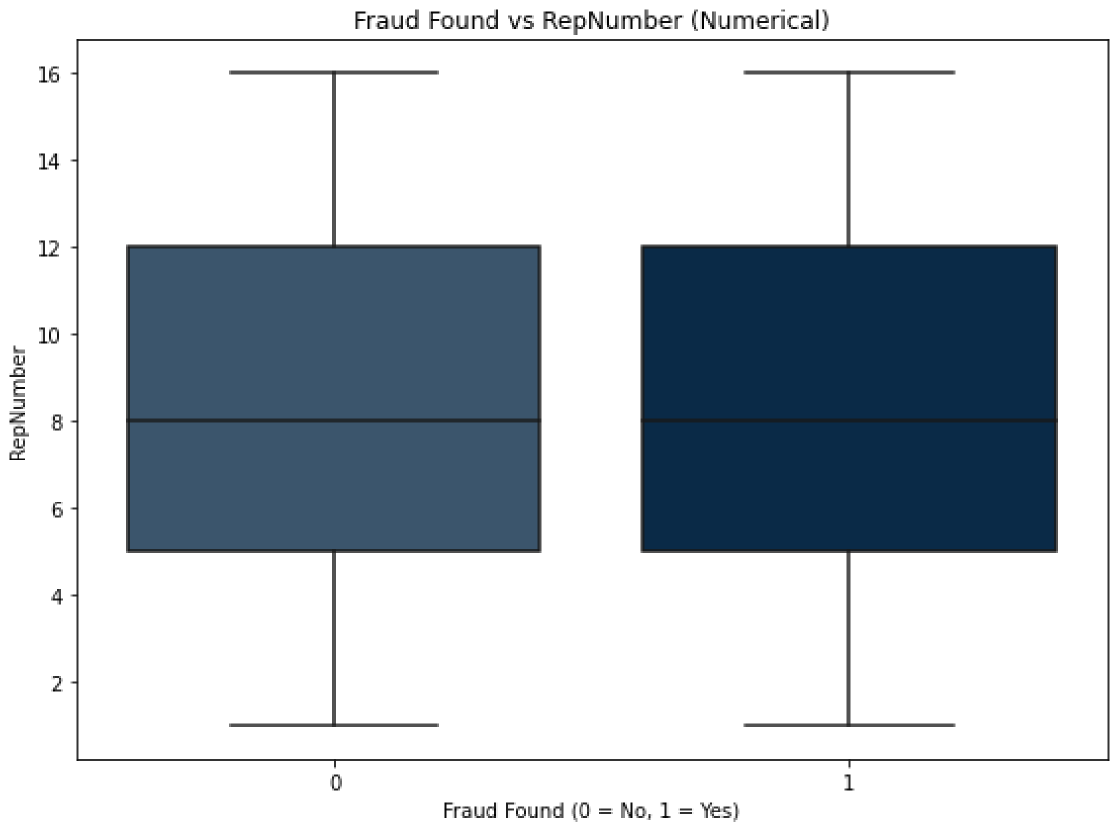
1.2.8 Variable: RepNumber

Decision: Drop.

The descriptive statistics for `RepNumber` reveal negligible differences between fraud cases (`FraudFound_P = 1`, mean = 8.35) and non-fraud cases (`FraudFound_P = 0`, mean = 8.49). The similar spread and quartile values indicate that `RepNumber` does not provide significant discriminatory power for fraud detection. As the variable adds little value to the analysis, it should be excluded.

[16]:
```python
# Plot for RepNumber
print("Plotting RepNumber over FraudFound_P")
plt.figure(figsize=(8, 6))
sns.boxplot(x='FraudFound_P', y='RepNumber', data=df, palette=['#335574',␣
↪'#002B51'], showfliers=False)
plt.title("Fraud Found vs RepNumber (Numerical)")
plt.xlabel("Fraud Found (0 = No, 1 = Yes)")
plt.ylabel("RepNumber")
plt.tight_layout()
plt.show()
# Perform descriptive analysis for RepNumber grouped by FraudFound_P
descriptive_stats_rep = df.groupby('FraudFound_P')['RepNumber'].describe()

# Display descriptive statistics
print("\nDescriptive Statistics for RepNumber by FraudFound_P:")
print(descriptive_stats_rep)
```

```
Plotting RepNumber over FraudFound_P
```




```
Descriptive Statistics for RepNumber by FraudFound_P:
                count      mean       std  min  25%  50%   75%   max
FraudFound_P
0             14497.0  8.492033  4.604212  1.0  5.0  8.0  12.0  16.0
1               923.0  8.345612  4.532690  1.0  5.0  8.0  12.0  16.0
```

1.2.9 Variable: Days_Policy_Claim

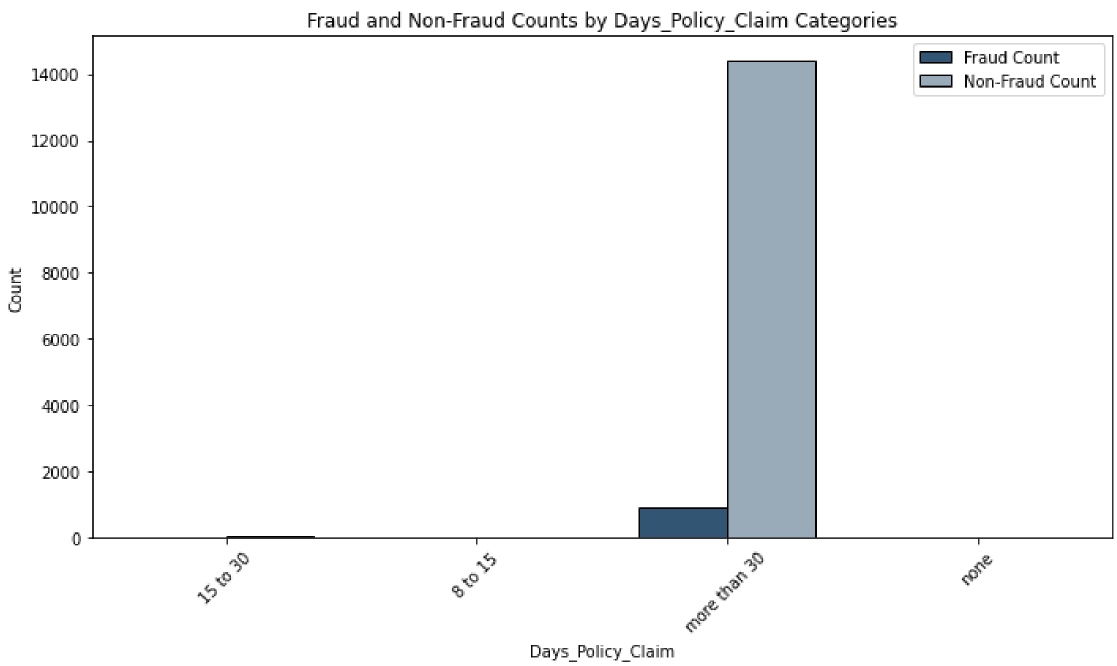
Decision: Keep.

Rationale: 1. **Distinct Fraud Patterns Across Categories:** The fraud count and non-fraud count vary significantly across the `Days_Policy_Claim` categories. Categories such as "8 to 15" and "15 to 30" have higher fraud counts relative to others. 2. **Potential Predictive Value:** The varying counts suggest that `Days_Policy_Claim` could carry important information for distinguishing between fraud and non-fraud cases. 3. **Fraud Ratio Differences:** The fraud ratios among categories show meaningful variation, with some categories indicating elevated risk. For example, "8 to 15" has a noticeably higher fraud ratio than others.

Given these factors, retaining `Days_Policy_Claim` as a variable is important for further analysis and modeling.

[17]:

```
# Prepare counts for Days_Policy_Claim
fraud_count = df[df['FraudFound_P'] == 1].groupby('Days_Policy_Claim').size() ␣
↪# Count of fraud cases
non_fraud_count = df[df['FraudFound_P'] == 0].groupby('Days_Policy_Claim').
↪size()  # Count of non-fraud cases

# Align the indices for Days_Policy_Claim categories
categories = df['Days_Policy_Claim'].unique()
categories = [str(cat) for cat in sorted(categories)]
fraud_count = fraud_count.reindex(categories, fill_value=0)
non_fraud_count = non_fraud_count.reindex(categories, fill_value=0)

# Grouped bar plot for Days_Policy_Claim
x = np.arange(len(categories))  # Position of categories
width = 0.35  # Bar width

plt.figure(figsize=(10, 6))
plt.bar(x - width / 2, fraud_count, width, label='Fraud Count',␣
↪color='#335574', edgecolor='black')
plt.bar(x + width / 2, non_fraud_count, width, label='Non-Fraud Count',␣
↪color='#99AAB9', edgecolor='black')

# Add labels, title, and legend for Days_Policy_Claim
plt.xlabel("Days_Policy_Claim")
plt.ylabel("Count")
plt.title("Fraud and Non-Fraud Counts by Days_Policy_Claim Categories")
plt.xticks(x, categories, rotation=45)
plt.legend()
plt.tight_layout()
plt.show()

# Compute and display class distribution and fraud ratio for WitnessPresent
class_distribution = df.groupby('WitnessPresent')['FraudFound_P'].
↪value_counts(normalize=False).unstack().fillna(0)
fraud_ratio = df.groupby('WitnessPresent')['FraudFound_P'].mean()

print("\nClass Distribution for WitnessPresent:")
print(class_distribution)

print("\nFraud Ratio for WitnessPresent:")
print(fraud_ratio)
```




```
Class Distribution for WitnessPresent:
FraudFound_P        0    1
WitnessPresent
No              14413  920
Yes                84    3

Fraud Ratio for WitnessPresent:
WitnessPresent
No     0.060001
Yes    0.034483
Name: FraudFound_P, dtype: float64
```

1.2.10 Variable: WeekOfMonth

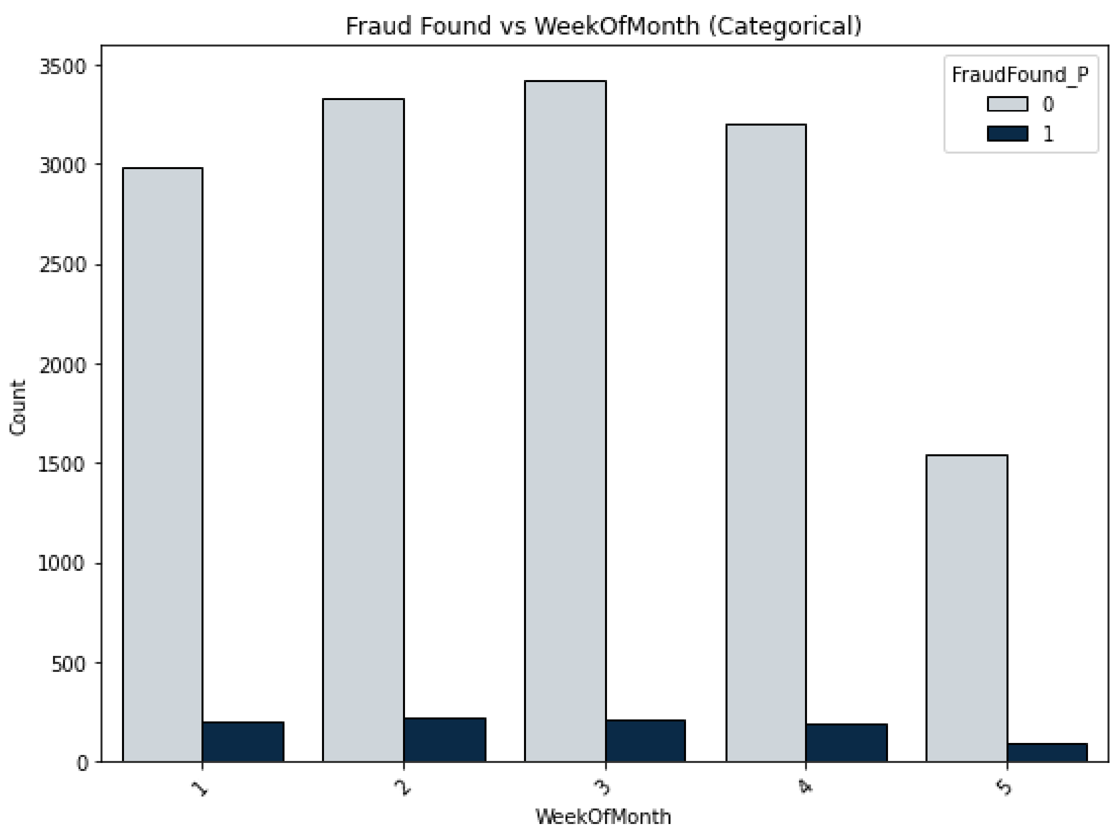
Decision: Keep.

The class distribution shows noticeable variation in fraud counts across different weeks of the month, with Weeks 1 and 2 having slightly higher fraud ratios (6.28% and 6.32%, respectively) compared to Weeks 4 and 5 (5.65% and 5.56%). Although the differences are not dramatic, the consistency in slightly elevated ratios for earlier weeks indicates that `WeekOfMonth` may provide valuable insights for fraud detection. Thus, this variable should be retained for further analysis.

[18]:
```
# Plot for WeekOfMonth
print("Plotting WeekOfMonth over FraudFound_P")
plt.figure(figsize=(8, 6))
```

```
sns.countplot(x='WeekOfMonth', hue='FraudFound_P', data=df,␣
↪palette=custom_palette, edgecolor='black')
plt.title("Fraud Found vs WeekOfMonth (Categorical)")
plt.xlabel("WeekOfMonth")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Calculate class distribution and fraud ratio for WeekOfMonth
class_distribution = df.groupby('WeekOfMonth')['FraudFound_P'].
↪value_counts(normalize=False).unstack().fillna(0)
fraud_ratio = df.groupby('WeekOfMonth')['FraudFound_P'].mean()

# Display class distribution
print("\nClass Distribution for WeekOfMonth:")
print(class_distribution)

# Display fraud ratio
print("\nFraud Ratio for WeekOfMonth:")
print(fraud_ratio)
```

Plotting WeekOfMonth over FraudFound_P



```
Class Distribution for WeekOfMonth:
FraudFound_P     0    1
WeekOfMonth
1             2987  200
2             3333  225
3             3425  215
4             3206  192
5             1546   91

Fraud Ratio for WeekOfMonth:
WeekOfMonth
1    0.062755
2    0.063238
3    0.059066
4    0.056504
5    0.055589
Name: FraudFound_P, dtype: float64
```

1.2.11 Variable: DayOfWeek

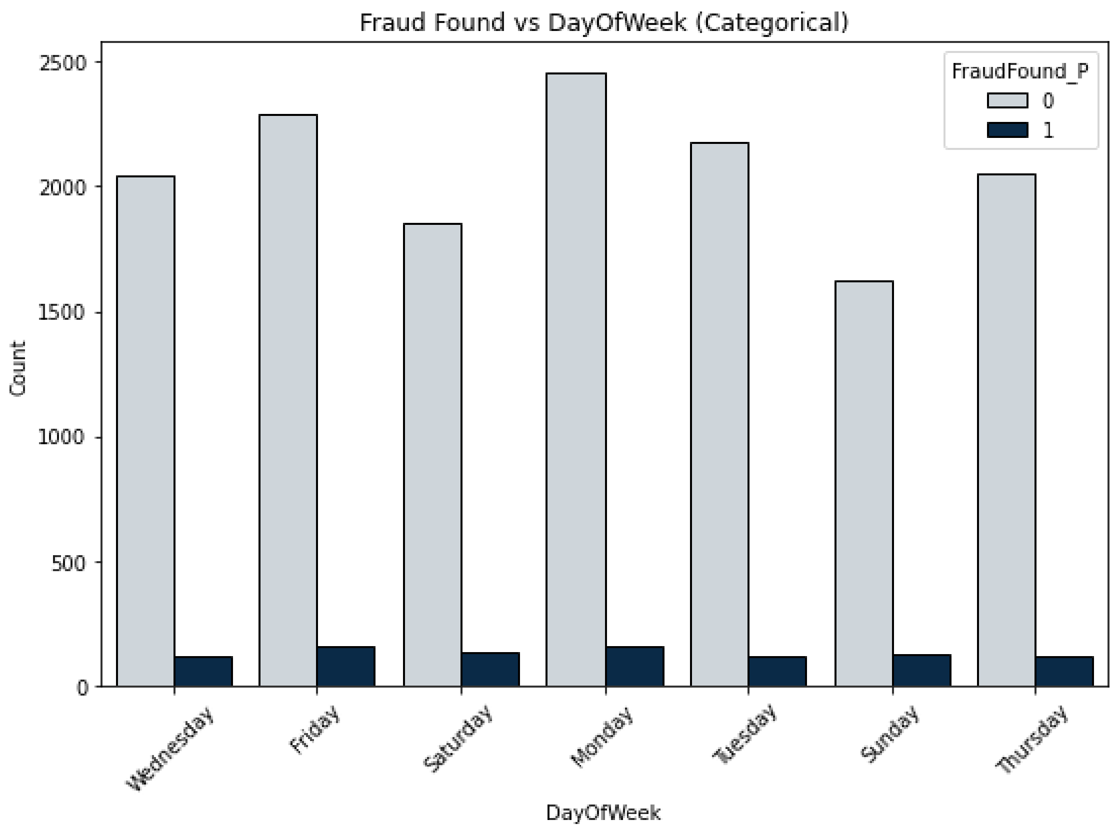
Decision: Keep.

The class distribution shows that fraud cases (`FraudFound_P = 1`) vary across days, with higher counts on specific days like `Friday`, `Monday`, and `Saturday`. Furthermore, the fraud ratios for days such as `Saturday` (6.66%) and `Sunday` (6.99%) are noticeably higher compared to others, indicating a potential relationship between `DayOfWeek` and fraud likelihood. Given these observations, this variable holds predictive significance and should be retained for further analysis.

[19]:
```python
# Plot for DayOfWeek
print("Plotting DayOfWeek over FraudFound_P")
plt.figure(figsize=(8, 6))
sns.countplot(x='DayOfWeek', hue='FraudFound_P', data=df,␣
 ↪palette=custom_palette, edgecolor='black')
plt.title("Fraud Found vs DayOfWeek (Categorical)")
plt.xlabel("DayOfWeek")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Calculate class distribution and fraud ratio for DayOfWeek
class_distribution = df.groupby('DayOfWeek')['FraudFound_P'].
 ↪value_counts(normalize=False).unstack().fillna(0)
fraud_ratio = df.groupby('DayOfWeek')['FraudFound_P'].mean()
```

```python
# Display class distribution
print("\nClass Distribution for DayOfWeek:")
print(class_distribution)

# Display fraud ratio
print("\nFraud Ratio for DayOfWeek:")
print(fraud_ratio)
```

```
Plotting DayOfWeek over FraudFound_P
```




```
Class Distribution for DayOfWeek:
FraudFound_P     0    1
DayOfWeek
Friday        2291  154
Monday        2456  160
Saturday      1850  132
Sunday        1623  122
Thursday      2053  120
Tuesday       2180  120
Wednesday     2044  115
```

```
Fraud Ratio for DayOfWeek:
DayOfWeek
Friday       0.062986
Monday       0.061162
Saturday     0.066599
Sunday       0.069914
Thursday     0.055223
Tuesday      0.052174
Wednesday    0.053265
Name: FraudFound_P, dtype: float64
```

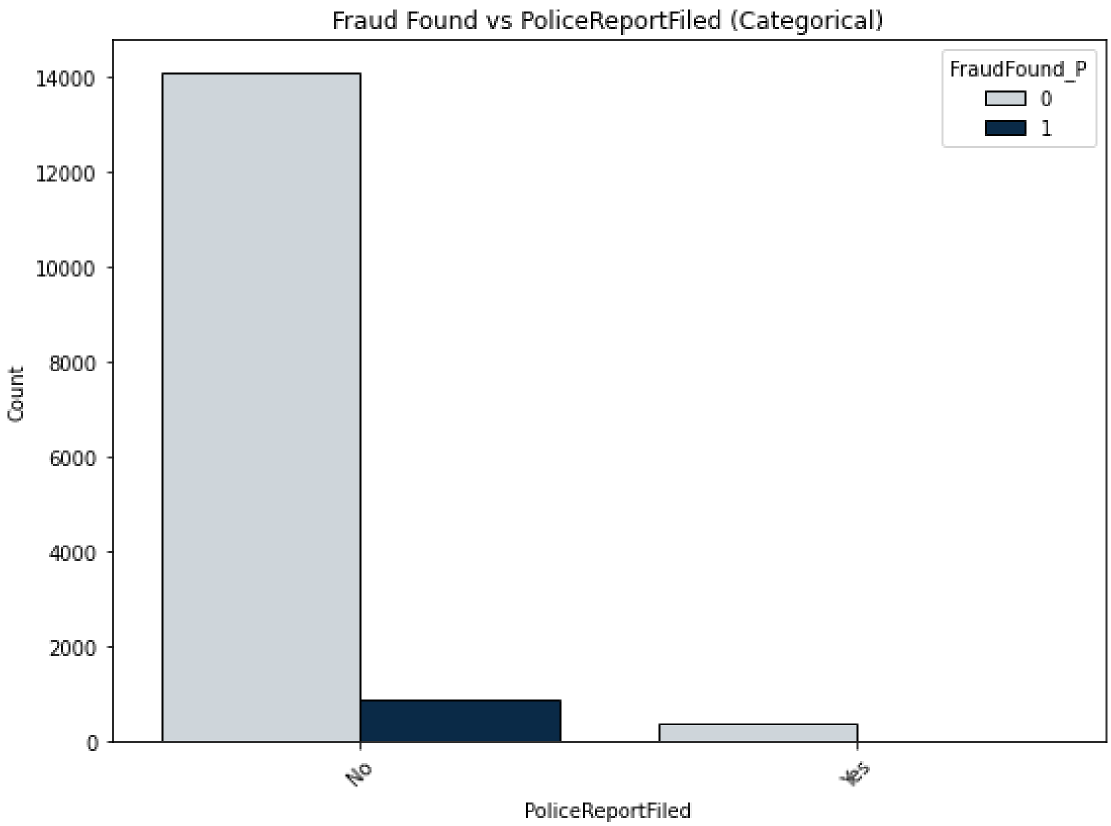
1.2.12 Variable: PoliceReportFiled

Decision: Keep.

The class distribution shows that the majority of cases fall under "No," with relatively few cases in the "Yes" category. However, the fraud ratio for "Yes" (3.74%) is noticeably lower compared to "No" (6.05%), indicating that filing a police report might correlate with a reduced likelihood of fraud. This potential relationship suggests that `PoliceReportFiled` could provide valuable predictive insights and should be retained for further analysis.

[20]:
```
# Plot for PoliceReportFiled
print("Plotting PoliceReportFiled over FraudFound_P")
plt.figure(figsize=(8, 6))
sns.countplot(x='PoliceReportFiled', hue='FraudFound_P', data=df,␣
 ↪palette=custom_palette, edgecolor='black')
plt.title("Fraud Found vs PoliceReportFiled (Categorical)")
plt.xlabel("PoliceReportFiled")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Calculate class distribution and fraud ratio for PoliceReportFiled
class_distribution = df.groupby('PoliceReportFiled')['FraudFound_P'].
 ↪value_counts(normalize=False).unstack().fillna(0)
fraud_ratio = df.groupby('PoliceReportFiled')['FraudFound_P'].mean()

# Display class distribution
print("\nClass Distribution for PoliceReportFiled:")
print(class_distribution)

# Display fraud ratio
print("\nFraud Ratio for PoliceReportFiled:")
print(fraud_ratio)
```

```
Plotting PoliceReportFiled over FraudFound_P
```




```
Class Distribution for PoliceReportFiled:
FraudFound_P           0    1
PoliceReportFiled
No                 14085  907
Yes                  412   16

Fraud Ratio for PoliceReportFiled:
PoliceReportFiled
No     0.060499
Yes    0.037383
Name: FraudFound_P, dtype: float64
```

1.3 Conclusion of the EDA for Feature Engineering

After conducting the exploratory data analysis (EDA), we conclude that most of the features are relevant and contribute to explaining the target variable (`FraudFound_P`). However, two features will be removed based on the following insights:

1. **RepNumber**: This numerical variable exhibits very similar patterns across different target values (fraud vs. non-fraud). It does not provide significant discrimination for the prediction task, thus will be removed.

2. **PolicyNumber**: This feature has a high correlation with `Year`, suggesting that it may be influenced by the year and may not add independent value to the model. Additionally, `PolicyNumber` is likely generated randomly based on the policy and does not have direct relevance to the fraud detection task based on contextual understanding.

These features will be removed to improve model performance and prevent redundancy in the dataset.

2 Data Pre-Processing

[21]:
```
# import packages
import pandas as pd
import numpy as np
import seaborn as sns
from sklearn.preprocessing import LabelEncoder, OneHotEncoder, StandardScaler
from sklearn.model_selection import train_test_split, cross_val_score,␣
↪RepeatedStratifiedKFold, GridSearchCV
from sklearn.metrics import classification_report, f1_score, roc_auc_score,␣
↪confusion_matrix, accuracy_score
from sklearn.metrics import roc_curve, ConfusionMatrixDisplay, recall_score,␣
↪precision_score
from imblearn.over_sampling import SMOTE
import lightgbm as lgb
```

[22]:
```
import numpy as np
import tensorflow as tf
import random

# Set random seeds for reproducibility
np.random.seed(42)
random.seed(42)
tf.random.set_seed(42)

# If using scikit-learn models
from sklearn.utils import check_random_state
check_random_state(42)
```

[22]:
```
RandomState(MT19937) at 0x297239E40
```

[23]:
```
# set pd to display full output
# pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)
```

[24]:
```
df.head()
```

[24]:
```
  Month  WeekOfMonth  DayOfWeek    Make AccidentArea DayOfWeekClaimed  \
0   Dec            5  Wednesday  Honda        Urban          Tuesday
```

```
1   Jan            3  Wednesday   Honda       Urban          Monday
2   Oct            5     Friday   Honda       Urban        Thursday
3   Jun            2   Saturday  Toyota       Rural          Friday
4   Jan            5     Monday   Honda       Urban         Tuesday

  MonthClaimed  WeekOfMonthClaimed     Sex MaritalStatus  Age         Fault  \
0          Jan                   1  Female        Single   21  Policy Holder
1          Jan                   4    Male        Single   34  Policy Holder
2          Nov                   2    Male       Married   47  Policy Holder
3          Jul                   1    Male       Married   65    Third Party
4          Feb                   2  Female        Single   27    Third Party

          PolicyType VehicleCategory     VehiclePrice  FraudFound_P  \
0  Sport - Liability           Sport  more than 69000             0
1  Sport - Collision           Sport  more than 69000             0
2  Sport - Collision           Sport  more than 69000             0
3  Sedan - Liability           Sport   20000 to 29000             0
4  Sport - Collision           Sport  more than 69000             0

   PolicyNumber  RepNumber  Deductible  DriverRating Days_Policy_Accident  \
0             1         12         300             1         more than 30
1             2         15         400             4         more than 30
2             3          7         400             3         more than 30
3             4          4         400             2         more than 30
4             5          3         400             1         more than 30

  Days_Policy_Claim PastNumberOfClaims AgeOfVehicle AgeOfPolicyHolder  \
0      more than 30               none      3 years          26 to 30
1      more than 30               none      6 years          31 to 35
2      more than 30                  1      7 years          41 to 50
3      more than 30                  1  more than 7          51 to 65
4      more than 30               none      5 years          31 to 35

  PoliceReportFiled WitnessPresent AgentType NumberOfSuppliments  \
0                No             No  External                none
1               Yes             No  External                none
2                No             No  External                none
3               Yes             No  External         more than 5
4                No             No  External                none

  AddressChange_Claim NumberOfCars  Year BasePolicy
0              1 year       3 to 4  1994  Liability
1           no change    1 vehicle  1994  Collision
2           no change    1 vehicle  1994  Collision
3           no change    1 vehicle  1994  Liability
4           no change    1 vehicle  1994  Collision
```

[25]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15420 entries, 0 to 15419
Data columns (total 33 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Month                 15420 non-null  object
 1   WeekOfMonth           15420 non-null  int64
 2   DayOfWeek             15420 non-null  object
 3   Make                  15420 non-null  object
 4   AccidentArea          15420 non-null  object
 5   DayOfWeekClaimed      15420 non-null  object
 6   MonthClaimed          15420 non-null  object
 7   WeekOfMonthClaimed    15420 non-null  int64
 8   Sex                   15420 non-null  object
 9   MaritalStatus         15420 non-null  object
 10  Age                   15420 non-null  int64
 11  Fault                 15420 non-null  object
 12  PolicyType            15420 non-null  object
 13  VehicleCategory       15420 non-null  object
 14  VehiclePrice          15420 non-null  object
 15  FraudFound_P          15420 non-null  int64
 16  PolicyNumber          15420 non-null  int64
 17  RepNumber             15420 non-null  int64
 18  Deductible            15420 non-null  int64
 19  DriverRating          15420 non-null  int64
 20  Days_Policy_Accident  15420 non-null  object
 21  Days_Policy_Claim     15420 non-null  object
 22  PastNumberOfClaims    15420 non-null  object
 23  AgeOfVehicle          15420 non-null  object
 24  AgeOfPolicyHolder     15420 non-null  object
 25  PoliceReportFiled     15420 non-null  object
 26  WitnessPresent        15420 non-null  object
 27  AgentType             15420 non-null  object
 28  NumberOfSuppliments   15420 non-null  object
 29  AddressChange_Claim   15420 non-null  object
 30  NumberOfCars          15420 non-null  object
 31  Year                  15420 non-null  int64
 32  BasePolicy            15420 non-null  object
dtypes: int64(9), object(24)
memory usage: 3.9+ MB
```

[26]:
```
#check missing value
df.isnull().sum()
```

```
[26]: Month                   0
      WeekOfMonth             0
      DayOfWeek               0
      Make                    0
      AccidentArea            0
      DayOfWeekClaimed        0
      MonthClaimed            0
      WeekOfMonthClaimed      0
      Sex                     0
      MaritalStatus           0
      Age                     0
      Fault                   0
      PolicyType              0
      VehicleCategory         0
      VehiclePrice            0
      FraudFound_P            0
      PolicyNumber            0
      RepNumber               0
      Deductible              0
      DriverRating            0
      Days_Policy_Accident    0
      Days_Policy_Claim       0
      PastNumberOfClaims      0
      AgeOfVehicle            0
      AgeOfPolicyHolder       0
      PoliceReportFiled       0
      WitnessPresent          0
      AgentType               0
      NumberOfSuppliments     0
      AddressChange_Claim     0
      NumberOfCars            0
      Year                    0
      BasePolicy              0
      dtype: int64
```

[27]:
```
#check for unique values in each column
for column in df:
    if column != 'PolicyNumber':
        print(column)
        print(sorted(df[column].unique()), "\n")
```

```
Month
['Apr', 'Aug', 'Dec', 'Feb', 'Jan', 'Jul', 'Jun', 'Mar', 'May', 'Nov', 'Oct',
'Sep']

WeekOfMonth
[1, 2, 3, 4, 5]
```

```
DayOfWeek
['Friday', 'Monday', 'Saturday', 'Sunday', 'Thursday', 'Tuesday', 'Wednesday']

Make
['Accura', 'BMW', 'Chevrolet', 'Dodge', 'Ferrari', 'Ford', 'Honda', 'Jaguar',
'Lexus', 'Mazda', 'Mecedes', 'Mercury', 'Nisson', 'Pontiac', 'Porche', 'Saab',
'Saturn', 'Toyota', 'VW']

AccidentArea
['Rural', 'Urban']

DayOfWeekClaimed
['0', 'Friday', 'Monday', 'Saturday', 'Sunday', 'Thursday', 'Tuesday',
'Wednesday']

MonthClaimed
['0', 'Apr', 'Aug', 'Dec', 'Feb', 'Jan', 'Jul', 'Jun', 'Mar', 'May', 'Nov',
'Oct', 'Sep']

WeekOfMonthClaimed
[1, 2, 3, 4, 5]

Sex
['Female', 'Male']

MaritalStatus
['Divorced', 'Married', 'Single', 'Widow']

Age
[0, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34,
35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54,
55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74,
75, 76, 77, 78, 79, 80]

Fault
['Policy Holder', 'Third Party']

PolicyType
['Sedan - All Perils', 'Sedan - Collision', 'Sedan - Liability', 'Sport - All
Perils', 'Sport - Collision', 'Sport - Liability', 'Utility - All Perils',
'Utility - Collision', 'Utility - Liability']

VehicleCategory
['Sedan', 'Sport', 'Utility']

VehiclePrice
['20000 to 29000', '30000 to 39000', '40000 to 59000', '60000 to 69000', 'less
```

```
than 20000', 'more than 69000']

FraudFound_P
[0, 1]

RepNumber
[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16]

Deductible
[300, 400, 500, 700]

DriverRating
[1, 2, 3, 4]

Days_Policy_Accident
['1 to 7', '15 to 30', '8 to 15', 'more than 30', 'none']

Days_Policy_Claim
['15 to 30', '8 to 15', 'more than 30', 'none']

PastNumberOfClaims
['1', '2 to 4', 'more than 4', 'none']

AgeOfVehicle
['2 years', '3 years', '4 years', '5 years', '6 years', '7 years', 'more than
7', 'new']

AgeOfPolicyHolder
['16 to 17', '18 to 20', '21 to 25', '26 to 30', '31 to 35', '36 to 40', '41 to
50', '51 to 65', 'over 65']

PoliceReportFiled
['No', 'Yes']

WitnessPresent
['No', 'Yes']

AgentType
['External', 'Internal']

NumberOfSuppliments
['1 to 2', '3 to 5', 'more than 5', 'none']

AddressChange_Claim
['1 year', '2 to 3 years', '4 to 8 years', 'no change', 'under 6 months']

NumberOfCars
['1 vehicle', '2 vehicles', '3 to 4', '5 to 8', 'more than 8']
```

```
Year
[1994, 1995, 1996]

BasePolicy
['All Perils', 'Collision', 'Liability']
```

[28]:
```
# we observe that certain values do not make sense
# 1. df["DayOfWeekClaimed"] == 0
# 2. df["MonthClaimed"] == 0
# 3. df["Age"] == 0

# check point 1 & 2
df[df['DayOfWeekClaimed']=='0']
df[df['MonthClaimed']=='0']
# only one row with point 1 & 2, drop it.
df = df[~(df['MonthClaimed']=='0')]

# check point 3
df[df['Age']==0]
# Since "AgeOfPolicyHolder" is all "16 to 17" for these rows, i set the Age to␣
↪16.5
df['Age'] =df['Age'].replace({0:16.5})
```

[29]:
```
# check distribution of target
fraud_counts = df['FraudFound_P'].value_counts()
print(fraud_counts)
```

```
0    14496
1      923
Name: FraudFound_P, dtype: int64
```

2.1 Pre-Processing Steps

[30]:
```
# Step 1: Drop multiple columns - based on EDA
df = df.drop(columns=['PolicyNumber', 'RepNumber'])
```

[31]:
```
# Step 2: Encoding
# One-hot encoding
one_hot_cols = [
    'Sex', 'MaritalStatus', 'AccidentArea', 'BasePolicy',
    'PoliceReportFiled', 'WitnessPresent', 'AgentType', 'VehicleCategory',
    'Fault'
]
df = pd.get_dummies(df, columns= one_hot_cols, drop_first=True)
```

```python
# Label encoding
# Label encode high-cardinality categorical variables
high_cardinality_cols = [
    'Month', 'WeekOfMonth', 'DayOfWeek', 'Make',
    'DayOfWeekClaimed', 'MonthClaimed', 'WeekOfMonthClaimed',
    'PolicyType'
]
label_enc = LabelEncoder()
for col in high_cardinality_cols:
    df[col] = label_enc.fit_transform(df[col])


# Ordinal encoding for ordinal categorical variables
categorical_mappings = {
    'AddressChange_Claim': {
        'under 6 months': 1, '1 year': 2, '2 to 3 years': 3,
        '4 to 8 years': 4, 'no change': 0
    },
    'NumberOfCars': {
        '1 vehicle': 1, '2 vehicles': 2, '3 to 4': 3,
        '5 to 8': 4, 'more than 8': 5
    },
    'VehiclePrice': {
        'less than 20000': 1, '20000 to 29000': 2, '30000 to 39000': 3,
        '40000 to 59000': 4, '60000 to 69000': 5, 'more than 69000': 6
    },
    'Days_Policy_Accident': {
        'none': 0, '1 to 7' :1, '8 to 15':2, '15 to 30':3, 'more than 30':4
    },
    'Days_Policy_Claim': {
         '8 to 15':1,'15 to 30':2, 'more than 30': 3, 'none':0
    },
    'PastNumberOfClaims': {
        'none': 0, '1': 1, '2 to 4': 2, 'more than 4': 3
    },
    'AgeOfVehicle': {
        'new': 0, '2 years': 2, '3 years': 3, '4 years': 4,
        '5 years': 5, '6 years': 6, '7 years': 7, 'more than 7': 8
    },
    'AgeOfPolicyHolder': {
        '16 to 17': 1, '18 to 20': 2, '21 to 25': 3, '26 to 30': 4,
        '31 to 35': 5, '36 to 40': 6, '41 to 50': 7, '51 to 65': 8,
        'over 65': 9
    },
    'NumberOfSuppliments': {
    'none': 0, '1 to 2': 1, '3 to 5': 2, 'more than 5': 3
    },
```

```
     'Year': {
        1994: 1, 1995: 2, 1996: 3
    },
    'Deductible': {
        300: 1, 400: 2, 500: 3, 700: 4
    }

}

# Apply mappings to the respective columns
for col, mapping in categorical_mappings.items():
    if col in df.columns:
        df[col] = df[col].map(mapping)

df = df.astype("int")
```

[32]:
```
# Step 3: standard scaling

scale_cols = ["Age"]
scaler = StandardScaler()
df[scale_cols] = scaler.fit_transform(df[scale_cols])
```

[33]:
```
df.isnull().sum()
```

[33]:
```
Month                      0
WeekOfMonth                0
DayOfWeek                  0
Make                       0
DayOfWeekClaimed           0
MonthClaimed               0
WeekOfMonthClaimed         0
Age                        0
PolicyType                 0
VehiclePrice               0
FraudFound_P               0
Deductible                 0
DriverRating               0
Days_Policy_Accident       0
Days_Policy_Claim          0
PastNumberOfClaims         0
AgeOfVehicle               0
AgeOfPolicyHolder          0
NumberOfSuppliments        0
AddressChange_Claim        0
NumberOfCars               0
Year                       0
Sex_Male                   0
```

```
MaritalStatus_Married      0
MaritalStatus_Single       0
MaritalStatus_Widow        0
AccidentArea_Urban         0
BasePolicy_Collision       0
BasePolicy_Liability       0
PoliceReportFiled_Yes      0
WitnessPresent_Yes         0
AgentType_Internal         0
VehicleCategory_Sport      0
VehicleCategory_Utility    0
Fault_Third Party          0
dtype: int64
```

[34]:

```
df.head()
```

[34]:

```
   Month  WeekOfMonth  DayOfWeek  Make  DayOfWeekClaimed  MonthClaimed  \
0      2            4          6     6                 5             4
1      4            2          6     6                 1             4
2     10            4          0     6                 4             9
3      6            1          2    17                 0             5
4      4            4          1     6                 5             3

   WeekOfMonthClaimed       Age  PolicyType  VehiclePrice  FraudFound_P  \
0                   0 -1.513552           5             6             0
1                   3 -0.488180           4             6             0
2                   1  0.537191           4             6             0
3                   0  1.956936           2             2             0
4                   1 -1.040303           4             6             0

   Deductible  DriverRating  Days_Policy_Accident  Days_Policy_Claim  \
0           1             1                     4                  3
1           2             4                     4                  3
2           2             3                     4                  3
3           2             2                     4                  3
4           2             1                     4                  3

   PastNumberOfClaims  AgeOfVehicle  AgeOfPolicyHolder  NumberOfSuppliments  \
0                   0             3                  4                    0
1                   0             6                  5                    0
2                   1             7                  7                    0
3                   1             8                  8                    3
4                   0             5                  5                    0

   AddressChange_Claim  NumberOfCars  Year  Sex_Male  MaritalStatus_Married  \
0                    2             3     1         0                      0
1                    0             1     1         1                      0
```

```
2                      0             1     1          1                       1
3                      0             1     1          1                       1
4                      0             1     1          0                       0

   MaritalStatus_Single  MaritalStatus_Widow  AccidentArea_Urban  \
0                     1                    0                   1
1                     1                    0                   1
2                     0                    0                   1
3                     0                    0                   0
4                     1                    0                   1

   BasePolicy_Collision  BasePolicy_Liability  PoliceReportFiled_Yes  \
0                     0                     1                      0
1                     1                     0                      1
2                     1                     0                      0
3                     0                     1                      1
4                     1                     0                      0

   WitnessPresent_Yes  AgentType_Internal  VehicleCategory_Sport  \
0                   0                   0                      1
1                   0                   0                      1
2                   0                   0                      1
3                   0                   0                      1
4                   0                   0                      1

   VehicleCategory_Utility  Fault_Third Party
0                        0                  0
1                        0                  0
2                        0                  0
3                        0                  1
4                        0                  1
```

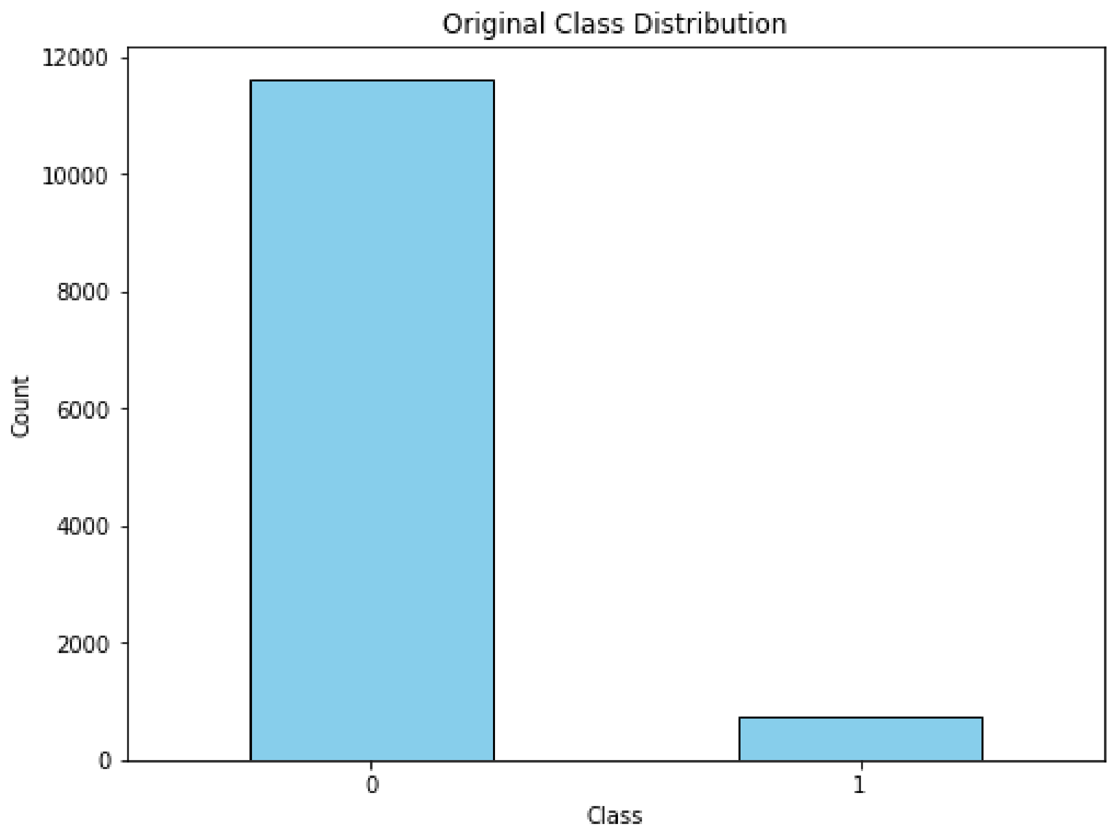
2.2 Split Data

[35]:
```
# Split into features and target
X = df.drop('FraudFound_P', axis=1)  # Features
y = df['FraudFound_P']  # Target
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
```

[36]:
```
import matplotlib.pyplot as plt
# Original distribution before re-sampling
fraud_counts = y_train.value_counts()

# Displaying the class distribution
print("Class Distribution:\n", fraud_counts)
# Plotting the class distribution
```

```
plt.figure(figsize=(8, 6))
fraud_counts.plot(kind='bar', color='skyblue', edgecolor='black')
plt.title('Original Class Distribution')
plt.xlabel('Class')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.show()
```

```
Class Distribution:
 0    11611
1      724
Name: FraudFound_P, dtype: int64
```



2.3 SMOTE Over Sampling

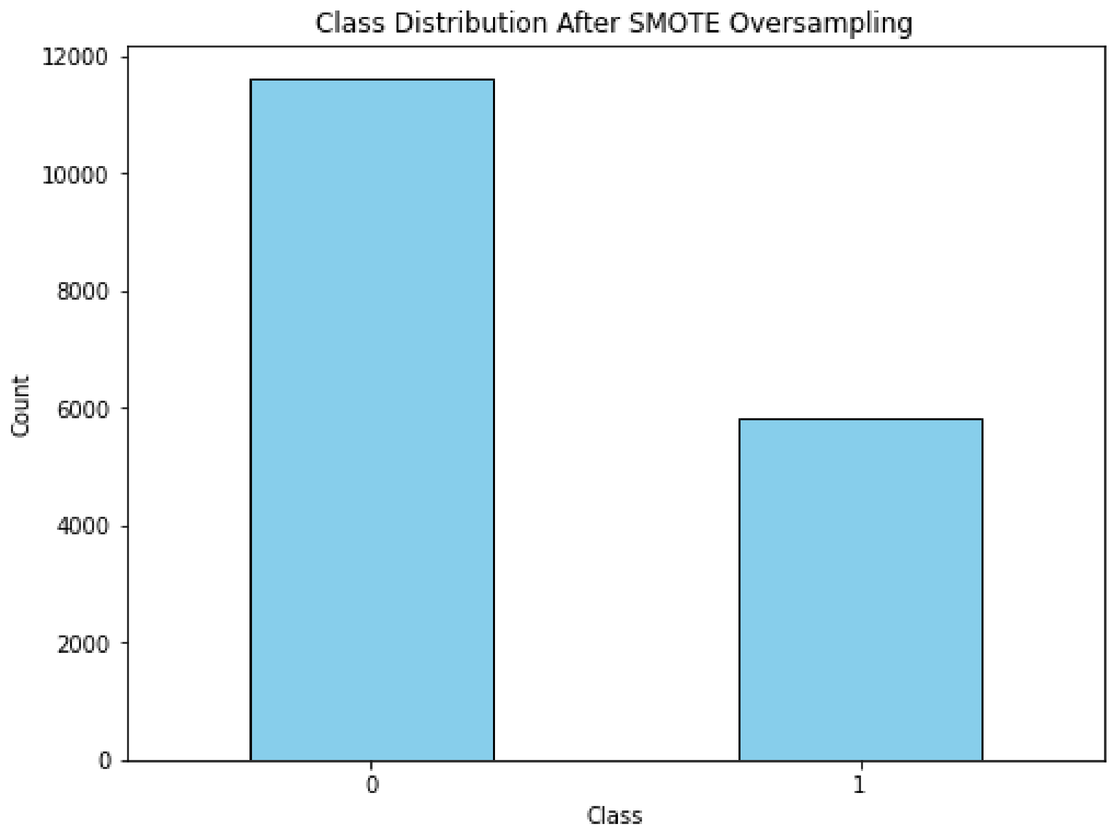
- Upsampled the minority class (1) by generating synthetic samples.
- Increased the minority class size to 1.5 times its original size, leaving the majority class unchanged.

We employ oversampling by increasing the number of minority cases until they reach half of the majority cases, which allows us to address class imbalance effectively without overwhelming the model with synthetic data. This method enhances the model's ability to learn from underrepresented cases while maintaining diversity in the dataset, ultimately leading to more balanced decision-making.

2.3.1 Over Sampling Implementation

[37]:
```python
# Assuming X_train and y_train are defined
oversample = SMOTE(sampling_strategy=0.5)
X_train_over, y_train_over = oversample.fit_resample(X_train, y_train)

# Get the value counts for the target variable after oversampling
y_train_over_counts = y_train_over.value_counts()
# Display the class distribution
print("Class Distribution After SMOTE Oversampling:\n", y_train_over_counts)
print("\nClass Distribution (Percentage):\n", (y_train_over_counts /␣
 ↪y_train_over_counts.sum()) * 100)



# Plot the class distribution
plt.figure(figsize=(8, 6))
y_train_over_counts.plot(kind='bar', color='skyblue', edgecolor='black')
plt.title('Class Distribution After SMOTE Oversampling')
plt.xlabel('Class')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.show()
```

```
Class Distribution After SMOTE Oversampling:
 0    11611
1     5805
Name: FraudFound_P, dtype: int64

Class Distribution (Percentage):
 0    66.668581
1    33.331419
Name: FraudFound_P, dtype: float64
```

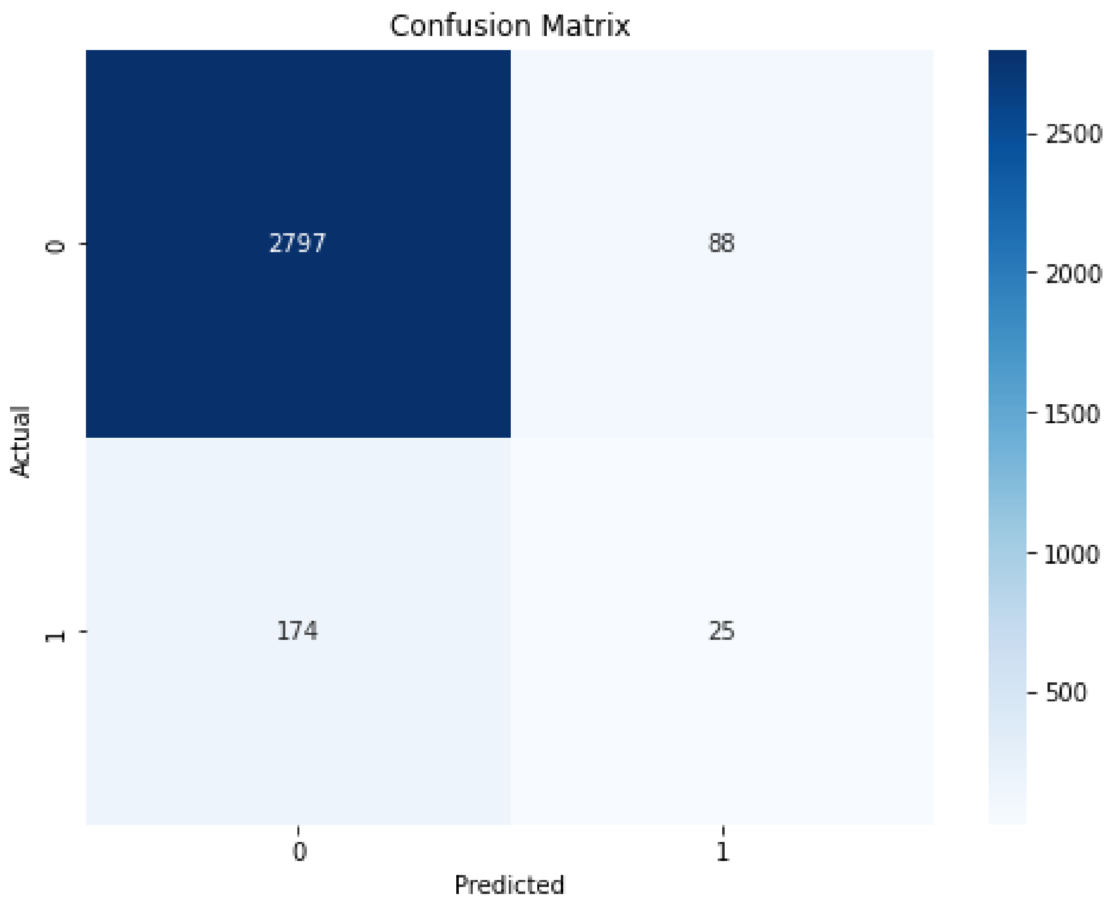


2.3.2 Model Testing for Oversampling Technique

[38]:
```
# Import necessary libraries
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix,␣
↪accuracy_score, recall_score
import matplotlib.pyplot as plt
import seaborn as sns

# Step 2: Train a Random Forest Classifier
rf_model = RandomForestClassifier(random_state=42, n_estimators=100)
rf_model.fit(X_train_over, y_train_over)

# Step 3: Make predictions
y_pred = rf_model.predict(X_test)

# Step 4: Evaluate the model
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

```python
print("Confusion Matrix:")
conf_matrix = confusion_matrix(y_test, y_pred)
print(conf_matrix)

# Plot the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

print("Accuracy Score:")
print(accuracy_score(y_test, y_pred))
print("Recall Score:")
print(recall_score(y_test, y_pred))
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.97      0.96      2885
           1       0.22      0.13      0.16       199

    accuracy                           0.92      3084
   macro avg       0.58      0.55      0.56      3084
weighted avg       0.89      0.92      0.90      3084

Confusion Matrix:
[[2797   88]
 [ 174   25]]
```

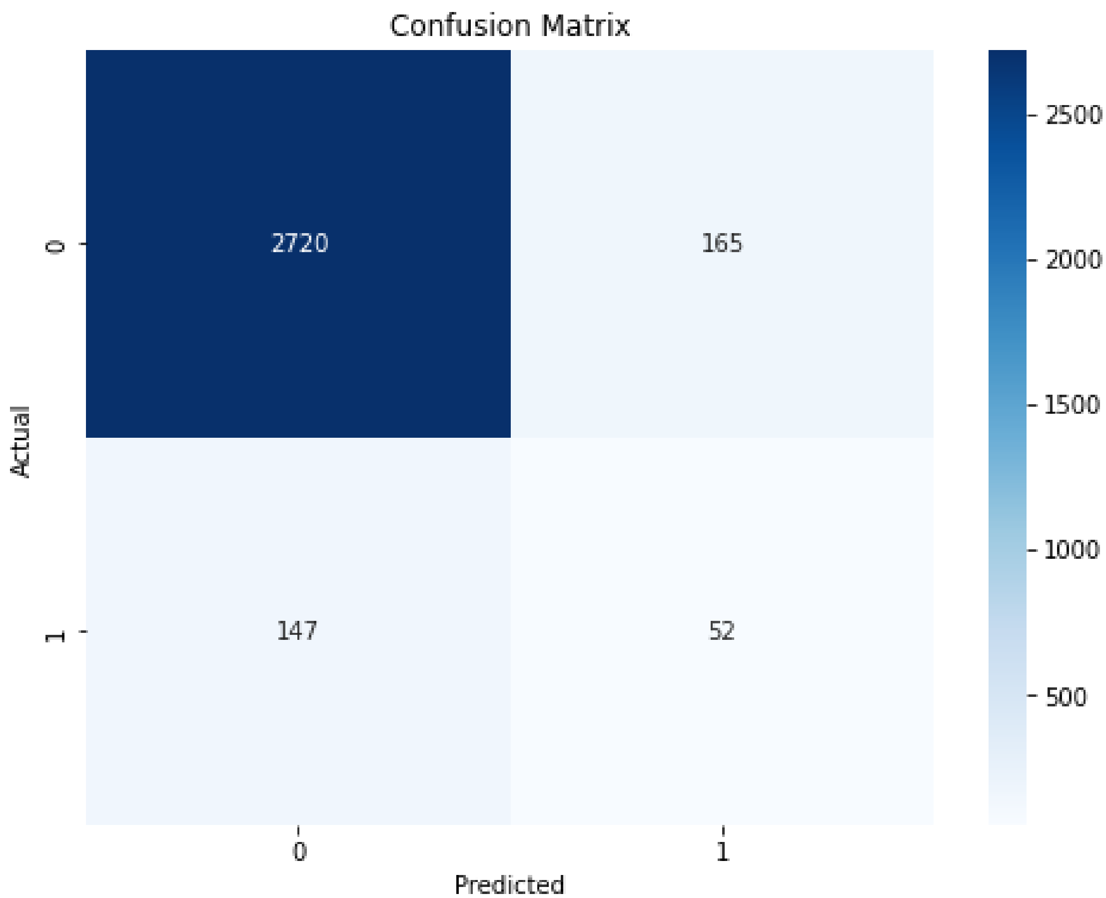



```
Accuracy Score:
0.9150453955901426
Recall Score:
0.12562814070351758
```

[39]:
```
# Step 1: Initialize and Train the LightGBM model
lgb_model = lgb.LGBMClassifier(random_state=42, n_estimators=100,␣
↪learning_rate=0.1, is_unbalance=True)
lgb_model.fit(X_train_over, y_train_over)

# Step 2: Make predictions
y_pred = lgb_model.predict(X_test)

# Step 3: Evaluate the model
print("Classification Report:")
print(classification_report(y_test, y_pred))

print("Confusion Matrix:")
conf_matrix = confusion_matrix(y_test, y_pred)
```

```python
print(conf_matrix)

# Plot the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

print("Accuracy Score:")
print(accuracy_score(y_test, y_pred))
print("Recall Score:")
print(recall_score(y_test, y_pred))
```

```
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Info] Number of positive: 5805, number of negative: 11611
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.005466 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 424
[LightGBM] [Info] Number of data points in the train set: 17416, number of used
features: 34
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.333314 -> initscore=-0.693233
[LightGBM] [Info] Start training from score -0.693233
Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.94      0.95      2885
           1       0.24      0.26      0.25       199

    accuracy                           0.90      3084
   macro avg       0.59      0.60      0.60      3084
weighted avg       0.90      0.90      0.90      3084

Confusion Matrix:
[[2720  165]
 [ 147   52]]
```




```
Accuracy Score:
0.8988326848249028
Recall Score:
0.2613065326633166
```

3 Traditional Models

These models offer straightforward algorithms for handling the structured data in our dataset: - Logistic Regression - K-Nearest Neighbors - Support Vector Machine - Naive Bayes - Decision Tree

3.1 Model Evaluation

[40]:
```python
# import packages
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
```

```
from sklearn.metrics import classification_report, confusion_matrix,␣
↪accuracy_score, recall_score
```

```
[41]: def evaluate_model(model, X_train, y_train, X_test, y_test, model_name):
    """
    Train and evaluate a machine learning model

    Parameters:
    - model: The machine learning model to train
    - X_train, y_train: Training data
    - X_test, y_test: Test data
    - model_name: Name of the model for printing

    Returns:
    - Dictionary with evaluation metrics
    """
    # Fit the model
    model.fit(X_train, y_train)

    # Make predictions
    y_pred = model.predict(X_test)

    # Print results
    print(f"\nModel Evaluation - {model_name}")
    print("=" * 40)

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

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

    # Plot confusion matrix
    plt.figure(figsize=(8, 6))
    sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')
    plt.title(f"{model_name} Confusion Matrix")
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.tight_layout()
    plt.show()

    # Calculate and print metrics
    accuracy = accuracy_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)
```

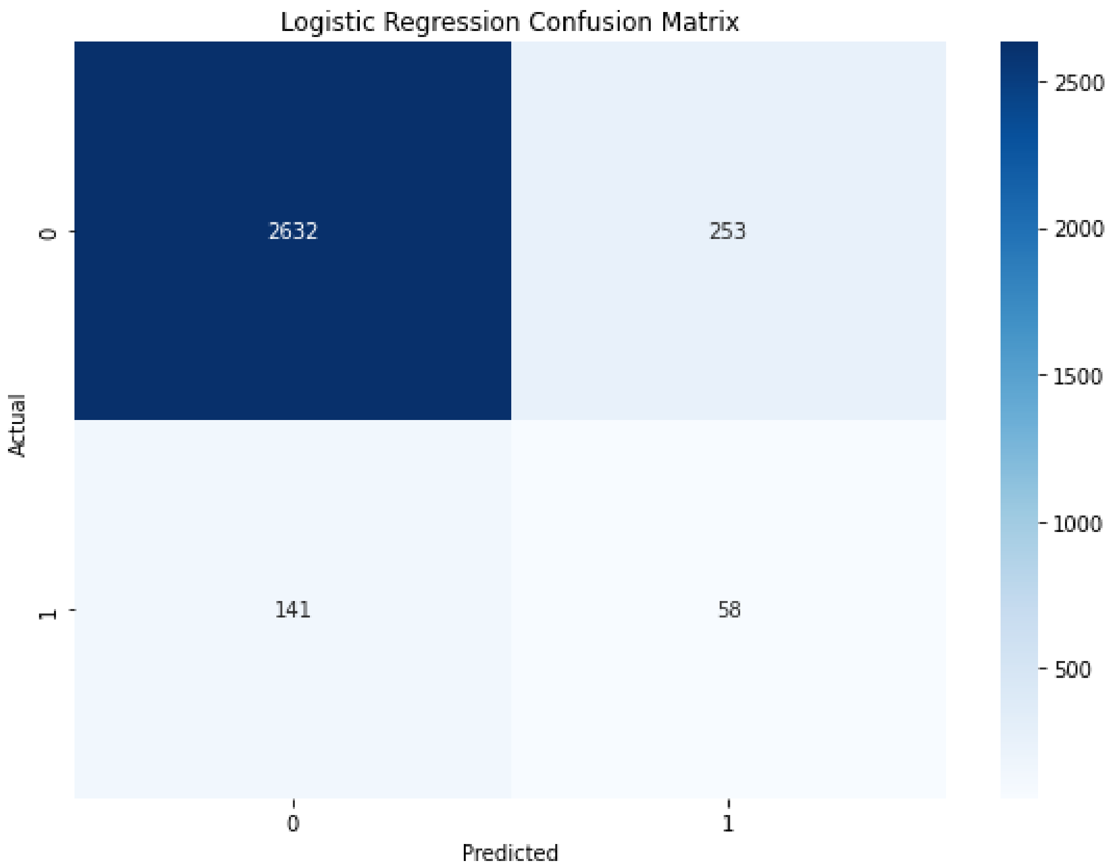
```
    roc_auc = roc_auc_score(y_test, y_pred, multi_class='ovr',␣
↪average='weighted')

    print(f"\nAccuracy Score: {accuracy}")
    print(f"Recall Score: {recall}")
    print(f"Precision Score: {precision}")
    print(f"F1 Score: {f1}")
    print(f"ROC AUC Score: {roc_auc}")

    return {
        'model': model_name,
        'accuracy': accuracy,
        'recall': recall,
        'precision': precision,
        'f1_score': f1,
        'roc_auc_score': roc_auc
    }
```

[42]:
```
def run_classifiers(X_train_over, y_train_over, X_test, y_test):
    """
    Run multiple classifiers on oversampled training data

    Parameters:
    - X_train_over, y_train_over: Oversampled training data
    - X_test, y_test: Test data

    Returns:
    - List of evaluation results
    """
    # Initialize models
    models = [
        (LogisticRegression(random_state=42, max_iter=1000), "Logistic␣
↪Regression"),
        (KNeighborsClassifier(n_neighbors=5), "K-Nearest Neighbors"),
        (SVC(random_state=42), "Support Vector Machine"),
        (GaussianNB(), "Naive Bayes"),
        (DecisionTreeClassifier(random_state=42), "Decision Tree")
    ]

    # Results storage
    all_results = []

    # Run each model
    for model, model_name in models:
        result = evaluate_model(
            model,
            X_train_over, y_train_over,
```

```python
            X_test, y_test,
            model_name
        )
        all_results.append(result)

    return all_results
```

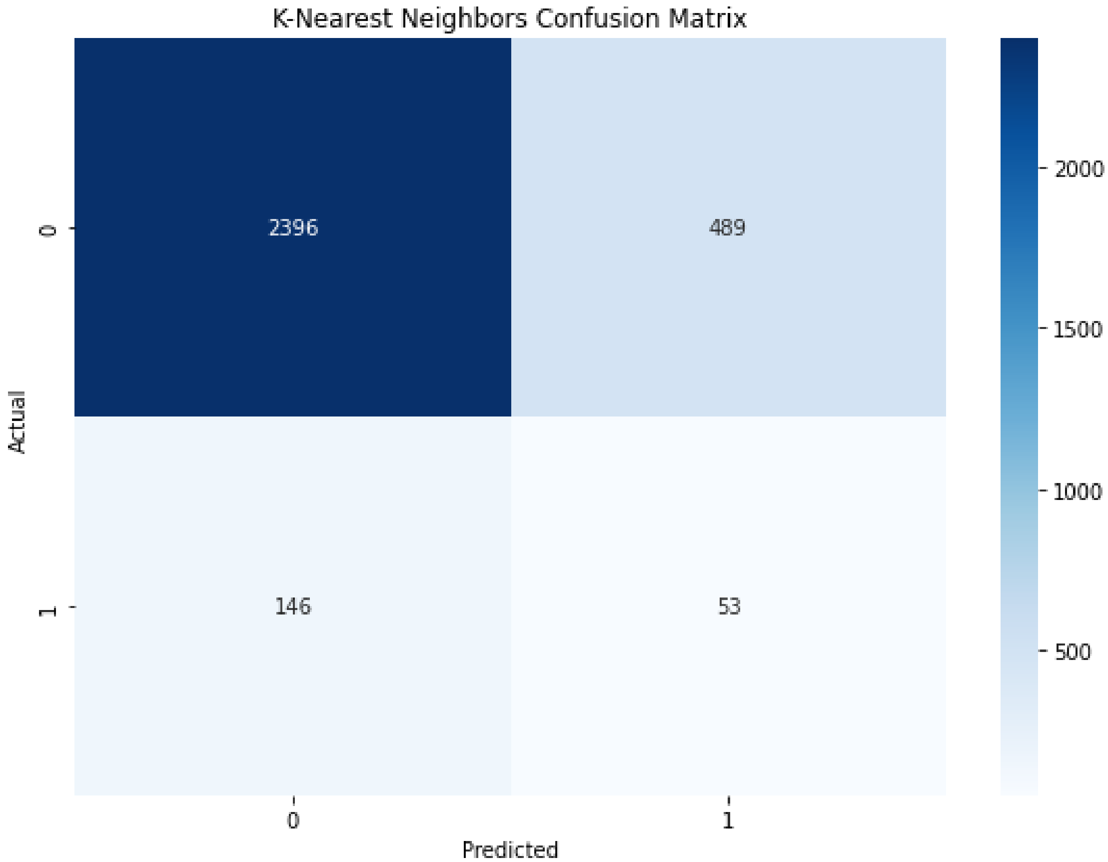
[43]:
```python
# model running
def main():
    """
    Main function to run the model evaluation pipeline
    """

    # Run classifiers
    results = run_classifiers(
        X_train_over, y_train_over,
        X_test, y_test
    )

    # Create a summary DataFrame of results
    results_df = pd.DataFrame(results)
    print("\nResults Summary:")
    print(results_df)

if __name__ == "__main__":
    main()
```

```
Model Evaluation - Logistic Regression
========================================

Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.91      0.93      2885
           1       0.19      0.29      0.23       199

    accuracy                           0.87      3084
   macro avg       0.57      0.60      0.58      3084
weighted avg       0.90      0.87      0.89      3084


Confusion Matrix:
[[2632  253]
 [ 141   58]]
```



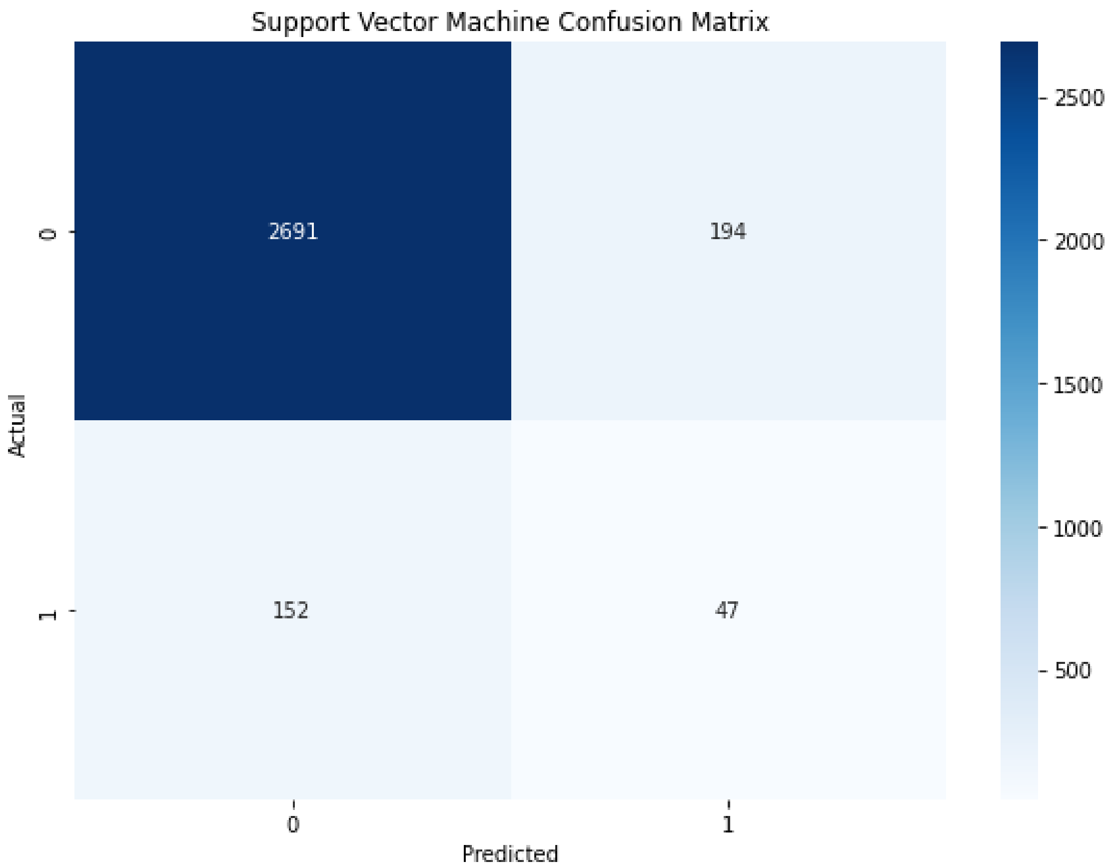

```
Accuracy Score: 0.8722438391699092
Recall Score: 0.2914572864321608
Precision Score: 0.1864951768488746
F1 Score: 0.22745098039215686
ROC AUC Score: 0.6018811562143472

Model Evaluation - K-Nearest Neighbors
========================================

Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.83      0.88      2885
           1       0.10      0.27      0.14       199

    accuracy                           0.79      3084
   macro avg       0.52      0.55      0.51      3084
weighted avg       0.89      0.79      0.84      3084
```

```
Confusion Matrix:
[[2396  489]
 [ 146   53]]
```



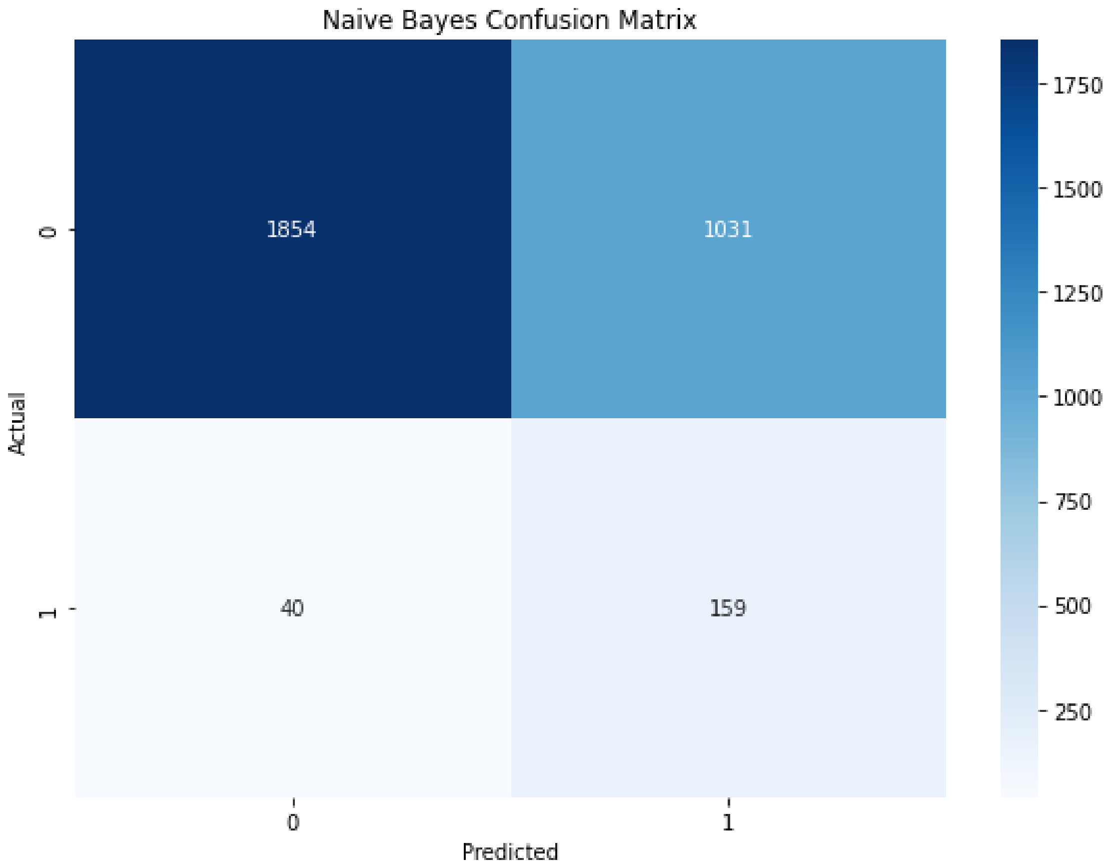

```
Accuracy Score: 0.7940985732814526
Recall Score: 0.2663316582914573
Precision Score: 0.09778597785977859
F1 Score: 0.14304993252361672
ROC AUC Score: 0.5484171289724183

Model Evaluation - Support Vector Machine
========================================

Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.93      0.94      2885
           1       0.20      0.24      0.21       199
```

```
    accuracy                           0.89      3084
   macro avg       0.57      0.58      0.58      3084
weighted avg       0.90      0.89      0.89      3084


Confusion Matrix:
[[2691  194]
 [ 152   47]]
```



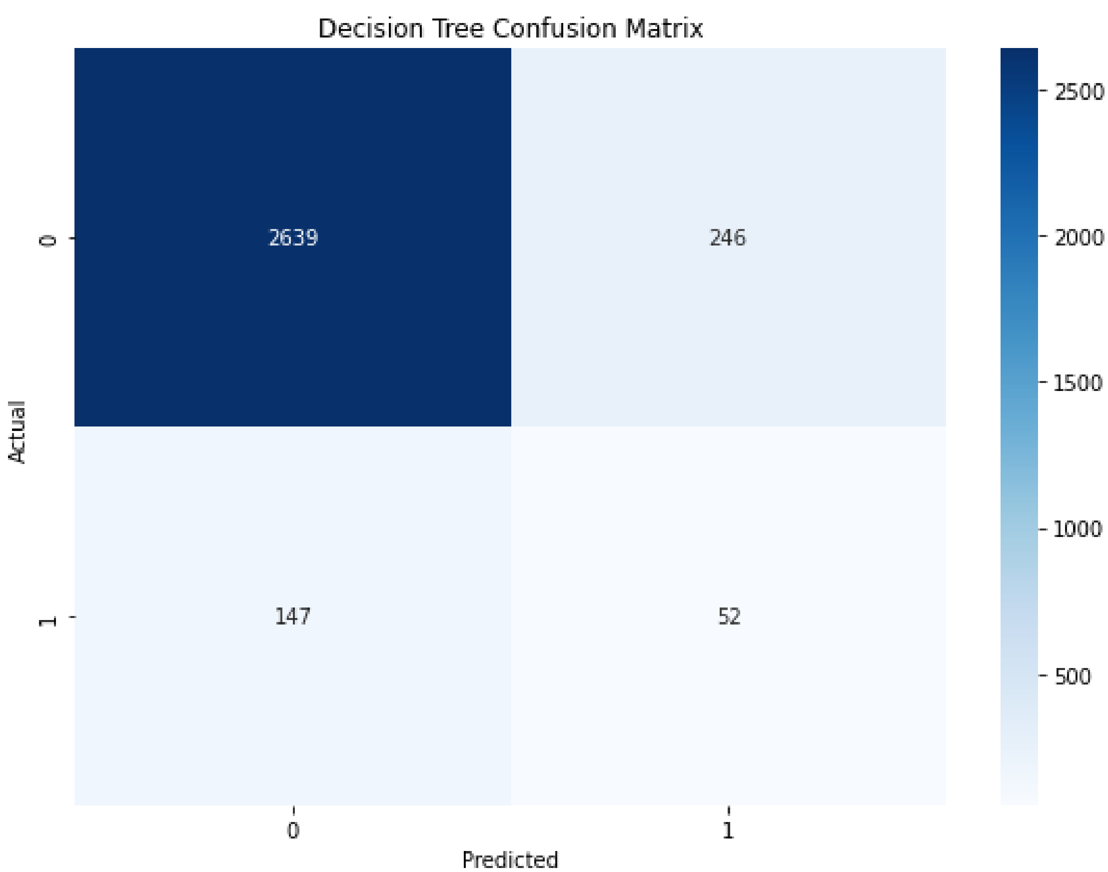

```
Accuracy Score: 0.8878080415045395
Recall Score: 0.23618090452261306
Precision Score: 0.1950207468879668
F1 Score: 0.21363636363636362
ROC AUC Score: 0.5844682685524677

Model Evaluation - Naive Bayes
========================================
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.64      0.78      2885
           1       0.13      0.80      0.23       199

    accuracy                           0.65      3084
   macro avg       0.56      0.72      0.50      3084
weighted avg       0.92      0.65      0.74      3084


Confusion Matrix:
[[1854 1031]
 [  40  159]]
```




```
Accuracy Score: 0.6527237354085603
Recall Score: 0.7989949748743719
Precision Score: 0.13361344537815126
F1 Score: 0.22894168466522677
```

```
ROC AUC Score: 0.720814645149491

Model Evaluation - Decision Tree
========================================

Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.91      0.93      2885
           1       0.17      0.26      0.21       199

    accuracy                           0.87      3084
   macro avg       0.56      0.59      0.57      3084
weighted avg       0.90      0.87      0.88      3084


Confusion Matrix:
[[2639  246]
 [ 147   52]]
```



```
Accuracy Score: 0.872568093385214
Recall Score: 0.2613065326633166
Precision Score: 0.174496644295302
F1 Score: 0.20925553319919518
ROC AUC Score: 0.5880189509070483

Results Summary:
                    model  accuracy    recall  precision  f1_score  \
0     Logistic Regression  0.872244  0.291457   0.186495  0.227451
1     K-Nearest Neighbors  0.794099  0.266332   0.097786  0.143050
2  Support Vector Machine  0.887808  0.236181   0.195021  0.213636
3             Naive Bayes  0.652724  0.798995   0.133613  0.228942
4           Decision Tree  0.872568  0.261307   0.174497  0.209256

   roc_auc_score
0       0.601881
1       0.548417
2       0.584468
3       0.720815
4       0.588019
```

Traditional Results Summary:

Model	Accuracy	Recall	Precision	F1 Score	ROC AUC Score
Logistic Regression	0.8722	0.2915	0.1865	0.2275	0.6019
K-Nearest Neighbors	0.7941	0.2663	0.0978	0.1431	0.5484
Support Vector Machine	0.8878	0.2362	0.1950	0.2136	0.5845
Naive Bayes	0.6527	0.7990	0.1336	0.2289	0.7208
Decision Tree	0.8726	0.2613	0.1745	0.2093	0.5880

[44]:
```
import pandas as pd

# Creating a DataFrame with the provided data
data = {
    'model': ['Logistic Regression', 'K-Nearest Neighbors', 'Support Vector␣
 ↪Machine', 'Naive Bayes', 'Decision Tree'],
    'accuracy': [0.872244, 0.794099, 0.887808, 0.652724, 0.872568],
    'recall': [0.291457, 0.266332, 0.236181, 0.798995, 0.261307],
    'precision': [0.186495, 0.097786, 0.195021, 0.133613, 0.174497],
    'f1_score': [0.227451, 0.143050, 0.213636, 0.228942, 0.209256],
    'roc_auc_score': [0.601881, 0.548417, 0.584468, 0.720815, 0.588019]
}

df = pd.DataFrame(data)
```

```python
# Calculating the average for each metric
averages = df.mean(numeric_only=True)

# Formatting the averages to four decimal places
formatted_averages = averages.apply(lambda x: f"{x:.4f}")

# Creating a DataFrame to display the results
average_df = pd.DataFrame(formatted_averages).T
average_df.index = ['traditional_model_average']

# Printing the formatted averages
print(average_df)
```

```
                          accuracy  recall precision f1_score roc_auc_score
traditional_model_average   0.8159  0.3709    0.1575   0.2045        0.6087
```

3.2 Feature Importance

In this section, we have generated plots of feature importance for models including Decision Tree, Random Forest, and Logistic Regression.

[45]:
```python
import joblib
import os
```

[46]:
```python
# extract and display feature importance from saved models using feature names
def extract_feature_importance(models_directory, X_train_over):
    feature_importance_results = []

    # Iterate through all files in the given directory
    for filename in os.listdir(models_directory):
        if filename.endswith(".pkl") and "Oversampled" in filename:
            model_path = os.path.join(models_directory, filename)
            model = joblib.load(model_path)

            # Extract feature names
            feature_names = X_train_over.columns

            # Check if the model has feature_importances_ attribute
            if hasattr(model, "feature_importances_"):
                feature_importances = model.feature_importances_
                feature_importance_results.append({
                    'model': filename,
                    'feature_importances': feature_importances,
                    'feature_names': feature_names
                })
            # Check if the model is Logistic Regression
            elif isinstance(model, LogisticRegression):
                feature_importances = np.abs(model.coef_[0])
```

```
                feature_importance_results.append({
                    'model': filename,
                    'feature_importances': feature_importances,
                    'feature_names': feature_names
                })

    # Create a summary DataFrame
    summary_data = []
    for result in feature_importance_results:
        for i, importance in enumerate(result['feature_importances']):
            summary_data.append({
                'model': result['model'],
                'feature': result['feature_names'][i],
                'importance': importance
            })

    feature_importance_df = pd.DataFrame(summary_data)
    return feature_importance_df
```

[47]:
```
# visualizations of feature importance
def plot_feature_importance(feature_importance_df):
    plt.figure(figsize=(12, 6))
    sns.barplot(data=feature_importance_df,
                x='importance',
                y='feature',
                hue='model',
                ci=None)
    plt.title('Feature Importance by Model (Oversampled Data)')
    plt.xlabel('Importance')
    plt.ylabel('Feature')
    plt.tight_layout()
    plt.show()

# Set display options for pandas
pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)
```

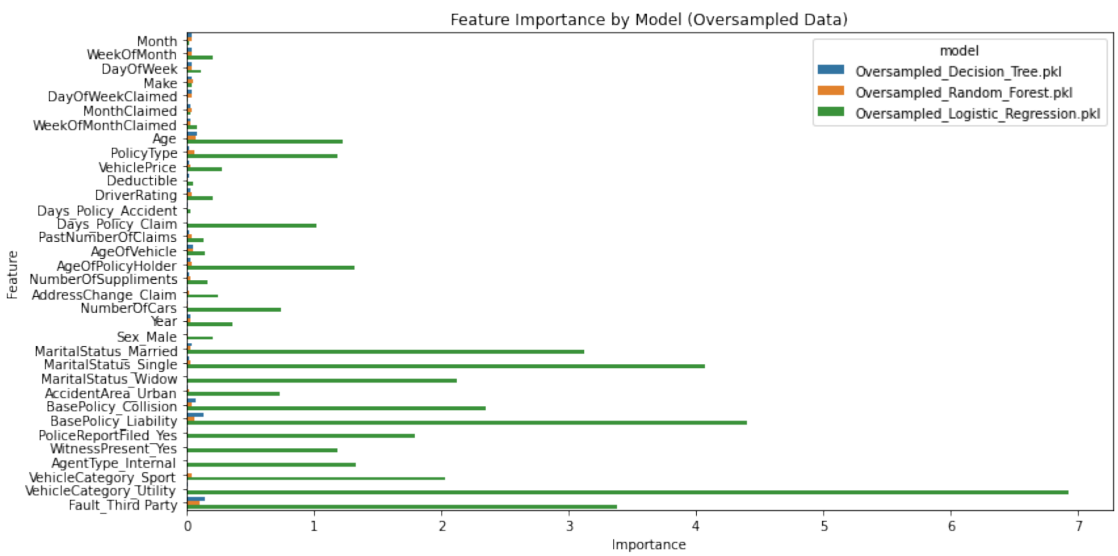
[48]:
```
# main function to run the feature importance analysis.
def main():
    models_directory = "."  # Current directory, modify as needed

    try:
        feature_importance_df = extract_feature_importance(models_directory,␣
 ↪X_train_over)
        if not feature_importance_df.empty:
            print("\nFeature Importances:")
            print(feature_importance_df)
```

```python
            # Create visualization
            plot_feature_importance(feature_importance_df)
        else:
            print("No oversampled models with feature importance found.")
    except NameError:
        print("Please load your oversampled data (X_train_over) before running␣
↪the analysis.")

if __name__ == "__main__":
    main()
```

```
Feature Importances:
                                   model                 feature  importance
0          Oversampled_Decision_Tree.pkl                   Month    0.043935
1          Oversampled_Decision_Tree.pkl             WeekOfMonth    0.036581
2          Oversampled_Decision_Tree.pkl               DayOfWeek    0.036993
3          Oversampled_Decision_Tree.pkl                    Make    0.034057
4          Oversampled_Decision_Tree.pkl        DayOfWeekClaimed    0.035760
5          Oversampled_Decision_Tree.pkl            MonthClaimed    0.032351
6          Oversampled_Decision_Tree.pkl      WeekOfMonthClaimed    0.025204
7          Oversampled_Decision_Tree.pkl                     Age    0.075679
8          Oversampled_Decision_Tree.pkl              PolicyType    0.015492
9          Oversampled_Decision_Tree.pkl            VehiclePrice    0.018270
10         Oversampled_Decision_Tree.pkl              Deductible    0.018087
11         Oversampled_Decision_Tree.pkl            DriverRating    0.031167
12         Oversampled_Decision_Tree.pkl    Days_Policy_Accident    0.003240
13         Oversampled_Decision_Tree.pkl       Days_Policy_Claim    0.001691
14         Oversampled_Decision_Tree.pkl      PastNumberOfClaims    0.015602
15         Oversampled_Decision_Tree.pkl            AgeOfVehicle    0.050999
16         Oversampled_Decision_Tree.pkl       AgeOfPolicyHolder    0.029426
17         Oversampled_Decision_Tree.pkl    NumberOfSuppliments    0.021032
18         Oversampled_Decision_Tree.pkl     AddressChange_Claim    0.007396
19         Oversampled_Decision_Tree.pkl            NumberOfCars    0.003802
20         Oversampled_Decision_Tree.pkl                    Year    0.026655
21         Oversampled_Decision_Tree.pkl                Sex_Male    0.005667
22         Oversampled_Decision_Tree.pkl   MaritalStatus_Married    0.041889
23         Oversampled_Decision_Tree.pkl    MaritalStatus_Single    0.015936
24         Oversampled_Decision_Tree.pkl     MaritalStatus_Widow    0.000962
25         Oversampled_Decision_Tree.pkl      AccidentArea_Urban    0.012002
26         Oversampled_Decision_Tree.pkl    BasePolicy_Collision    0.068442
27         Oversampled_Decision_Tree.pkl    BasePolicy_Liability    0.136304
28         Oversampled_Decision_Tree.pkl   PoliceReportFiled_Yes    0.003450
29         Oversampled_Decision_Tree.pkl      WitnessPresent_Yes    0.000000
30         Oversampled_Decision_Tree.pkl      AgentType_Internal    0.000064
31         Oversampled_Decision_Tree.pkl   VehicleCategory_Sport    0.001720
```

32	Oversampled_Decision_Tree.pkl	VehicleCategory_Utility	0.003561
33	Oversampled_Decision_Tree.pkl	Fault_Third Party	0.146585
34	Oversampled_Random_Forest.pkl	Month	0.042241
35	Oversampled_Random_Forest.pkl	WeekOfMonth	0.035399
36	Oversampled_Random_Forest.pkl	DayOfWeek	0.039721
37	Oversampled_Random_Forest.pkl	Make	0.045109
38	Oversampled_Random_Forest.pkl	DayOfWeekClaimed	0.035434
39	Oversampled_Random_Forest.pkl	MonthClaimed	0.042777
40	Oversampled_Random_Forest.pkl	WeekOfMonthClaimed	0.031215
41	Oversampled_Random_Forest.pkl	Age	0.066052
42	Oversampled_Random_Forest.pkl	PolicyType	0.060255
43	Oversampled_Random_Forest.pkl	VehiclePrice	0.026933
44	Oversampled_Random_Forest.pkl	Deductible	0.008157
45	Oversampled_Random_Forest.pkl	DriverRating	0.037808
46	Oversampled_Random_Forest.pkl	Days_Policy_Accident	0.001919
47	Oversampled_Random_Forest.pkl	Days_Policy_Claim	0.001823
48	Oversampled_Random_Forest.pkl	PastNumberOfClaims	0.035747
49	Oversampled_Random_Forest.pkl	AgeOfVehicle	0.045013
50	Oversampled_Random_Forest.pkl	AgeOfPolicyHolder	0.036601
51	Oversampled_Random_Forest.pkl	NumberOfSuppliments	0.028160
52	Oversampled_Random_Forest.pkl	AddressChange_Claim	0.014211
53	Oversampled_Random_Forest.pkl	NumberOfCars	0.006438
54	Oversampled_Random_Forest.pkl	Year	0.032606
55	Oversampled_Random_Forest.pkl	Sex_Male	0.008958
56	Oversampled_Random_Forest.pkl	MaritalStatus_Married	0.029631
57	Oversampled_Random_Forest.pkl	MaritalStatus_Single	0.025142
58	Oversampled_Random_Forest.pkl	MaritalStatus_Widow	0.000390
59	Oversampled_Random_Forest.pkl	AccidentArea_Urban	0.017128
60	Oversampled_Random_Forest.pkl	BasePolicy_Collision	0.037911
61	Oversampled_Random_Forest.pkl	BasePolicy_Liability	0.063012
62	Oversampled_Random_Forest.pkl	PoliceReportFiled_Yes	0.003180
63	Oversampled_Random_Forest.pkl	WitnessPresent_Yes	0.000358
64	Oversampled_Random_Forest.pkl	AgentType_Internal	0.000423
65	Oversampled_Random_Forest.pkl	VehicleCategory_Sport	0.034645
66	Oversampled_Random_Forest.pkl	VehicleCategory_Utility	0.002456
67	Oversampled_Random_Forest.pkl	Fault_Third Party	0.103145
68	Oversampled_Logistic_Regression.pkl	Month	0.018059
69	Oversampled_Logistic_Regression.pkl	WeekOfMonth	0.204388
70	Oversampled_Logistic_Regression.pkl	DayOfWeek	0.115209
71	Oversampled_Logistic_Regression.pkl	Make	0.039670
72	Oversampled_Logistic_Regression.pkl	DayOfWeekClaimed	0.008431
73	Oversampled_Logistic_Regression.pkl	MonthClaimed	0.028801
74	Oversampled_Logistic_Regression.pkl	WeekOfMonthClaimed	0.078156
75	Oversampled_Logistic_Regression.pkl	Age	1.225379
76	Oversampled_Logistic_Regression.pkl	PolicyType	1.186240
77	Oversampled_Logistic_Regression.pkl	VehiclePrice	0.281262
78	Oversampled_Logistic_Regression.pkl	Deductible	0.047063
79	Oversampled_Logistic_Regression.pkl	DriverRating	0.202933

80	Oversampled_Logistic_Regression.pkl	Days_Policy_Accident	0.024340
81	Oversampled_Logistic_Regression.pkl	Days_Policy_Claim	1.017886
82	Oversampled_Logistic_Regression.pkl	PastNumberOfClaims	0.128202
83	Oversampled_Logistic_Regression.pkl	AgeOfVehicle	0.143274
84	Oversampled_Logistic_Regression.pkl	AgeOfPolicyHolder	1.318266
85	Oversampled_Logistic_Regression.pkl	NumberOfSuppliments	0.167986
86	Oversampled_Logistic_Regression.pkl	AddressChange_Claim	0.245061
87	Oversampled_Logistic_Regression.pkl	NumberOfCars	0.737351
88	Oversampled_Logistic_Regression.pkl	Year	0.357813
89	Oversampled_Logistic_Regression.pkl	Sex_Male	0.206666
90	Oversampled_Logistic_Regression.pkl	MaritalStatus_Married	3.121314
91	Oversampled_Logistic_Regression.pkl	MaritalStatus_Single	4.069754
92	Oversampled_Logistic_Regression.pkl	MaritalStatus_Widow	2.124144
93	Oversampled_Logistic_Regression.pkl	AccidentArea_Urban	0.727252
94	Oversampled_Logistic_Regression.pkl	BasePolicy_Collision	2.346712
95	Oversampled_Logistic_Regression.pkl	BasePolicy_Liability	4.396301
96	Oversampled_Logistic_Regression.pkl	PoliceReportFiled_Yes	1.792484
97	Oversampled_Logistic_Regression.pkl	WitnessPresent_Yes	1.182626
98	Oversampled_Logistic_Regression.pkl	AgentType_Internal	1.323305
99	Oversampled_Logistic_Regression.pkl	VehicleCategory_Sport	2.027250
100	Oversampled_Logistic_Regression.pkl	VehicleCategory_Utility	6.927433
101	Oversampled_Logistic_Regression.pkl	Fault_Third Party	3.379450



4 Ensemble Models

Ensemble models are used to improve prediction accuracy by combining multiple learners: - Random Forest - AdaBoost - CatBoost - XGBoost - LightGBM

4.1 Model Evaluation & SHAP Charts

We have included the feature importance analysis for vehicle insurance fraud detection as it provides key insights into the factors that contribute most significantly to identifying fraudulent claims. For both CatBoost and LightGBM models, we have genenerated interpretable SHAP plots along with respective SHAP values, highlighting several impactful features.

[49]:
```python
# import packages
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier

# Other Boosting Libraries
import xgboost as xgb
import lightgbm as lgb
!pip install catboost
import catboost as cb

# Sklearn Metrics
from sklearn.metrics import (
    classification_report,
    confusion_matrix,
    accuracy_score,
    recall_score,
    precision_score,
    f1_score,
    roc_auc_score
)

import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import shap
```

```
Requirement already satisfied: catboost in
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packages
(1.2.7)
Requirement already satisfied: graphviz in
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packages
(from catboost) (0.20.3)
Requirement already satisfied: matplotlib in
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packages
(from catboost) (3.4.3)
Requirement already satisfied: numpy<2.0,>=1.16.0 in
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packages
(from catboost) (1.26.4)
Requirement already satisfied: pandas>=0.24 in
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packages
(from catboost) (1.4.2)
```

```
Requirement already satisfied: scipy in
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packages
(from catboost) (1.12.0)
Requirement already satisfied: plotly in
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packages
(from catboost) (5.18.0)
Requirement already satisfied: six in
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packages
(from catboost) (1.16.0)
Requirement already satisfied: python-dateutil>=2.8.1 in
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packages
(from pandas>=0.24->catboost) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packages
(from pandas>=0.24->catboost) (2023.3.post1)
Requirement already satisfied: cycler>=0.10 in
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packages
(from matplotlib->catboost) (0.11.0)
Requirement already satisfied: kiwisolver>=1.0.1 in
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packages
(from matplotlib->catboost) (1.4.2)
Requirement already satisfied: pillow>=6.2.0 in
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packages
(from matplotlib->catboost) (10.2.0)
Requirement already satisfied: pyparsing>=2.2.1 in
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packages
(from matplotlib->catboost) (3.0.9)
Requirement already satisfied: tenacity>=6.2.0 in
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packages
(from plotly->catboost) (8.2.3)
Requirement already satisfied: packaging in
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packages
(from plotly->catboost) (24.1)
```

[50]:

```
# generate SHAP plots for a given model
def generate_shap_plots(model, X_data, model_name):
    # Calculate SHAP values
    explainer = shap.TreeExplainer(model)
    shap_values = explainer.shap_values(X_data)

    # Handle different SHAP value formats
    if isinstance(shap_values, list):
        # For binary classification, take class 1
        shap_values = shap_values[1]

    # Feature Importance Bar Plot
    plt.figure(figsize=(10, 6))
```

```
    shap.summary_plot(
        shap_values,
        X_data,
        plot_type="bar",
        show=False
    )
    plt.title(f'{model_name} SHAP Feature Importance')
    plt.tight_layout()
    plt.show()

    # Summary Dot Plot
    plt.figure(figsize=(10, 8))
    shap.summary_plot(
        shap_values,
        X_data,
        show=False
    )
    plt.title(f'{model_name} SHAP Summary Plot')
    plt.tight_layout()
    plt.show()
```

[51]:
```
# model evaluation functioin for ensemble models
def evaluate_ensemble_model(model, X_train, y_train, X_test, y_test,␣
 ↪model_name):
    # Fit the model
    model.fit(X_train, y_train)

    # Predictions
    y_pred = model.predict(X_test)

    # Print results header
    print(f"\nOversampled - {model_name}")
    print("=" * 40)

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

    # Confusion Matrix
    conf_matrix = confusion_matrix(y_test, y_pred)
    print("\nConfusion Matrix:")
    print(conf_matrix)

    # Visualization of Confusion Matrix
    plt.figure(figsize=(8, 6))
    sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')
    plt.title(f"Oversampled - {model_name} Confusion Matrix")
```

```
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.tight_layout()
    plt.show()

    # Calculate Metrics
    accuracy = accuracy_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)
    roc_auc = roc_auc_score(y_test, y_pred, multi_class='ovr',␣
↪average='weighted')

    print(f"\nAccuracy Score: {accuracy:.4f}")
    print(f"Recall Score: {recall:.4f}")
    print(f"Precision Score: {precision:.4f}")
    print(f"F1 Score: {f1:.4f}")
    print(f"ROC AUC Score: {roc_auc:.4f}")

    # Generate SHAP plots for CatBoost and LightGBM
    if model_name in ['CatBoost', 'LightGBM']:
        print(f"\nGenerating SHAP plots for {model_name}")
        generate_shap_plots(model, X_train, model_name)

    return {
        'model': model_name,
        'accuracy': accuracy,
        'recall': recall,
        'precision': precision,
        'f1_score': f1,
        'roc_auc_score': roc_auc
    }
```

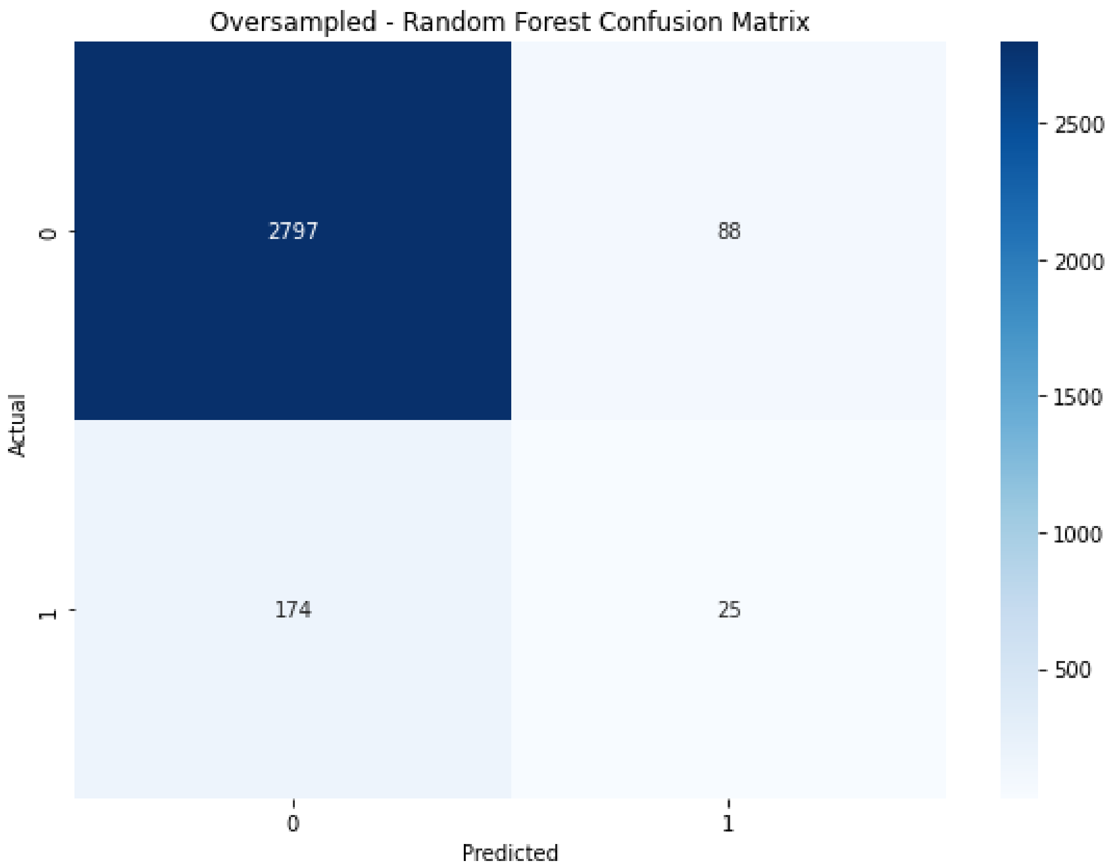
[52]:
```
# Run ensemble and boosting classifiers on oversampled training data
def run_ensemble_classifiers(X_train_over, y_train_over, X_test, y_test):
    # Initialize Ensemble Models
    models = [
        # Sklearn Ensemble Models
        (RandomForestClassifier(
            n_estimators=100,
            random_state=42,
            max_depth=None
        ), "Random Forest"),

        (AdaBoostClassifier(
            estimator=DecisionTreeClassifier(max_depth=1),
            n_estimators=50,
```

```
            random_state=42
        ), "AdaBoost"),

        # External Boosting Libraries
        (cb.CatBoostClassifier(
            iterations=100,
            random_seed=42,
            verbose=0
        ), "CatBoost"),

        (xgb.XGBClassifier(
            n_estimators=100,
            learning_rate=0.1,
            random_state=42
        ), "XGBoost"),

        (lgb.LGBMClassifier(
            n_estimators=100,
            learning_rate=0.1,
            random_state=42
        ), "LightGBM")
    ]

    # Results storage
    all_results = []

    # Run each model
    for model, model_name in models:
        result = evaluate_ensemble_model(
            model,
            X_train_over, y_train_over,
            X_test, y_test,
            model_name
        )
        all_results.append(result)

    # Convert results to DataFrame
    results_df = pd.DataFrame(all_results)

    # Display summary
    print("\nEnsemble Models Results Summary:")
    print(results_df)

    # Visualization of results
    plt.figure(figsize=(10, 6))
    results_df.set_index('model')[['accuracy', 'recall', 'precision',␣
↪'f1_score', 'roc_auc_score']].plot(kind='bar')
```

```
    plt.title("Model Performance Metrics")
    plt.xlabel("Models")
    plt.ylabel("Score")
    plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
    plt.tight_layout()
    plt.show()

    return results_df
```

[53]:
```
# model running & model evaluation
def main():
    # Run the evaluation
    results_df = run_ensemble_classifiers(
        X_train_over, y_train_over,
        X_test, y_test
    )

if __name__ == "__main__":
    main()
```

```
Oversampled - Random Forest
========================================

Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.97      0.96      2885
           1       0.22      0.13      0.16       199

    accuracy                           0.92      3084
   macro avg       0.58      0.55      0.56      3084
weighted avg       0.89      0.92      0.90      3084


Confusion Matrix:
[[2797   88]
 [ 174   25]]
```

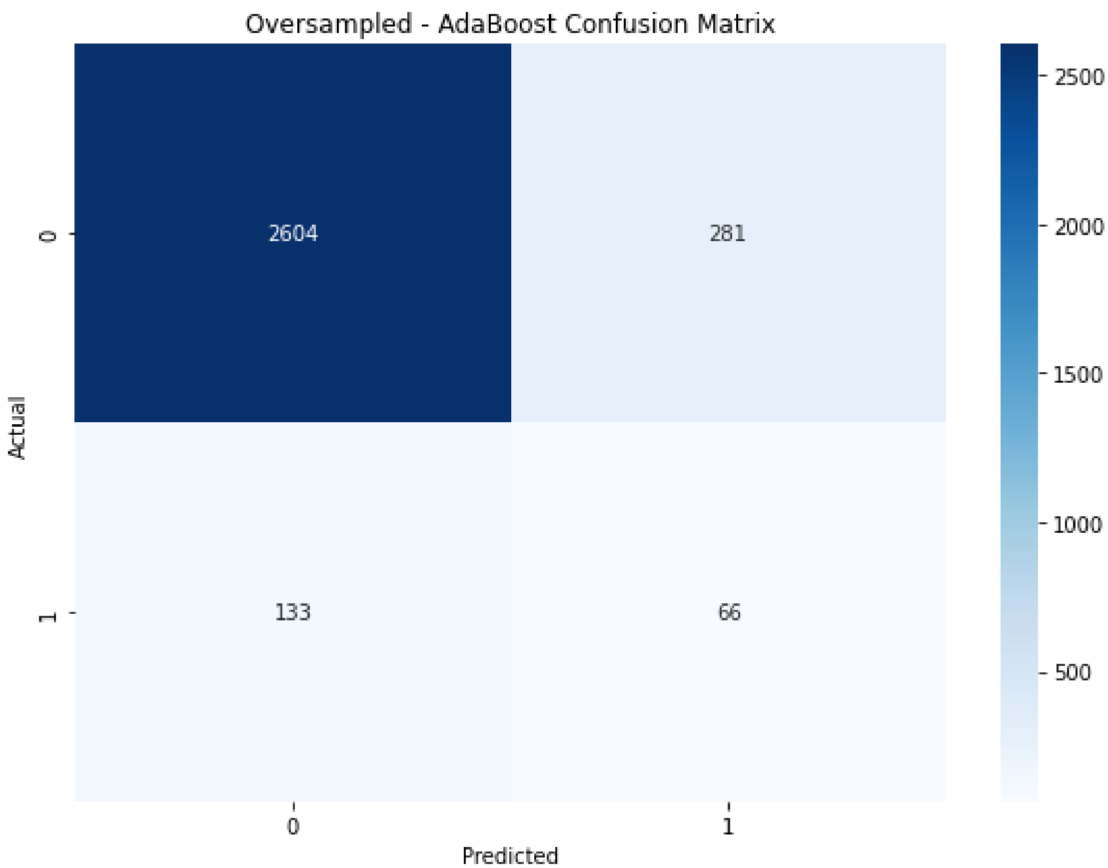



```
Accuracy Score: 0.9150
Recall Score: 0.1256
Precision Score: 0.2212
F1 Score: 0.1603
ROC AUC Score: 0.5476
```

```
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-
packages/sklearn/ensemble/_weight_boosting.py:527: FutureWarning: The SAMME.R
algorithm (the default) is deprecated and will be removed in 1.6. Use the SAMME
algorithm to circumvent this warning.
  warnings.warn(
```

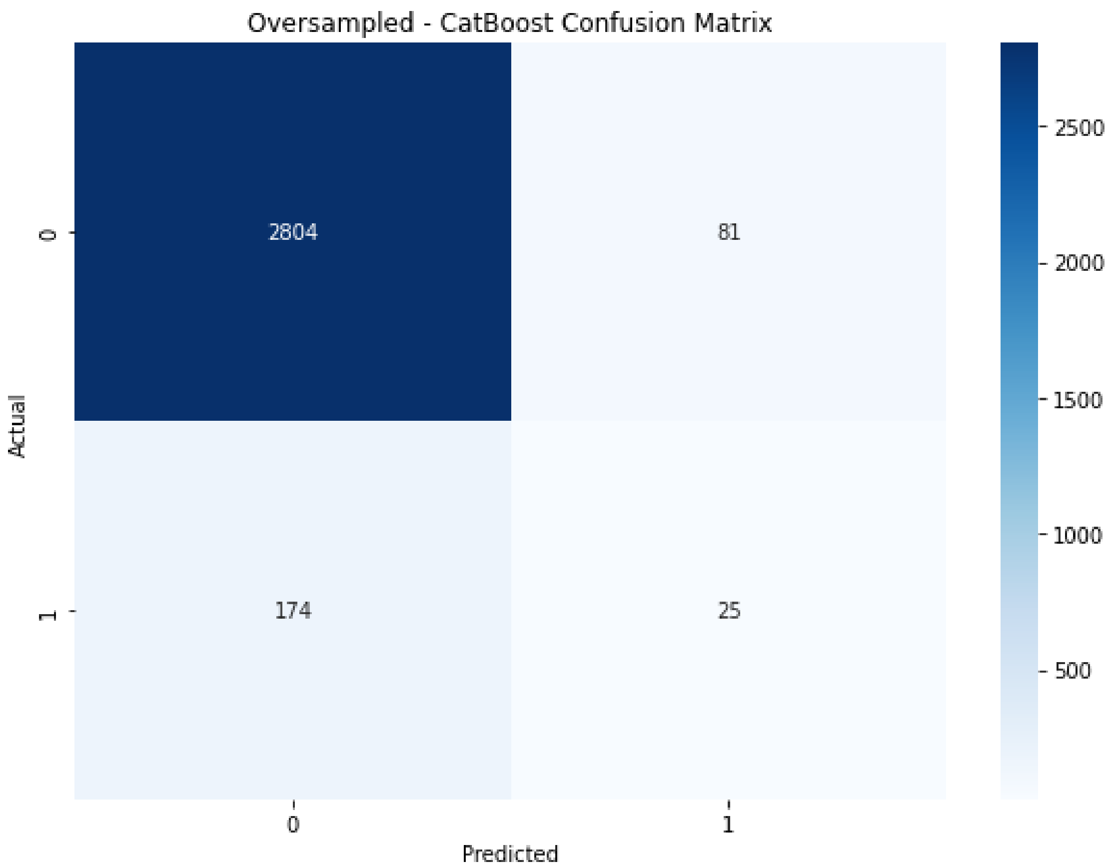
```
Oversampled - AdaBoost
========================================

Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.90      0.93      2885
```

```
           1       0.19      0.33      0.24       199

    accuracy                           0.87      3084
   macro avg       0.57      0.62      0.58      3084
weighted avg       0.90      0.87      0.88      3084


Confusion Matrix:
[[2604  281]
 [ 133   66]]
```



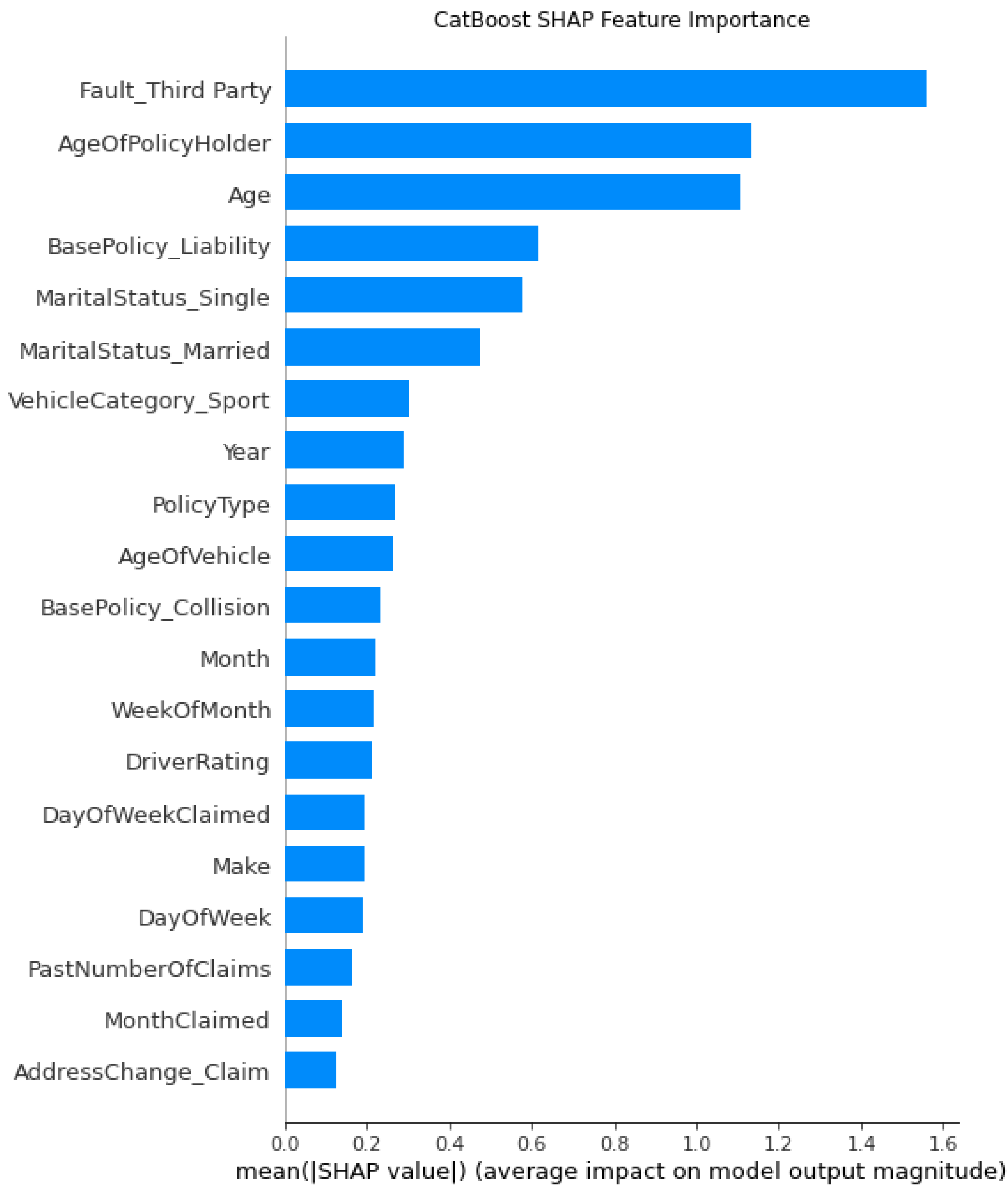

```
Accuracy Score: 0.8658
Recall Score: 0.3317
Precision Score: 0.1902
F1 Score: 0.2418
ROC AUC Score: 0.6171

Oversampled - CatBoost
========================================
```

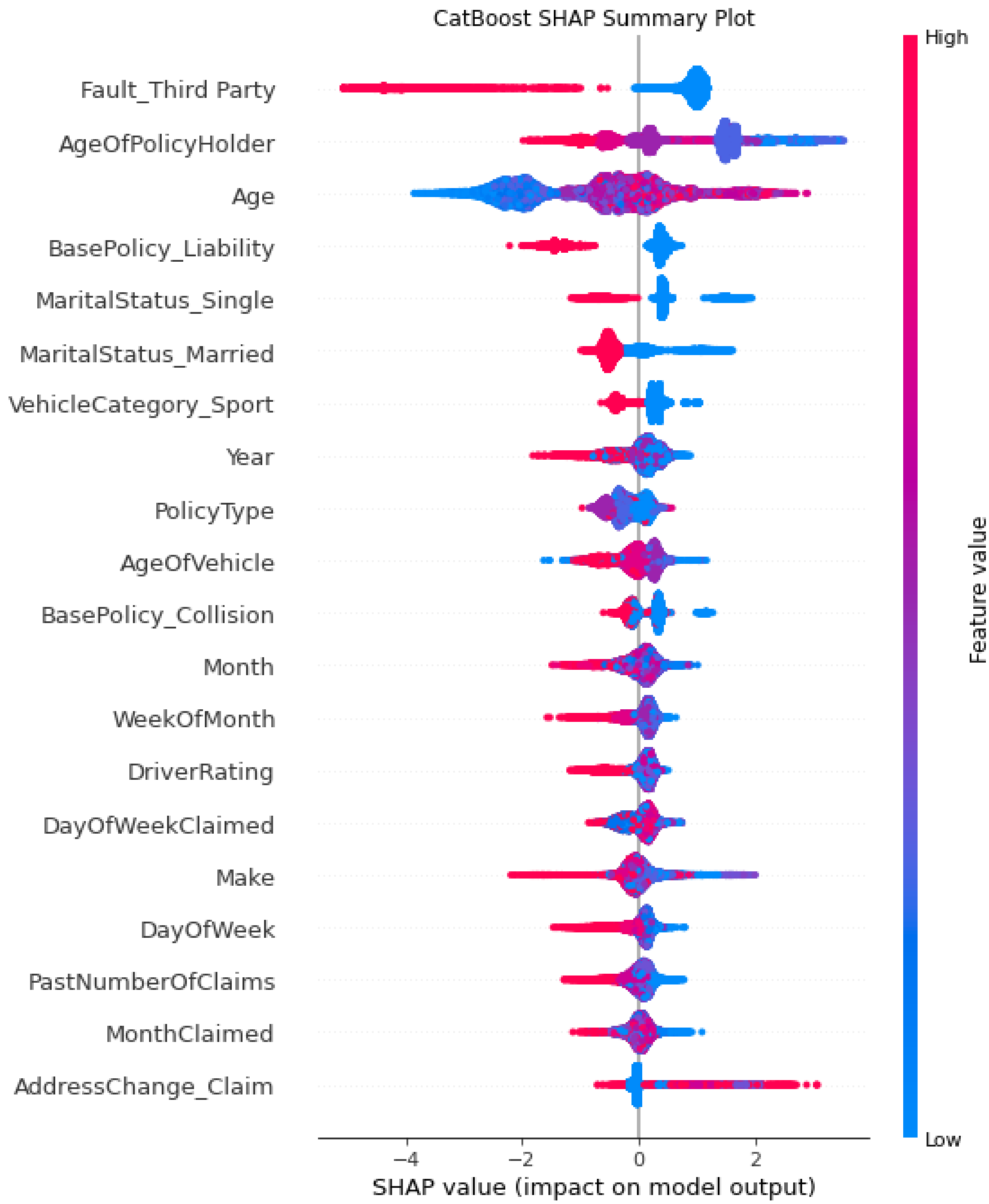
```
Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.97      0.96      2885
           1       0.24      0.13      0.16       199

    accuracy                           0.92      3084
   macro avg       0.59      0.55      0.56      3084
weighted avg       0.90      0.92      0.91      3084


Confusion Matrix:
[[2804   81]
 [ 174   25]]
```




```
Accuracy Score: 0.9173
Recall Score: 0.1256
Precision Score: 0.2358
```

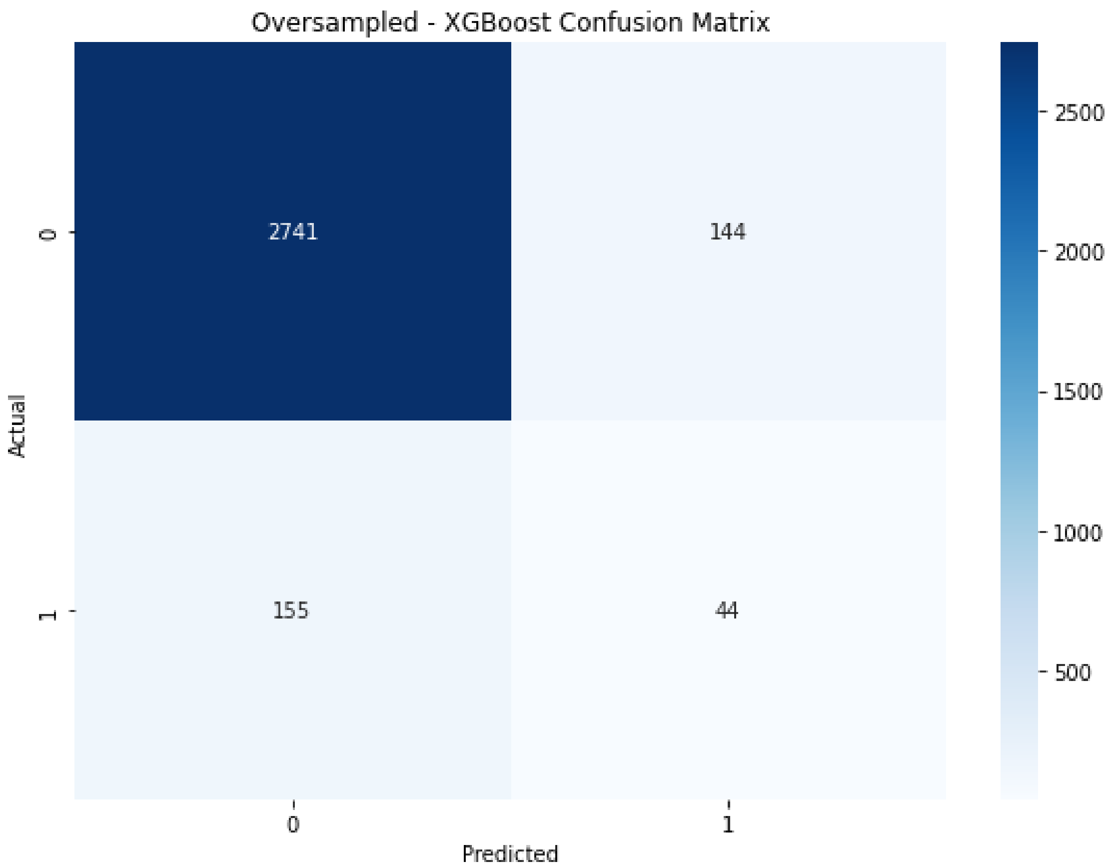
```
F1 Score: 0.1639
ROC AUC Score: 0.5488

Generating SHAP plots for CatBoost
```





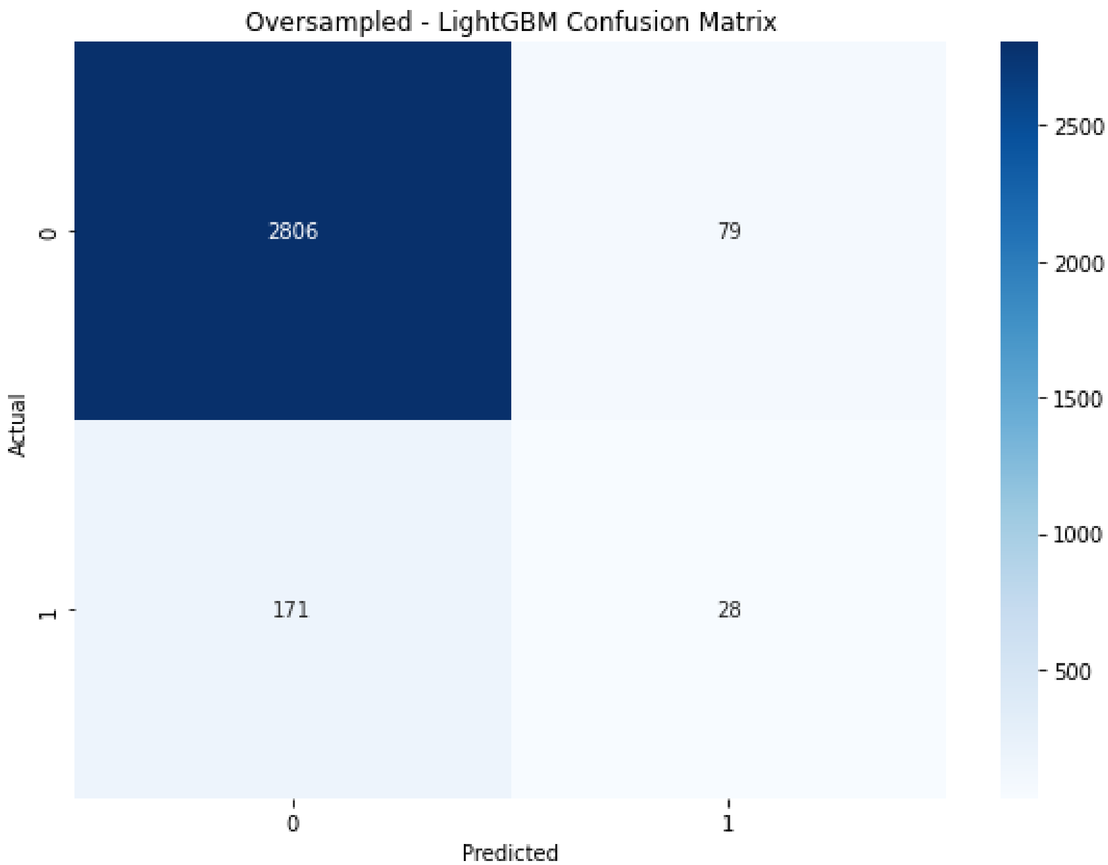

```
Oversampled - XGBoost
========================================

Classification Report:
              precision    recall  f1-score   support
```

```
           0       0.95      0.95      0.95      2885
           1       0.23      0.22      0.23       199

    accuracy                           0.90      3084
   macro avg       0.59      0.59      0.59      3084
weighted avg       0.90      0.90      0.90      3084


Confusion Matrix:
[[2741  144]
 [ 155   44]]
```



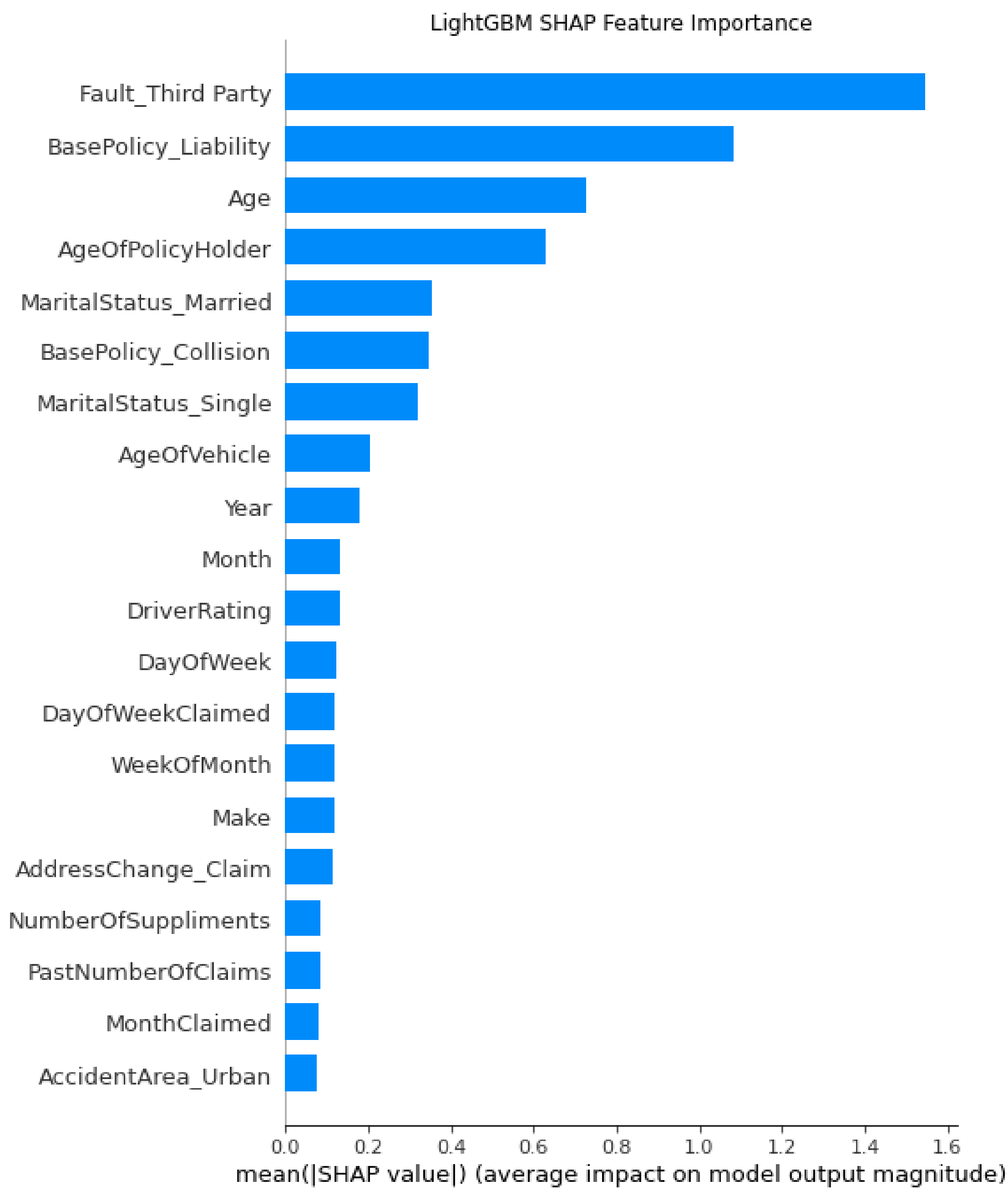

```
Accuracy Score: 0.9030
Recall Score: 0.2211
Precision Score: 0.2340
F1 Score: 0.2274
ROC AUC Score: 0.5856
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Info] Number of positive: 5805, number of negative: 11611
```

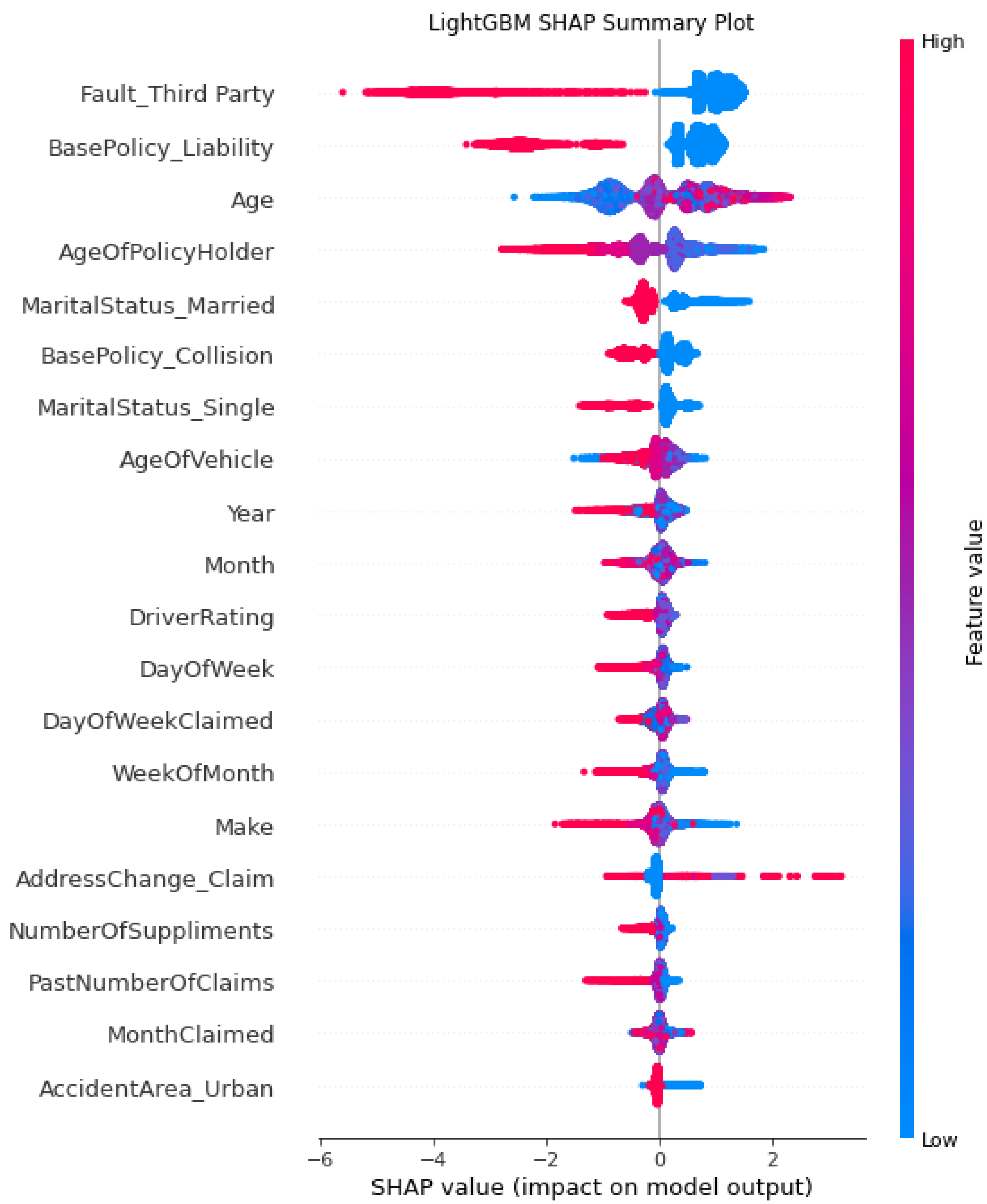
```
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.002094 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 424
[LightGBM] [Info] Number of data points in the train set: 17416, number of used
features: 34
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.333314 -> initscore=-0.693233
[LightGBM] [Info] Start training from score -0.693233

Oversampled - LightGBM
========================================

Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.97      0.96      2885
           1       0.26      0.14      0.18       199

    accuracy                           0.92      3084
   macro avg       0.60      0.56      0.57      3084
weighted avg       0.90      0.92      0.91      3084


Confusion Matrix:
[[2806   79]
 [ 171   28]]
```




```
Accuracy Score: 0.9189
Recall Score: 0.1407
Precision Score: 0.2617
F1 Score: 0.1830
ROC AUC Score: 0.5567

Generating SHAP plots for LightGBM
```

```
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-
packages/shap/explainers/_tree.py:448: UserWarning: LightGBM binary classifier
with TreeExplainer shap values output has changed to a list of ndarray
  warnings.warn('LightGBM binary classifier with TreeExplainer shap values
output has changed to a list of ndarray')
```


LightGBM SHAP Feature Importance
Fault_Third Party
BasePolicy_Liability
Age
AgeOfPolicyHolder
MaritalStatus_Married
BasePolicy_Collision
MaritalStatus_Single
AgeOfVehicle
Year
Month
DriverRating
DayOfWeek
DayOfWeekClaimed
WeekOfMonth
Make
AddressChange_Claim
NumberOfSuppliments
PastNumberOfClaims
MonthClaimed
AccidentArea_Urban
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
mean(|SHAP value|) (average impact on model output magnitude)

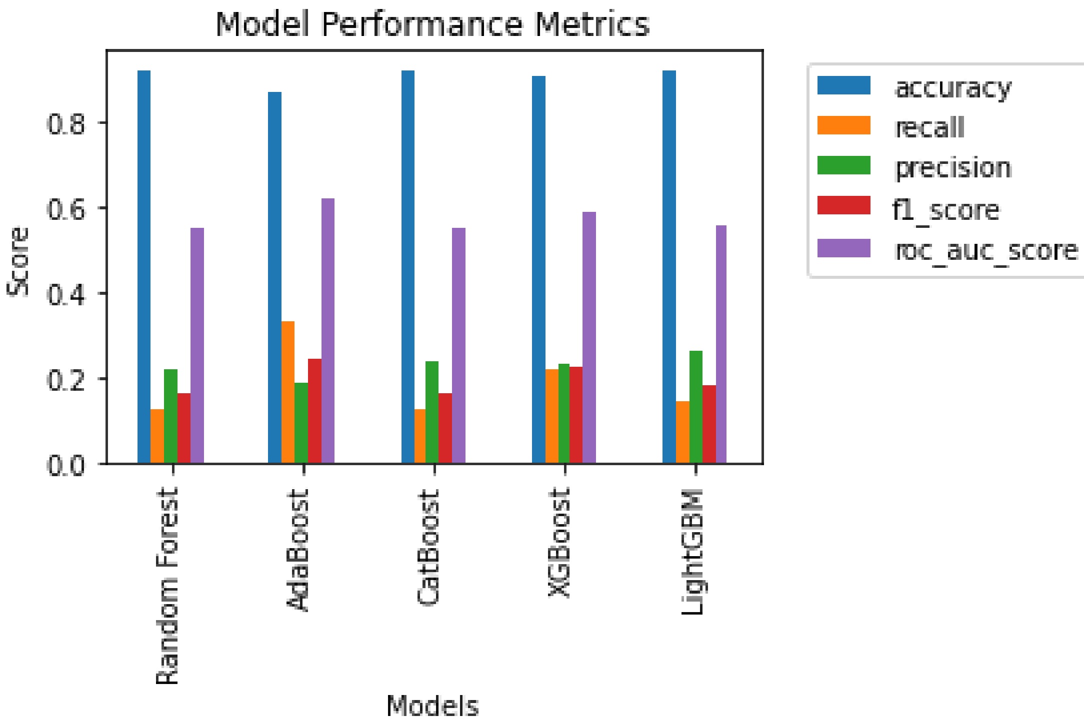


Ensemble Models Results Summary:

	model	accuracy	recall	precision	f1_score	roc_auc_score
0	Random Forest	0.915045	0.125628	0.221239	0.160256	0.547563
1	AdaBoost	0.865759	0.331658	0.190202	0.241758	0.617129
2	CatBoost	0.917315	0.125628	0.235849	0.163934	0.548776
3	XGBoost	0.903048	0.221106	0.234043	0.227390	0.585596

```
4       LightGBM  0.918936  0.140704   0.261682  0.183007       0.556660
```

```
<Figure size 720x432 with 0 Axes>
```



Ensemble Models Results Summary:

Model	Accuracy	Recall	Precision	F1 Score	ROC AUC Score
Random Forest	0.9150	0.1256	0.2212	0.1603	0.5476
AdaBoost	0.8658	0.3317	0.1902	0.2418	0.6171
CatBoost	0.9173	0.1256	0.2358	0.1639	0.5488
XGBoost	0.9030	0.2211	0.2340	0.2274	0.5856
LightGBM	0.9189	0.1407	0.2617	0.1830	0.5567

[54]:
```
import pandas as pd

# Creating a DataFrame with the provided data
data = {
    'model': ['Random Forest', 'AdaBoost', 'CatBoost', 'XGBoost', 'LightGBM'],
    'accuracy': [0.915045, 0.865759, 0.917315, 0.903048, 0.918936],
    'recall': [0.125628, 0.331658, 0.125628, 0.221106, 0.140704],
    'precision': [0.221239, 0.190202, 0.235849, 0.234043, 0.261682],
    'f1_score': [0.160256, 0.241758, 0.163934, 0.227390, 0.183007],
    'roc_auc_score': [0.547563, 0.617129, 0.548776, 0.585596, 0.556660]
```

```
}

df = pd.DataFrame(data)

# Calculating the average for each metric and creating a new DataFrame with␣
↪results in rows
averages = df.mean(numeric_only=True).to_frame(name='ensemble_model_average').T

# Printing the transposed averages
print(averages)
```

```
                        accuracy    recall  precision  f1_score  roc_auc_score
ensemble_model_average  0.904021  0.188945   0.228603  0.195269       0.571145
```

5 Advanced Models

To handle the complexity of the fraud detection task, we utilized advanced neural networks models: - Sklearn Multi-Layer Perceptron - Dense Neural Network - Bidirectional LSTM - 1D Convolutional Network - Gated Recurrent Unit (GRU) - Self-Attention Network - Transformer-Inspired Model - Residual Network - Deep Belief Network

[55]:
```
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.layers import (
    Reshape, Dense, Dropout, Bidirectional, LSTM, GRU, Flatten, Input,
    LayerNormalization, GlobalAveragePooling1D, Conv1D, MaxPooling1D,
    MultiHeadAttention
)
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.utils import to_categorical
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import (
    classification_report, confusion_matrix, accuracy_score,
    recall_score, precision_score, f1_score, roc_auc_score
)
from sklearn.neural_network import MLPClassifier
```

[56]:
```
# dense neural network
def create_dense_model(input_shape, num_classes):
    model = Sequential([
        Dense(64, activation='relu', input_shape=input_shape),
        Dropout(0.3),
        Dense(32, activation='relu'),
```

```
        Dropout(0.3),
        Dense(num_classes, activation='softmax')
    ])
    model.compile(optimizer=Adam(0.001),
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])
    return model
```

[57]:
```
# bidirectional LSTM network
def create_bidirectional_lstm_model(input_shape, num_classes):
    model = Sequential([
        Reshape((1, input_shape[0]), input_shape=input_shape),
        Bidirectional(LSTM(64, return_sequences=True)),
        Dropout(0.3),
        Bidirectional(LSTM(32)),
        Dropout(0.3),
        Dense(32, activation='relu'),
        Dense(num_classes, activation='softmax')
    ])
    model.compile(optimizer=Adam(0.001),
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])
    return model
```

[58]:
```
# 1D CNN
def create_1d_cnn_model(input_shape, num_classes):
    model = Sequential([
        Reshape((input_shape[0], 1), input_shape=input_shape),
        Conv1D(64, 3, activation='relu'),
        MaxPooling1D(2),
        Conv1D(32, 3, activation='relu'),
        MaxPooling1D(2),
        Flatten(),
        Dense(64, activation='relu'),
        Dropout(0.3),
        Dense(num_classes, activation='softmax')
    ])
    model.compile(optimizer=Adam(0.001),
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])
    return model
```

[59]:
```
# GRU network
def create_gru_model(input_shape, num_classes):
    model = Sequential([
        Reshape((1, input_shape[0]), input_shape=input_shape),
        Bidirectional(GRU(64, return_sequences=True)),
```

```
        Dropout(0.3),
        Bidirectional(GRU(32)),
        Dropout(0.3),
        Dense(32, activation='relu'),
        Dense(num_classes, activation='softmax')
    ])
    model.compile(optimizer=Adam(0.001),
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])
    return model
```

[60]:
```
# self attention network
def create_self_attention_model(input_shape, num_classes):
    inputs = Input(shape=(input_shape[0], 1))
    x = Dense(64, activation='relu')(inputs)
    attention_output = MultiHeadAttention(num_heads=4, key_dim=32)(x, x)
    x = LayerNormalization()(attention_output + x)
    x = Dropout(0.3)(x)
    x = Flatten()(x)
    x = Dense(32, activation='relu')(x)
    x = Dropout(0.3)(x)
    outputs = Dense(num_classes, activation='softmax')(x)

    model = Model(inputs=inputs, outputs=outputs)
    model.compile(optimizer=Adam(0.001),
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])
    return model
```

[61]:
```
# transformer inspired model
def create_transformer_model(input_shape, num_classes):
    inputs = Input(shape=(input_shape[0], 1))
    x = Dense(64, activation='relu')(inputs)
    attention_output = MultiHeadAttention(num_heads=4, key_dim=32)(x, x)
    x = LayerNormalization()(x + attention_output)
    x = Dropout(0.3)(x)
    x = Flatten()(x)
    x = Dense(128, activation='relu')(x)
    x = Dropout(0.3)(x)
    x = Dense(64, activation='relu')(x)
    outputs = Dense(num_classes, activation='softmax')(x)

    model = Model(inputs=inputs, outputs=outputs)
    model.compile(optimizer=Adam(0.001),
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])
    return model
```

[62]:
```
# residual network
def create_residual_network_model(input_shape, num_classes):
    def residual_block(x, filters, downsample=False):
        shortcut = x
        x = Dense(filters, activation='relu')(x)
        x = Dropout(0.3)(x)
        x = Dense(filters)(x)
        if downsample:
            shortcut = Dense(filters)(shortcut)
        x = LayerNormalization()(x + shortcut)
        return x

    inputs = Input(shape=input_shape)
    x = Dense(64, activation='relu')(inputs)
    x = residual_block(x, 64)
    x = residual_block(x, 32, downsample=True)
    x = Flatten()(x)
    x = Dense(32, activation='relu')(x)
    outputs = Dense(num_classes, activation='softmax')(x)

    model = Model(inputs=inputs, outputs=outputs)
    model.compile(optimizer=Adam(0.001),
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])
    return model
```

[63]:
```
# Create neural network architectures
def create_neural_network_models(input_shape, num_classes):
    models = [
        (MLPClassifier(hidden_layer_sizes=(100, 50), max_iter=500,␣
 ↪random_state=42),
         "Sklearn MLP"),
        (create_dense_model(input_shape, num_classes),
         "Dense Network"),
        (create_bidirectional_lstm_model(input_shape, num_classes),
         "Bidirectional LSTM"),
        (create_1d_cnn_model(input_shape, num_classes),
         "1D CNN"),
        (create_gru_model(input_shape, num_classes),
         "GRU Network"),
        (create_self_attention_model(input_shape, num_classes),
         "Self-Attention Network"),
        (create_transformer_model(input_shape, num_classes),
         "Transformer-Inspired"),
        (create_residual_network_model(input_shape, num_classes),
         "Residual Network")
    ]
```

```
    return models
```

[64]:
```
# model evaluation
def evaluate_model(model, X_train, y_train, X_test, y_test, model_name,␣
↪is_keras_model=False):
    # Evaluate a single model
    scaler = StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_scaled = scaler.transform(X_test)

    if is_keras_model:
        y_train_encoded = to_categorical(y_train)
        y_test_encoded = to_categorical(y_test)

        early_stopping = EarlyStopping(
            monitor='val_loss',
            patience=10,
            restore_best_weights=True
        )

        history = model.fit(
            X_train_scaled, y_train_encoded,
            epochs=100,
            batch_size=32,
            validation_split=0.2,
            callbacks=[early_stopping],
            verbose=0
        )

        y_pred = model.predict(X_test_scaled)
        y_pred_classes = np.argmax(y_pred, axis=1)
        y_test_classes = np.argmax(y_test_encoded, axis=1)
    else:
        model.fit(X_train_scaled, y_train)
        y_pred_classes = model.predict(X_test_scaled)
        y_test_classes = y_test

    # Calculate metrics
    accuracy = accuracy_score(y_test_classes, y_pred_classes)
    recall = recall_score(y_test_classes, y_pred_classes, average='weighted')
    precision = precision_score(y_test_classes, y_pred_classes,␣
↪average='weighted')
    f1 = f1_score(y_test_classes, y_pred_classes, average='weighted')
    roc_auc = roc_auc_score(y_test_classes, y_pred_classes, multi_class='ovr',␣
↪average='weighted')

    # Print results
```

```
    print(f"\nModel: {model_name}")
    print("=" * 40)
    print("\nClassification Report:")
    print(classification_report(y_test_classes, y_pred_classes))

    # Plot confusion matrix
    conf_matrix = confusion_matrix(y_test_classes, y_pred_classes)
    plt.figure(figsize=(8, 6))
    sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')
    plt.title(f"{model_name} Confusion Matrix")
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.tight_layout()
    plt.show()

    return {
        'model': model_name,
        'accuracy': accuracy,
        'recall': recall,
        'precision': precision,
        'f1_score': f1,
        'roc_auc_score': roc_auc
    }
```

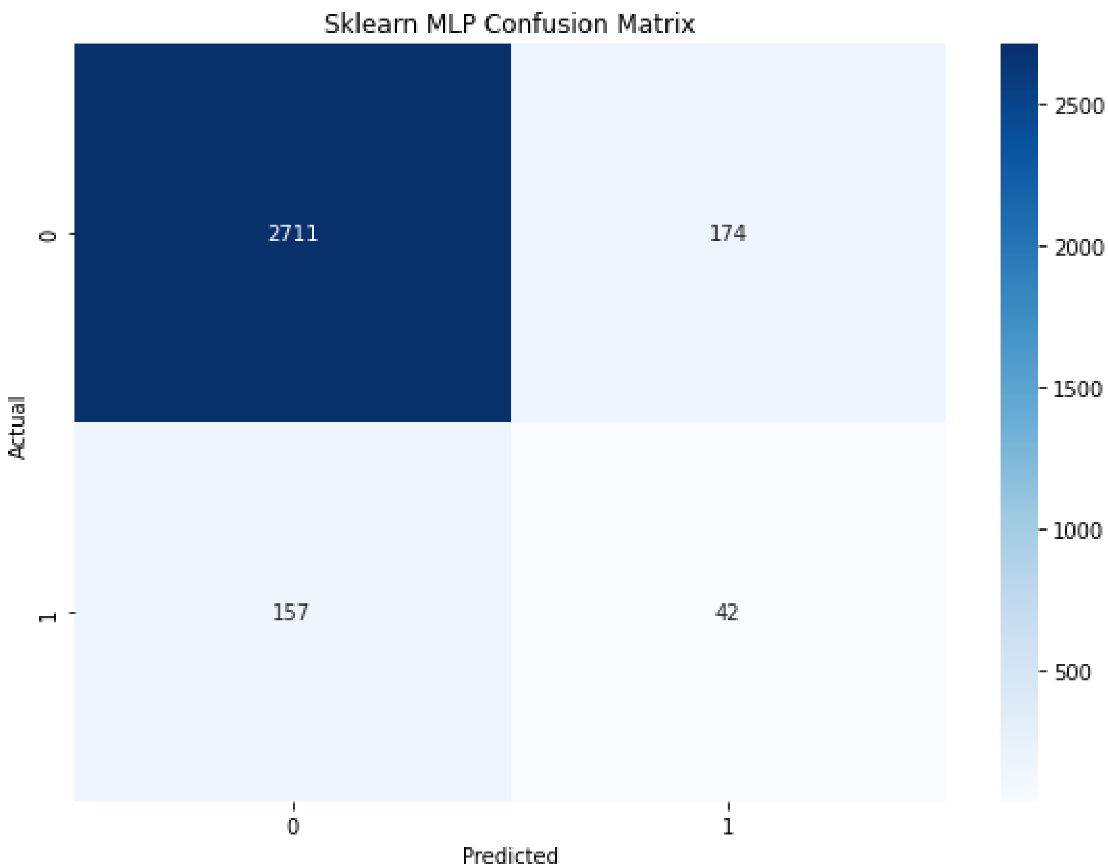
[65]:
```
# evaluation for all models
def run_neural_network_evaluation(X_train, y_train, X_test, y_test):
    num_classes = len(np.unique(y_test))
    input_shape = (X_train.shape[1],)
    models = create_neural_network_models(input_shape, num_classes)

    results = []
    for model, model_name in models:
        is_keras_model = isinstance(model, (Sequential, Model))
        result = evaluate_model(
            model, X_train, y_train,
            X_test, y_test,
            model_name, is_keras_model
        )
        results.append(result)

    # Create summary DataFrame
    results_df = pd.DataFrame(results)
    print("\nNeural Network Models Results Summary:")
    print(results_df)

    # Plot results
    plt.figure(figsize=(12, 6))
```

```
    results_df.set_index('model')[['accuracy', 'f1_score', 'roc_auc_score']].
↪plot(kind='bar')
    plt.title("Model Performance Metrics")
    plt.xlabel("Models")
    plt.ylabel("Score")
    plt.xticks(rotation=45)
    plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
    plt.tight_layout()
    plt.show()

    return results_df
```

[ ]:
```
results_df = run_neural_network_evaluation(
    X_train_over,
    y_train_over,
    X_test,
    y_test
)
results_df
```

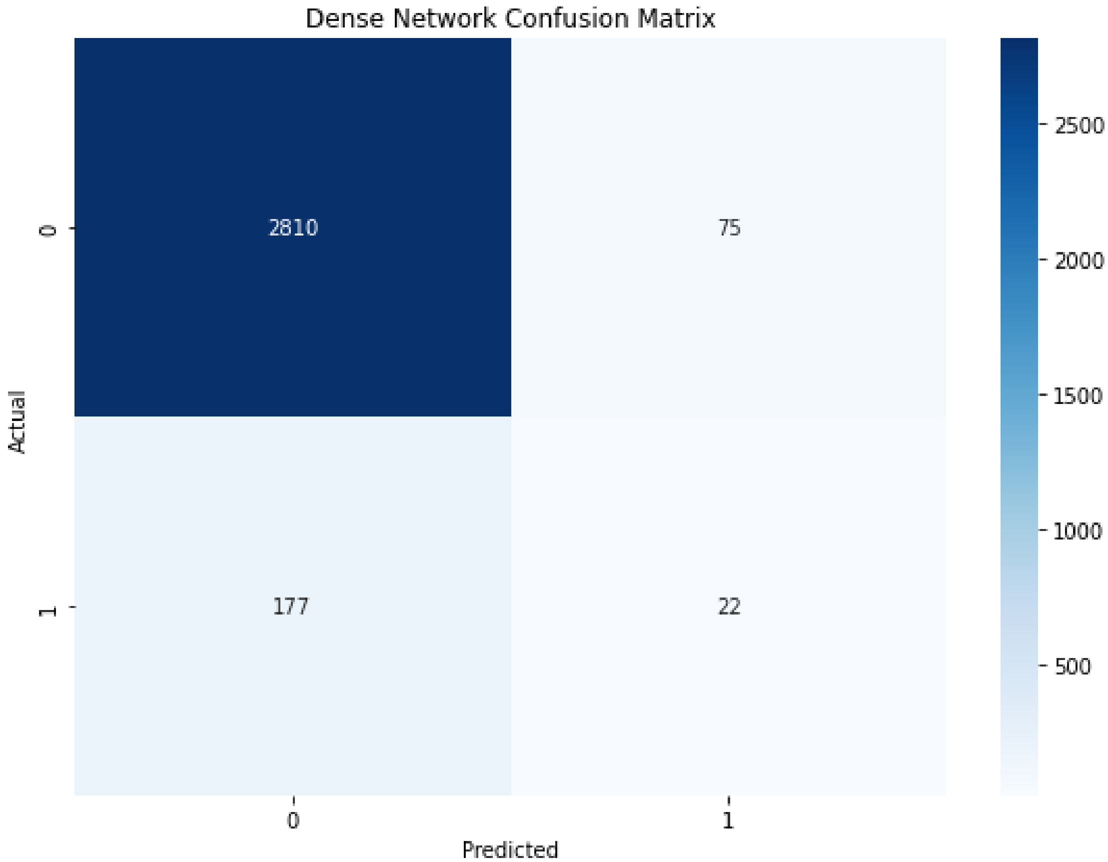
```
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.


Model: Sklearn MLP
========================================

Classification Report:
              precision    recall  f1-score   support
```

```
           0       0.95      0.94      0.94      2885
           1       0.19      0.21      0.20       199

    accuracy                           0.89      3084
   macro avg       0.57      0.58      0.57      3084
weighted avg       0.90      0.89      0.89      3084
```

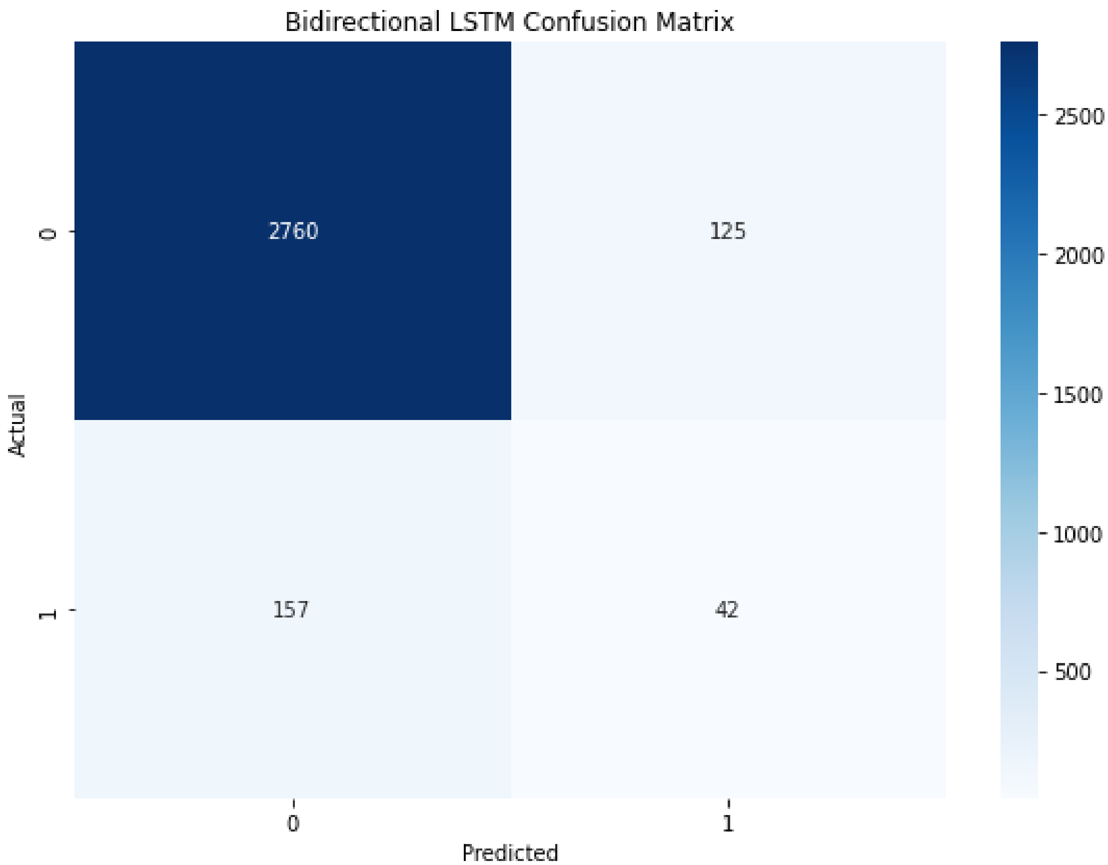



```
97/97 [==============================] - 0s 326us/step

Model: Dense Network
========================================

Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.97      0.96      2885
           1       0.23      0.11      0.15       199
```

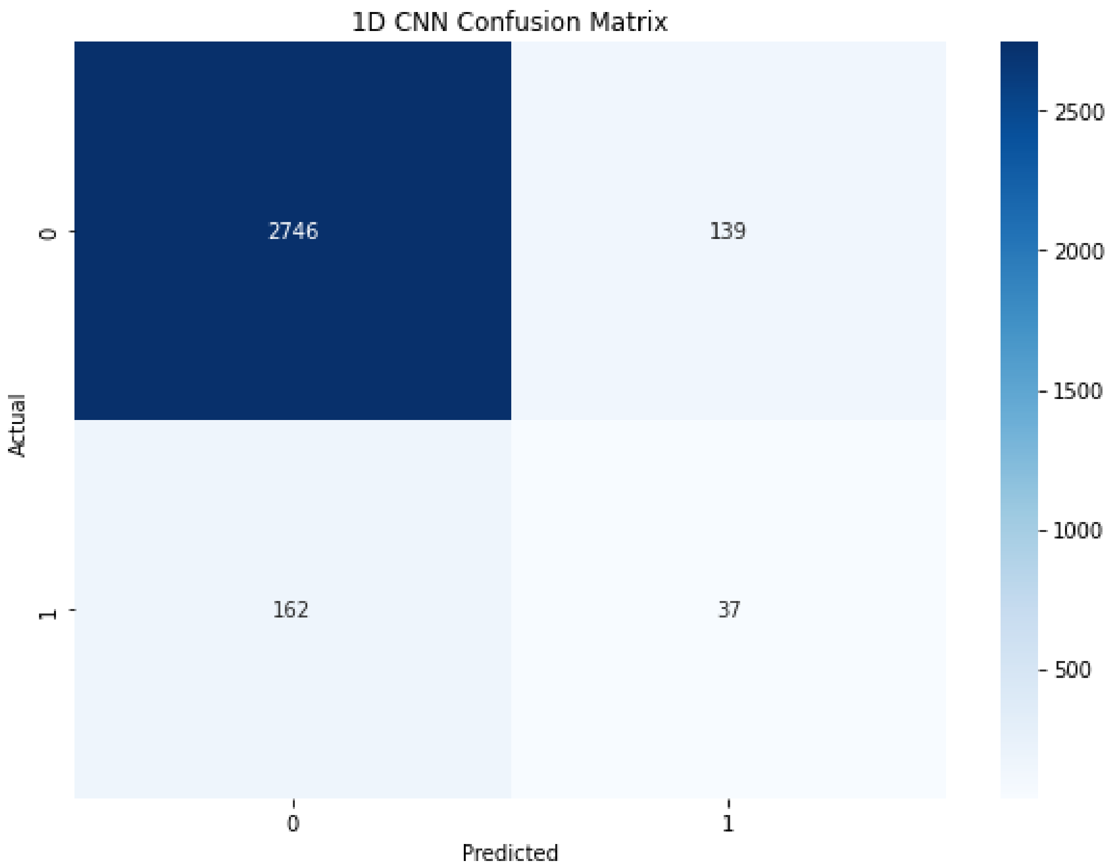
```
    accuracy                           0.92      3084
   macro avg       0.58      0.54      0.55      3084
weighted avg       0.89      0.92      0.90      3084
```




```
97/97 [==============================] - 1s 754us/step

Model: Bidirectional LSTM
========================================

Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.96      0.95      2885
           1       0.25      0.21      0.23       199

    accuracy                           0.91      3084
   macro avg       0.60      0.58      0.59      3084
weighted avg       0.90      0.91      0.90      3084
```




```
97/97 [==============================] - 0s 754us/step

Model: 1D CNN
========================================

Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.95      0.95      2885
           1       0.21      0.19      0.20       199

    accuracy                           0.90      3084
   macro avg       0.58      0.57      0.57      3084
weighted avg       0.90      0.90      0.90      3084
```



Neural Network Models Results Summary:

Model	Accuracy	Recall	Precision	F1 Score	ROC AUC Score
Sklearn MLP	0.8927	0.8927	0.8968	0.8947	0.5754
Dense Network	0.9183	0.9183	0.8947	0.9049	0.5423
Bidirectional LSTM	0.9086	0.9086	0.9014	0.9048	0.5839
1D CNN	0.9024	0.9024	0.8969	0.8996	0.5689
GRU Network	0.8920	0.8920	0.8933	0.8926	0.5587
Self-Attention Network	0.9073	0.9073	0.8932	0.8998	0.5481
Transformer-Inspired	0.9066	0.9066	0.8935	0.8997	0.5501
Residual Network	0.8911	0.8911	0.8964	0.8937	0.5745

5.0.1 Compare performance of different model categories

[ ]:
```
import pandas as pd

# Creating a DataFrame with the provided data
data = {
    'model': [
```

```
        'Sklearn MLP', 'Dense Network', 'Bidirectional LSTM', '1D CNN',
        'GRU Network', 'Self-Attention Network', 'Transformer-Inspired',␣
 ↪'Residual Network'
    ],
    'accuracy': [0.8927, 0.9183, 0.9086, 0.9024, 0.8920, 0.9073, 0.9066, 0.
 ↪8911],
    'recall': [0.8927, 0.9183, 0.9086, 0.9024, 0.8920, 0.9073, 0.9066, 0.8911],
    'precision': [0.8968, 0.8947, 0.9014, 0.8969, 0.8933, 0.8932, 0.8935, 0.
 ↪8964],
    'f1_score': [0.8947, 0.9049, 0.9048, 0.8996, 0.8926, 0.8998, 0.8997, 0.
 ↪8937],
    'roc_auc_score': [0.5754, 0.5423, 0.5839, 0.5689, 0.5587, 0.5481, 0.5501, 0.
 ↪5745]
}

df = pd.DataFrame(data)

# Calculating the average for each metric and creating a new DataFrame with␣
 ↪results in rows
averages = df.mean(numeric_only=True).to_frame(name='advanced_model_average').T

# Formatting the values to four decimal places
averages = averages.round(4)

# Printing the formatted averages
averages
```

[ ]:

```
                        accuracy  recall  precision  f1_score  roc_auc_score
advanced_model_average    0.9024  0.9024     0.8958    0.8987         0.5627
```