Fraudulent Claim Detection Report

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1. Problem Statement & Business Objective

Global Insure processes thousands of insurance claims daily and seeks to identify potentially fraudulent claims before approval. The key objectives were:

• Analyze historical claims to uncover patterns indicative of fraud.

• Identify the most predictive features for fraudulent behaviour.

• Build and evaluate classification models to flag high-risk claims early.

2. Data Overview

• Source: insurance_claims.csv, containing policy details, incident information, customer demographics, claim amounts, and a binary target fraud_reported (Y/N).

• Training–Validation Split:

- Training set: 699 × 0.75 ≈ 525 samples
- Validation set: 699 × 0.25 ≈ 174 samples

• Class Balance:

- Fraudulent: ~25%
- Non-fraudulent: ~75%
- Imbalance ratio ≈ 3 : 1 (majority : minority)

3. Data Preparation & Cleaning

• Missing Values

- Identified and dropped columns with excessive missingness.
- Imputed or removed rows for remaining nulls as appropriate.
- authorities_contacted has None as one of the categories, but np.nan interprets None as null. Therefore, we will skip all rows where authorities_contacted is np.nan.
- Empty columns: ['_c39']

- Redundant & Illogical Entries
    - Removed duplicate records.
    - Negative values in the dataset:

        umbrella_limit 1

        capital-loss 525

        dtype: int64

        Number of rows with negative values: 526

        Dropping rows with negative values in numeric columns (excluding 'capital loss')

    Dataset shape after removing rows with negative values: (999, 39)

    - Dropped features with constant or near-constant values.
    - Columns with their percentage of unique values:

        policy_number: 1.0000 (999 / 999)

        incident_location: 1.0000 (999 / 999)

        insured_zip: 0.9950 (994 / 999)

        policy_annual_premium: 0.9910 (990 / 999)

        policy_bind_date: 0.9510 (950 / 999)

        total_claim_amount: 0.7628 (762 / 999)

        vehicle_claim: 0.7257 (725 / 999)

        injury_claim: 0.6386 (638 / 999)

        property_claim: 0.6256 (625 / 999)

        months_as_customer: 0.3914 (391 / 999)

        capital-loss: 0.3544 (354 / 999)

        capital-gains: 0.3383 (338 / 999)

        incident_date: 0.0601 (60 / 999)

        age: 0.0460 (46 / 999)

        auto_model: 0.0390 (39 / 999)

        incident_hour_of_the_day: 0.0240 (24 / 999)

        auto_year: 0.0210 (21 / 999)

insured_hobbies: 0.0200 (20 / 999)

insured_occupation: 0.0140 (14 / 999)

auto_make: 0.0140 (14 / 999)

umbrella_limit: 0.0100 (10 / 999)

insured_education_level: 0.0070 (7 / 999)

incident_state: 0.0070 (7 / 999)

incident_city: 0.0070 (7 / 999)

insured_relationship: 0.0060 (6 / 999)

incident_type: 0.0040 (4 / 999)

collision_type: 0.0040 (4 / 999)

incident_severity: 0.0040 (4 / 999)

authorities_contacted: 0.0040 (4 / 999)

number_of_vehicles_involved: 0.0040 (4 / 999)

witnesses: 0.0040 (4 / 999)

policy_state: 0.0030 (3 / 999)

policy_csl: 0.0030 (3 / 999)

policy_deductable: 0.0030 (3 / 999)

property_damage: 0.0030 (3 / 999)

bodily_injuries: 0.0030 (3 / 999)

police_report_available: 0.0030 (3 / 999)

insured_sex: 0.0020 (2 / 999)

fraud_reported: 0.0020 (2 / 999)

Columns with high cardinality (>80% unique values):

['policy_number', 'policy_bind_date', 'policy_annual_premium', 'insured_zip', 'incident_location']

Removing 5 columns with high cardinality

Dataset shape after removing high cardinality columns: (999, 34)

- Data Types
  - Converted date fields to datetime objects.
    - Updated data types for date columns: incident_date: datetime64[ns]
  - Cast categorical columns to category dtype.

4. Exploratory Data Analysis (EDA)

• Univariate Analysis

Observations from histogram plots:

months_as_customer:

- Mean: 202.57, Median: 199.00

- Skewness: 0.37

- Distribution appears approximately symmetric

age:

- Mean: 38.85, Median: 38.00

- Skewness: 0.51

- Distribution is positively skewed (right-tailed)

policy_deductable:

- Mean: 1150.21, Median: 1000.00

- Skewness: 0.45

- Distribution appears approximately symmetric

umbrella_limit:

- Mean: 1077253.22, Median: 0.00

- Skewness: 1.79

- Distribution is positively skewed (right-tailed)

capital-gains:

- Mean: 25506.01, Median: 0.00

- Skewness: 0.45

- Distribution appears approximately symmetric

capital-loss:

- Mean: -26458.37, Median: -20800.00

- Skewness: -0.41

- Distribution appears approximately symmetric

incident_hour_of_the_day:

- Mean: 11.53, Median: 12.00

- Skewness: -0.01

- Distribution appears approximately symmetric

number_of_vehicles_involved:

- Mean: 1.83, Median: 1.00

- Skewness: 0.49

- Distribution appears approximately symmetric

bodily_injuries:

- Mean: 0.97, Median: 1.00

- Skewness: 0.06

- Distribution appears approximately symmetric

witnesses:

- Mean: 1.46, Median: 1.00

- Skewness: 0.06

- Distribution appears approximately symmetric

total_claim_amount:

- Mean: 52923.61, Median: 58300.00

- Skewness: -0.57

- Distribution is negatively skewed (left-tailed)

injury_claim:

- Mean: 7508.73, Median: 6780.00

- Skewness: 0.27

- Distribution appears approximately symmetric property_claim:

- Mean: 7399.20, Median: 6780.00

- Skewness: 0.33

- Distribution appears approximately symmetric

vehicle_claim:

- Mean: 38015.68, Median: 42420.00

- Skewness: -0.59

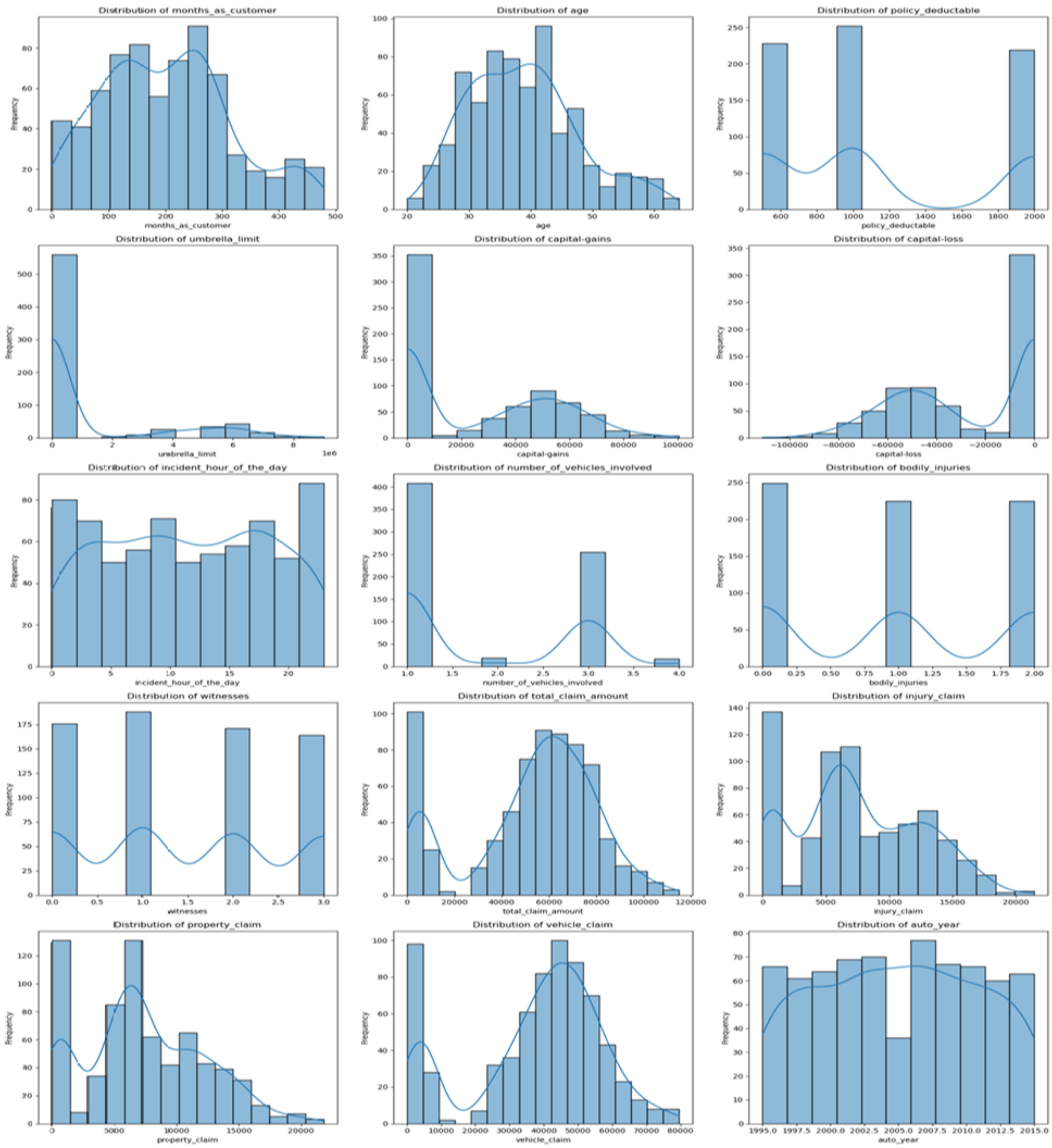
- Distribution is negatively skewed (left-tailed)

auto_year:

- Mean: 2004.96, Median: 2005.00

- Skewness: -0.00

- Distribution appears approximately symmetric


Distribution of months_as_customer
months_as_customer
Frequency
Distribution of age
age
Frequency
Distribution of policy_deductable
policy_deductable
Frequency
Distribution of umbrella_limit
umbrella_limit
1e6
Frequency
Distribution of capital-gains
capital-gains
Frequency
Distribution of capital-loss
capital-loss
Frequency
Distribution of incident_hour_of_the_day
incident_hour_of_the_day
Frequency
Distribution of number_of_vehicles_involved
number_of_vehicles_involved
Frequency
Distribution of bodily_injuries
bodily_injuries
Frequency
Distribution of witnesses
witnesses
Frequency
Distribution of total_claim_amount
total_claim_amount
Frequency
Distribution of injury_claim
injury_claim
Frequency
Distribution of property_claim
property_claim
Frequency
Distribution of vehicle_claim
vehicle_claim
Frequency
Distribution of auto_year
auto_year
Frequency

- **Class Balance**

  Class imbalance analysis:

  Majority class (N): 526 samples (75.25%)

  Minority class (Y): 173 samples (24.75%)

  Imbalance ratio (majority:minority): 3.04:1

  The dataset shows significant class imbalance. This may affect model performance.

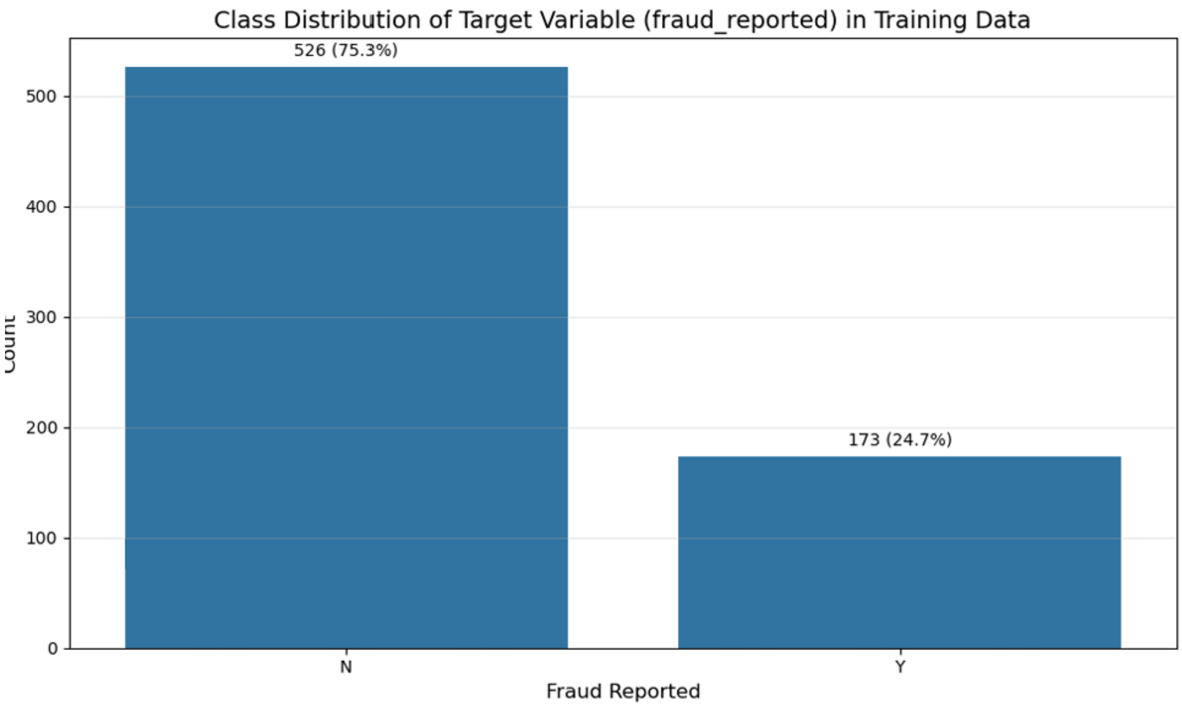
  Consider using techniques such as:

  1. Resampling methods (oversampling minority class or undersampling majority class)

  2. Using class weights during model training

  3. Using algorithms that handle imbalanced data well

  4. Using evaluation metrics appropriate for imbalanced datasets (e.g., precision, recall, F1-score, AUC-ROC)



- **Correlation Analysis**
    - Heatmaps indicated moderate correlations between certain numeric features (e.g., injuries_vehicles_interaction and total_claim_amount).
    - Highly correlated feature pairs (|correlation| > 0.7):

        age & months_as_customer: 0.920

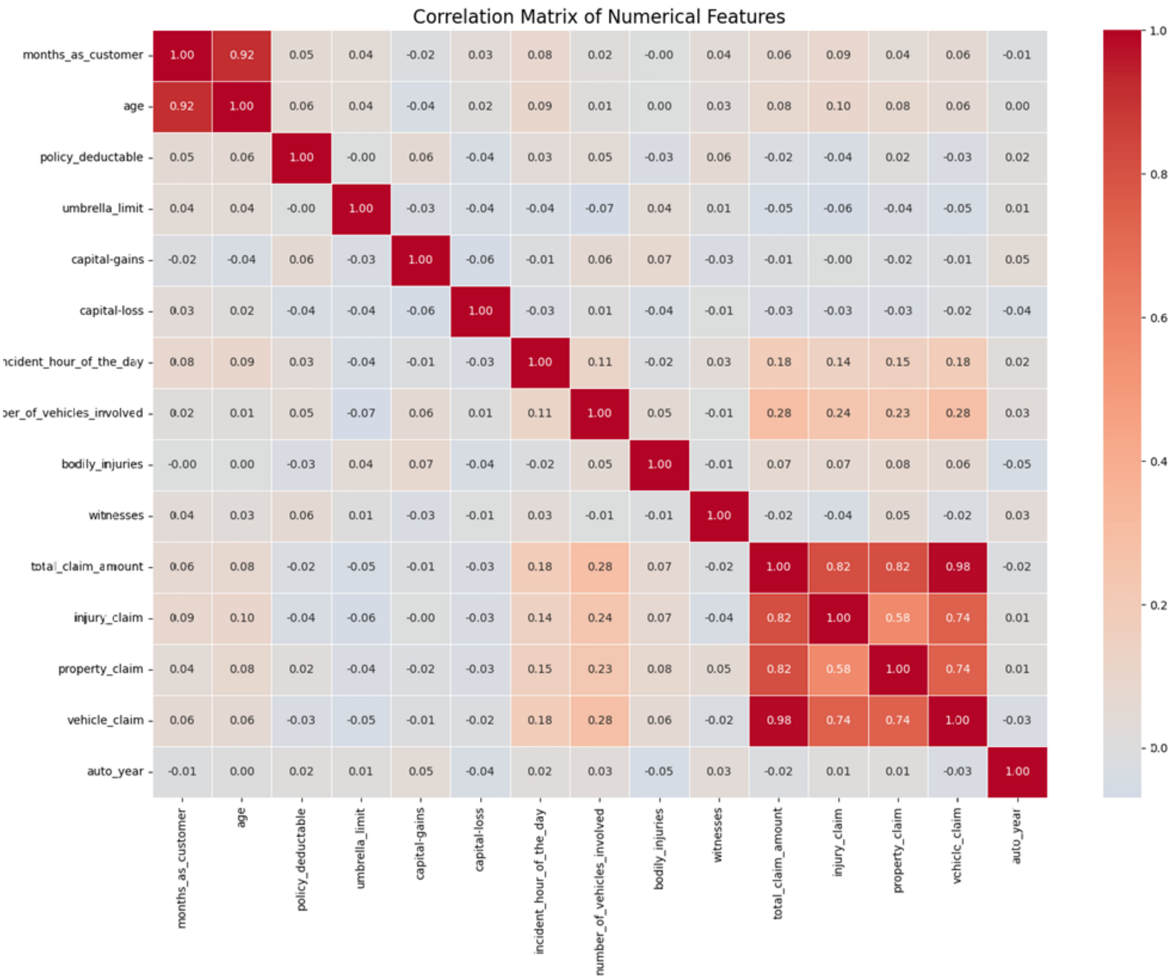
        injury_claim & total_claim_amount: 0.818

        property_claim & total_claim_amount: 0.815

        vehicle_claim & total_claim_amount: 0.984

        vehicle_claim & injury_claim: 0.743

        vehicle_claim & property_claim: 0.742



- **Bivariate Analysis**

  Feature importance based on variance in fraud rates:

  incident_severity: 655.5417

  insured_hobbies: 437.9118

  auto_model: 138.9059

  incident_type: 127.9124

  collision_type: 97.4883

  incident_state: 73.1274

  property_damage: 39.8805

  insured_occupation: 39.3522

  auto_make: 27.8186

  insured_relationship: 24.6759

  authorities_contacted: 23.6709

  incident_city: 14.4581

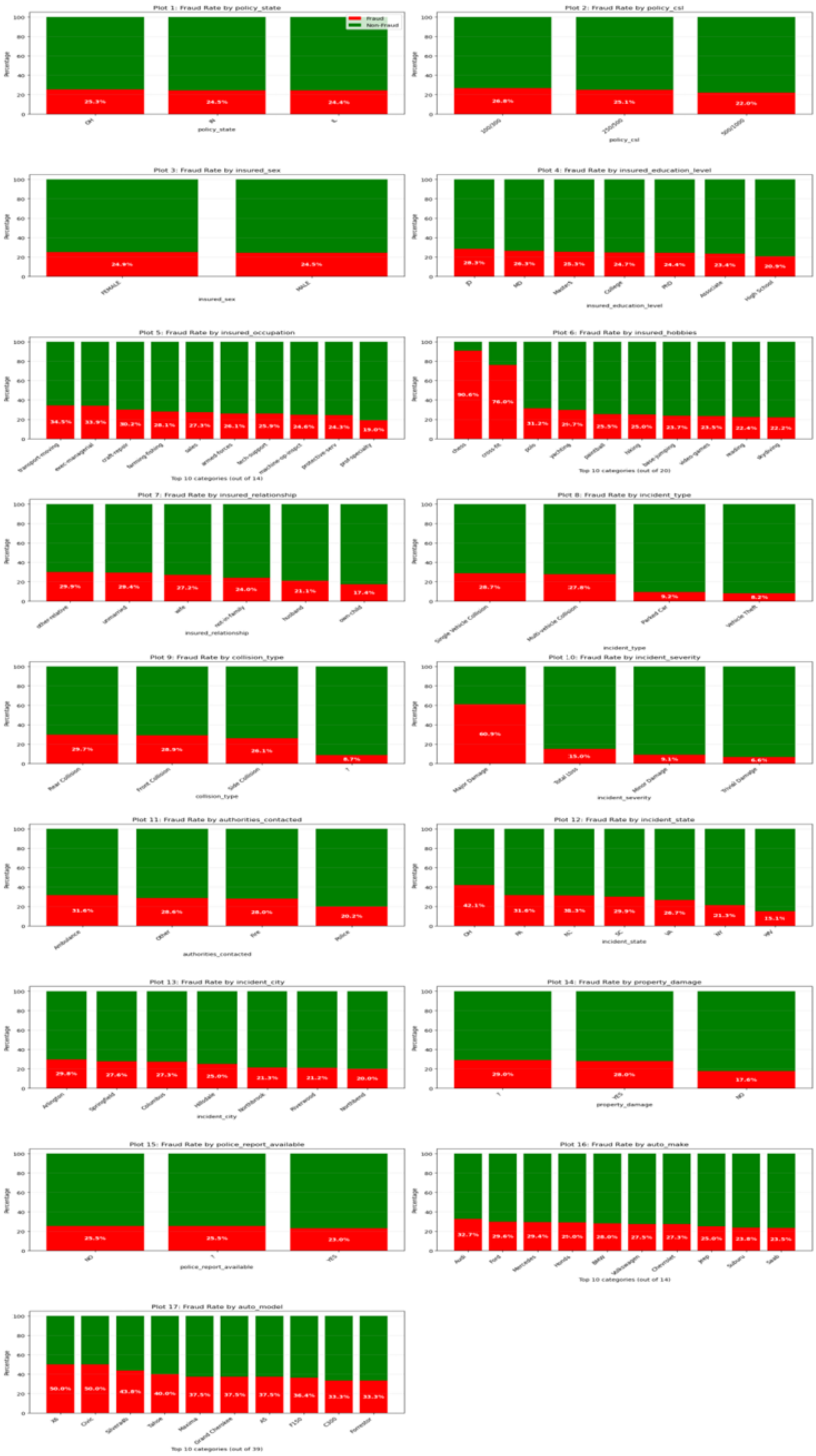
  policy_csl: 6.0253

  insured_education_level: 5.3411

  police_report_available: 2.156

  policy_state: 0.2506

  insured_sex: 0.0773


Plot 1: Fraud Rate by policy_state
Fraud
Non-Fraud
Plot 2: Fraud Rate by policy_csl
Plot 3: Fraud Rate by insured_sex
Plot 4: Fraud Rate by insured_education_level
Plot 5: Fraud Rate by insured_occupation
Plot 6: Fraud Rate by insured_hobbies
Plot 7: Fraud Rate by insured_relationship
Plot 8: Fraud Rate by incident_type
Plot 9: Fraud Rate by collision_type
Plot 10: Fraud Rate by incident_severity
Plot 11: Fraud Rate by authorities_contacted
Plot 12: Fraud Rate by incident_state
Plot 13: Fraud Rate by incident_city
Plot 14: Fraud Rate by property_damage
Plot 15: Fraud Rate by police_report_available
Plot 16: Fraud Rate by auto_make
Plot 17: Fraud Rate by auto_model

5. Feature Engineering

• Resampling: explored SMOTE and under sampling to address imbalance.

Class distribution before resampling:

fraud_reported

N 526

Y 173

Name: count, dtype: int64

Class distribution after resampling:

fraud_reported

N 526

Y 526

Name: count, dtype: int64

Original training set shape: (699, 33)

Resampled training set shape: (1052, 33)

• **Feature Creation:**

o Engineered interaction terms (e.g., time between policy inception and incident).

o Grouped low-frequency categories into "Other" for stability.

o Created date-based, claim ratio, time-of-day, interaction, age group, customer tenure features.

Training set shape after feature creation: (1052, 46)

Test set shape after feature creation: (300, 46)

New features:

o ['incident_day_of_week', 'incident_month', 'is_weekend', 'vehicle_age', 'injury_claim_ratio', 'property_claim_ratio', 'vehicle_claim_ratio', 'vehicles_witnesses_interaction', 'injuries_vehicles_interaction', 'high_claim_amount']

- **Handle Redundant Columns**
  - o **Found 3 highly correlated pairs (correlation > 0.85):**

    - age & months_as_customer: 0.9271

    - vehicle_claim & total_claim_amount: 0.9803

    - vehicle_age & auto_year: -1.0000

    Dropping 'incident_date' as we've created derived features from it:

    incident_day_of_week, incident_month, is_weekend

    Dropping 'auto_year' as we've created derived features from it: vehicle_age

    Dropping 'incident_hour_of_the_day' as we've created derived features from it: incident_time_of_day

    Dropping 'vehicle_claim' due to high correlation (0.9803) with 'total_claim_amount'

    Dropping 'months_as_customer' due to high correlation (0.9271) with 'age'

    Removed 5 redundant columns: ['incident_hour_of_the_day','incident_date',

    'vehicle_claim', 'months_as_customer', 'auto_year']

    Training data shape after removing redundant columns: (1052, 41)

    Testing data shape after removing redundant columns: (300, 41)

- **Combine values in Categorical Columns**

o Found 20 categorical features to analyze for combining values and updated below column.

  ▪ Column 'auto_model'

  Total unique values: 39

  Rare categories (< 2% of data): 11

  Reduced categories from 39 to 29

  Top 5 categories after combining: {'Other': 166, 'A5': 50, 'F150': 49, 'RAM': 43, 'A3': 43}

o Modified 2 categorical columns by combining rare categories

  ▪ incident_severity value distribution:

  Major Damage: 41.3%

Minor Damage: 28.6%

Total Loss: 23.9%

Trivial Damage: 6.2%

- insured_hobbies value distribution:

chess: 9.6%

paintball: 6.9%

reading: 6.2%

bungie-jumping: 6.1%

exercise: 5.3%

skydiving: 5.2%

yachting: 5.0%

base-jumping: 5.0%

board-games: 4.8%

hiking: 4.8%

polo: 4.7%

cross-fit: 4.7%

video-games: 4.6%

movies: 4.5%

golf: 4.5%

kayaking: 4.4%

camping: 4.3%

sleeping: 3.9%

dancing: 3.7%

Other: 1.9%

- incident_type value distribution:

Multi-vehicle Collision: 44.9%

Single Vehicle Collision: 41.2%

Parked Car: 7.7%

Vehicle Theft: 6.3%

- auto_make value distribution:

    Ford: 9.2%

    Audi: 8.8%

    Chevrolet: 8.7%

    Saab: 8.2%

    Dodge: 8.1%

    Nissan: 7.9%

    Suburu: 7.5%

    BMW: 7.3%

    Mercedes: 6.7%

    Accura: 6.3%

    Toyota: 5.8%

    Jeep: 5.7%

    Volkswagen: 5.4%

    Honda: 4.4%

- insured_relationship value distribution:

    other-relative: 18.3%

    wife: 17.5%

    not-in-family: 17.0%

    unmarried: 16.3%

    husband: 15.9%

    own-child: 15.1%

- **Encoding & Scaling:**

o One-hot encoded ~20 categorical variables.

- Cardinality of each categorical column:

    policy_state: 3 unique values

    policy_csl: 3 unique values

insured_sex: 2 unique values

insured_education_level: 7 unique values

insured_occupation: 14 unique values

insured_hobbies: 20 unique values

insured_relationship: 6 unique values

incident_type: 4 unique values

collision_type: 4 unique values

incident_severity: 4 unique values

authorities_contacted: 5 unique values

incident_state: 7 unique values

incident_city: 7 unique values

property_damage: 3 unique values

police_report_available: 3 unique values

auto_make: 14 unique values

auto_model: 29 unique values

incident_time_of_day: 4 unique values

age_group: 4 unique values

customer_tenure_group: 3 unique values

▪ Shape of X_train before creating dummy variables: (1052, 41)

▪ Shape of X_train after creating dummy variables: (1052, 147)

▪ Created dummy variables for dependent feature in training data {'Y': 1, 'N': 0}

o Standardized numeric features via Min–Max scaling.

- **Feature Selection:**

o Logistic Regression + RFECV: Recursive elimination with cross-validation selected the top ~52 predictors.

- Optimal number of features: 52

[

'policy_csl_250/500', 'insured_education_level_JD',

'insured_education_level_MD', 'insured_education_level_PhD',

'insured_occupation_exec-managerial',

'insured_occupation_farming-fishing',

'insured_occupation_handlers-cleaners',

'insured_occupation_other-service',

'insured_occupation_priv-house-serv', 'insured_hobbies_camping',

'insured_hobbies_chess', 'insured_hobbies_cross-fit',

'insured_hobbies_dancing', 'insured_hobbies_golf',

'insured_hobbies_movies', 'insured_hobbies_sleeping',

'insured_hobbies_video-games', 'insured_relationship_not-in-family',

'insured_relationship_own-child', 'insured_relationship_unmarried',

'incident_type_Vehicle Theft', 'collision_type_Side Collision',

'collision_type_Unknown', 'incident_severity_Minor Damage',

'incident_severity_Total Loss', 'incident_severity_Trivial Damage',

'incident_state_NY', 'incident_state_OH', 'incident_state_PA',

'incident_state_WV', 'incident_city_Northbrook',

'property_damage_Unknown', 'property_damage_YES',
'auto_make_Audi',

'auto_make_BMW', 'auto_make_Chevrolet', 'auto_make_Nissan',

'auto_model_A5', 'auto_model_Camry', 'auto_model_Civic',

'auto_model_F150', 'auto_model_Fusion', 'auto_model_Grand
Cherokee',

'auto_model_Legacy', 'auto_model_MDX', 'auto_model_Other', 'auto_model_Pathfinder', 'auto_model_Silverado', 'auto_model_Ultima',

'auto_model_Wrangler', 'auto_model_X5', 'age_group_Young'

]

o Random Forest: Feature importance thresholding (0.01) retained 28 variables. Hyper Parameter Tuning

- Hyperparameter tuning

Fitting 5 folds for each of 972 candidates, totalling 4860 fits

Best Parameters:

{'bootstrap': True, 'class_weight': 'balanced_subsample', 'criterion': 'entropy', 'max_depth': 12, 'max_features': 0.5, 'min_samples_leaf': 5, 'min_samples_split': 5, 'n_estimators': 200}

Best ROC-AUC Score: 0.9342

6. **Model Building & Evaluation**

Model	Validation Accuracy	Sensitivity (TPR)	Specificity (TNR)	Precision	Recall	F1-Score
Logistic Regression Optimized cutoff (0.5282)	0.8000	0.6757	0.8407	0.5814	0.6757	0.6250
Random Forest (Hyperparameter Tuning)	0.7233	0.3378	0.8496	0.4237	0.3378	0.3759

Logistic Regression *(Optimized cutoff at 0.5282)*

- **Validation Accuracy:** 80.00%
- **Sensitivity (Recall):** 67.57% → Effectively captures true fraud cases
- **Specificity:** 84.07% → Accurately identifies non-fraud cases
- **Precision:** 58.14% → Moderate confidence in flagged frauds

- **F1-Score:** 62.50% → Balanced trade-off between precision and recall

Random Forest

- **Validation Accuracy:** 72.33%
- **Sensitivity (Recall):** 33.78% → Misses many fraudulent cases
- **Specificity:** 84.96% → Slightly higher than Logistic Regression
- **Precision:** 42.37% → Lower confidence in fraud predictions
- **F1-Score:** 37.59% → Poor balance between precision and recall

7. Conclusion & Recommendations

Best Model: Logistic Regression with Threshold Tuning

- Outperforms Random Forest across key metrics:
    - Sensitivity: 67.57% vs 33.78% → *Captures nearly twice as many fraud cases*
    - Precision: 58.14% vs 42.37% → *Greater confidence in flagged claims*
    - F1-Score: 62.50% vs 37.59% → *Stronger balance of precision and recall*
    - Accuracy: 80.00% vs 72.33% → *Better overall performance*

Deployment Recommendation

- Use optimized threshold of 0.5282 to flag suspicious claims
- Integrate model into claims processing pipeline to trigger manual reviews
- Acceptable trade-off:
    - 41.86% false positives among flagged cases
    - But 67.57% of actual fraud cases successfully identified