Fraudulent Claim Detection: Model Evaluation Report

1. Problem Statement & Objective

Global Insure aims to automate fraud detection in insurance claims using machine learning, leveraging historical claim and customer data to classify claims as fraudulent or legitimate.

2. Data Preparation & Cleaning

Rows: 1000 Columns: 40 (after cleaning, redundant/identifier columns removed)

Key Steps:

Null values handled (dropped rows with missing authorities contacted)

Illogical values (negative amounts) removed

Dates converted to datetime

Feature engineering (ratios, policy age, etc.)

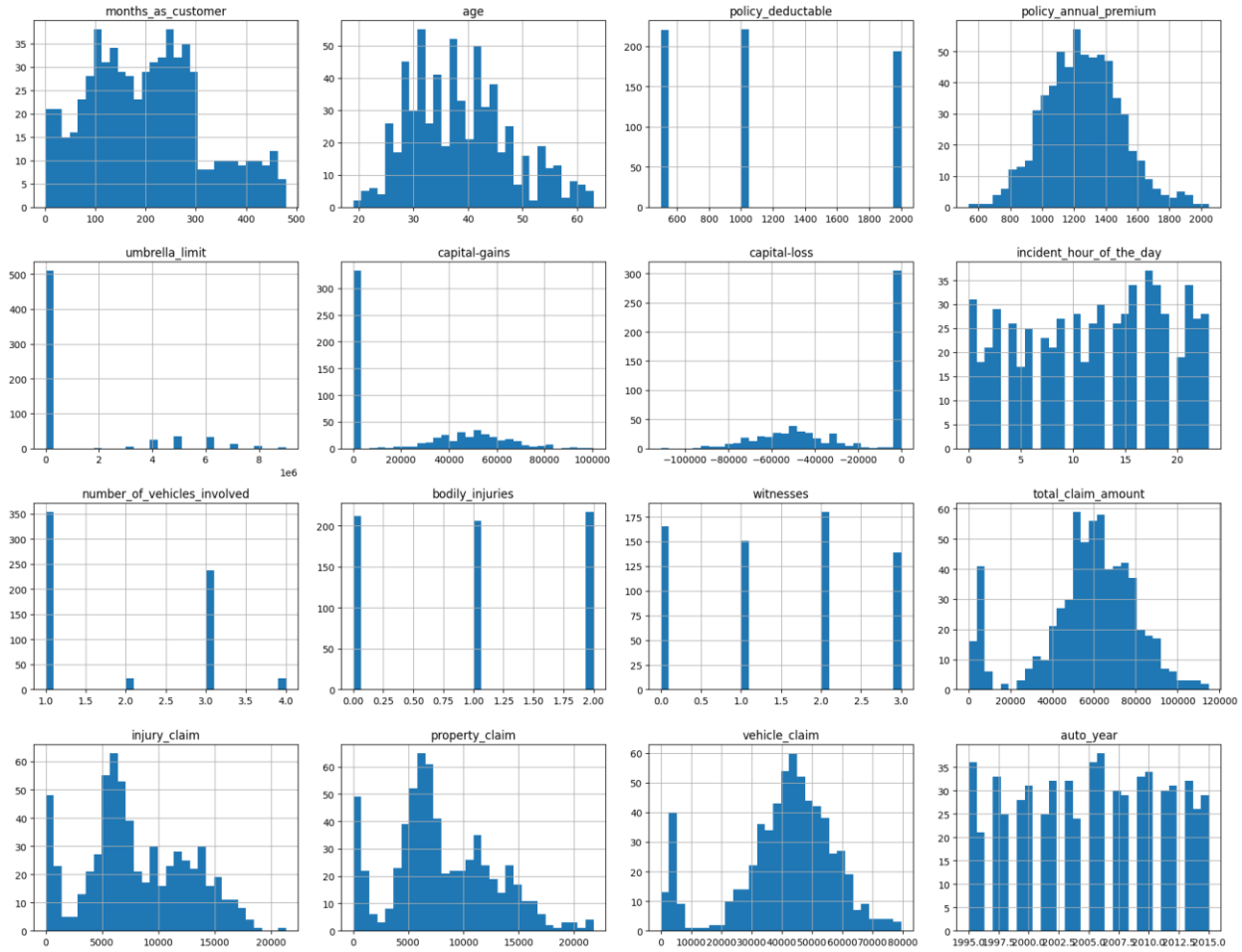
Categorical variables grouped and encoded

Numerical features scaled

3. Exploratory Data Analysis (EDA)

3.1 Univariate Analysis

Distribution of Numerical Features (Training Data):



Numerical Feature Distributions

Example: Most claim amounts are concentrated at lower values, with a long right tail.

3.2 Correlation Analysis

Correlation Matrix (Training Data):

Correlation Heatmap

Some features (e.g., injury_claim, property_claim, vehicle_claim) are highly correlated with total_claim_amount.

3.3 Class Balance

Result: The dataset is imbalanced, with fewer fraudulent claims.

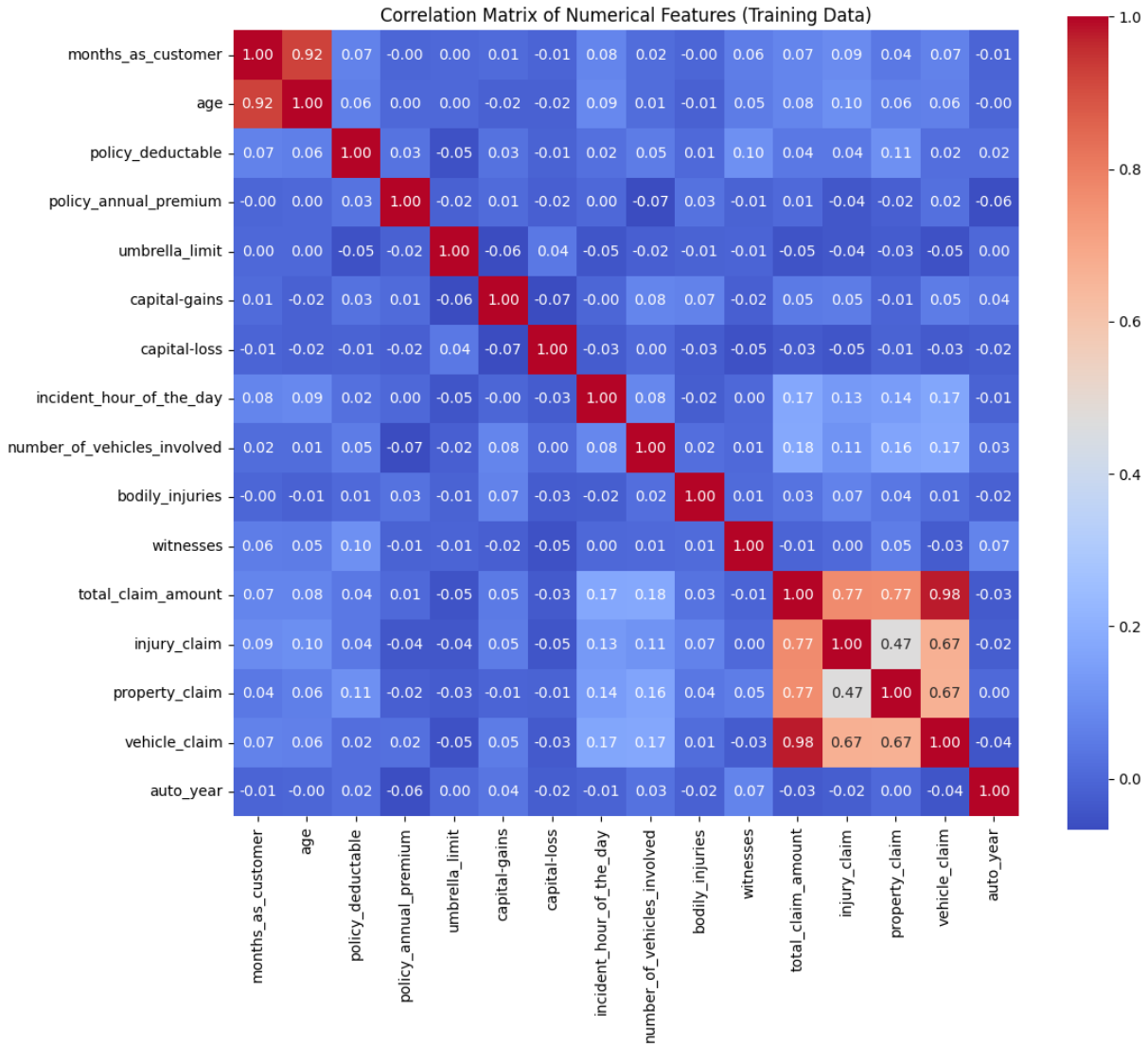
4. Feature Engineering

New Features: Days since policy bind, claim ratios, claim per vehicle, high deductible flag, policy age in years.

Categorical Grouping: Infrequent categories grouped as 'Other'.

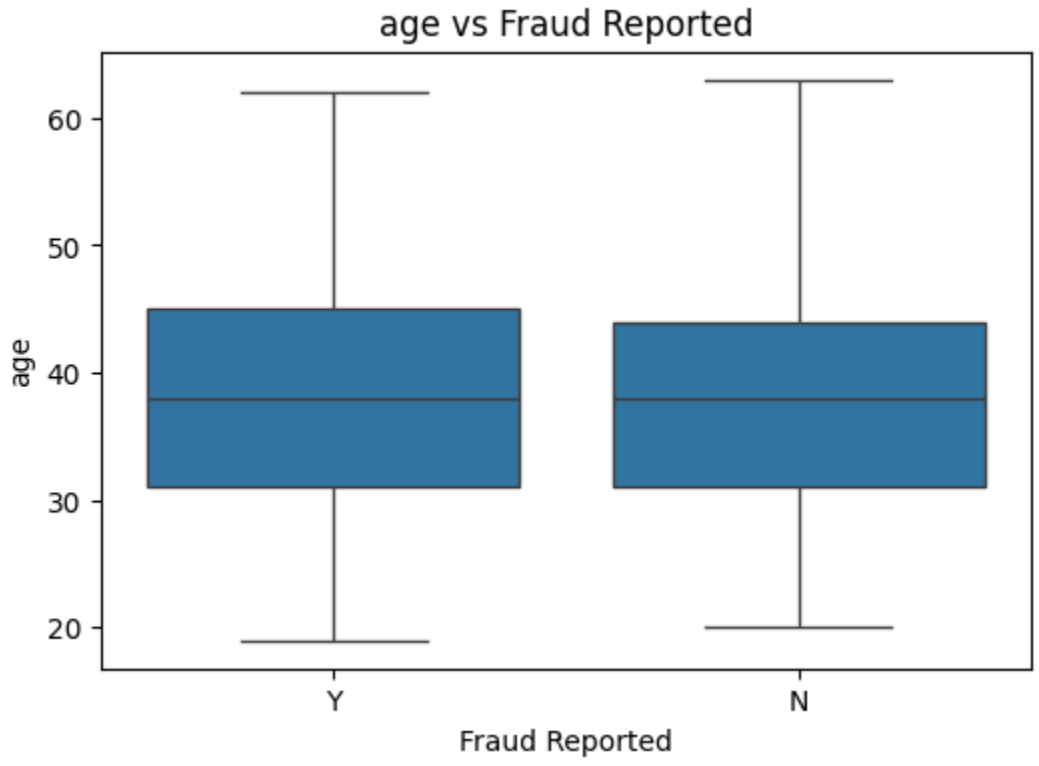
Dummy Variables: Created for all categorical features.

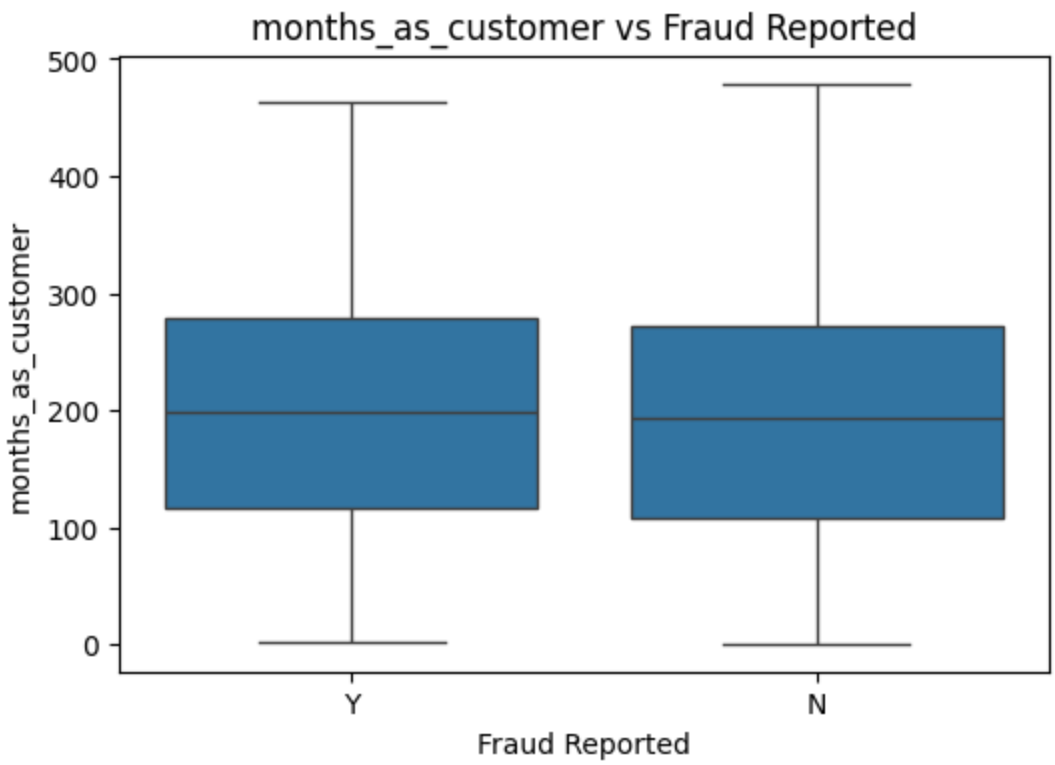
Scaling: StandardScaler applied to numerical features.

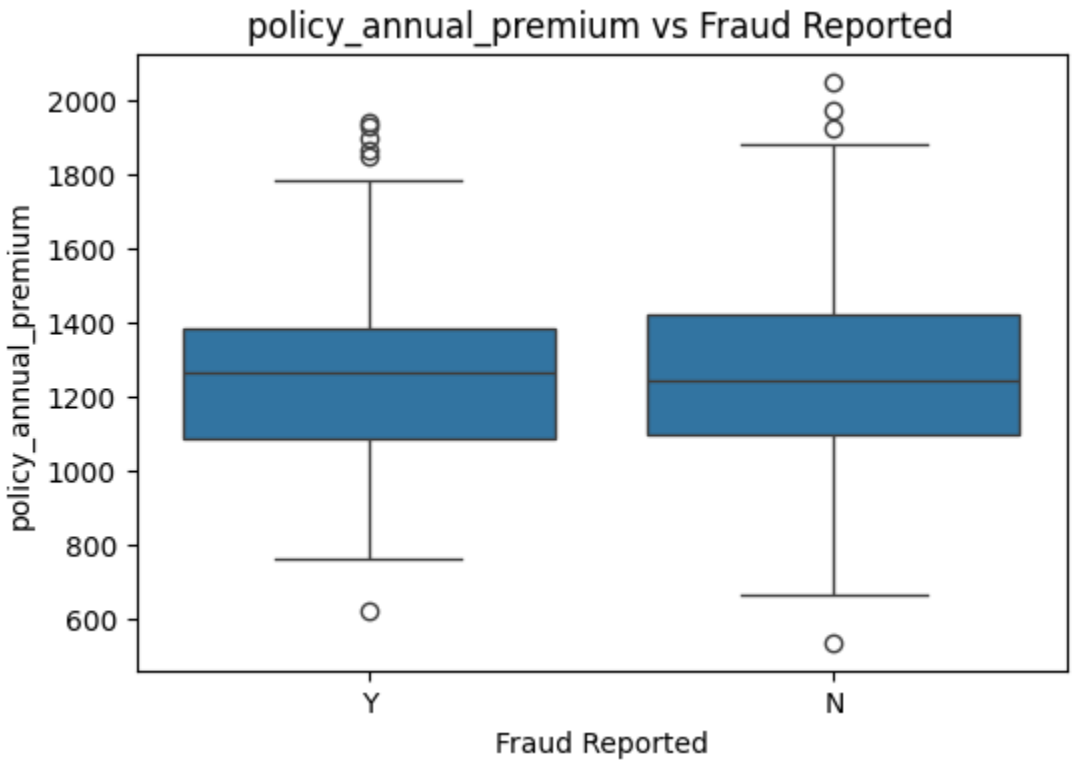



Class Balance in Training Data
Count
400
300
200
100
0
Y
N
Fraud Reported

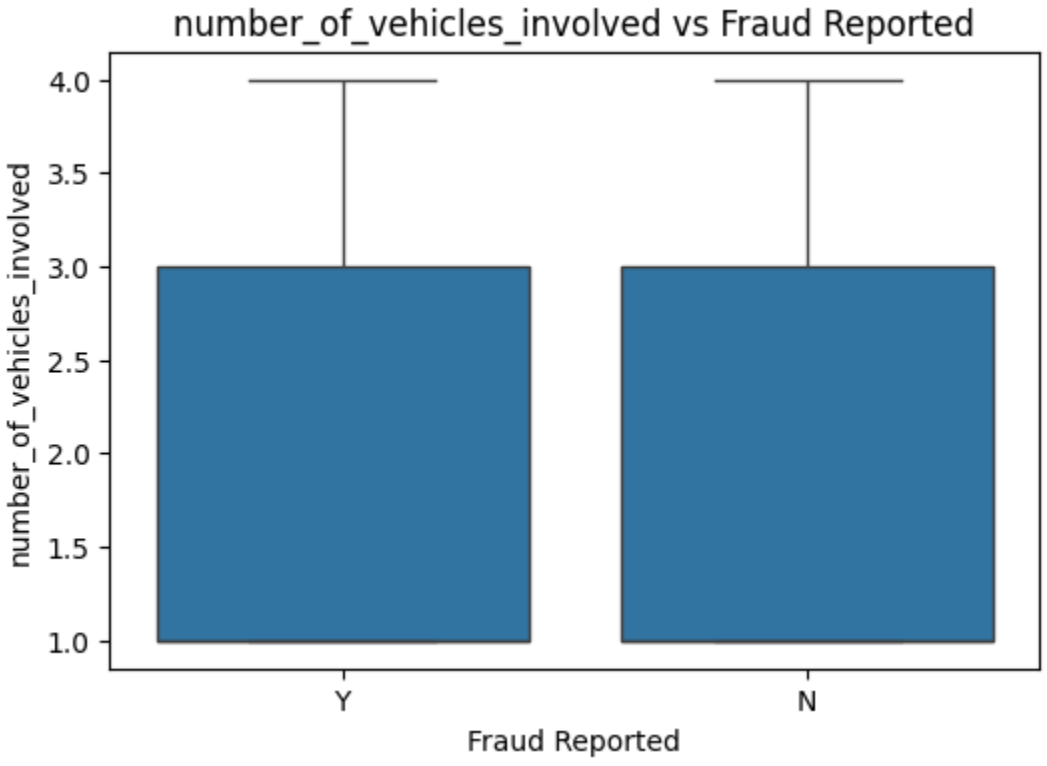

policy_deductable vs Fraud Reported
policy_deductable
2000
1800
1600
1400
1200
1000
800
600
Y
N
Fraud Reported

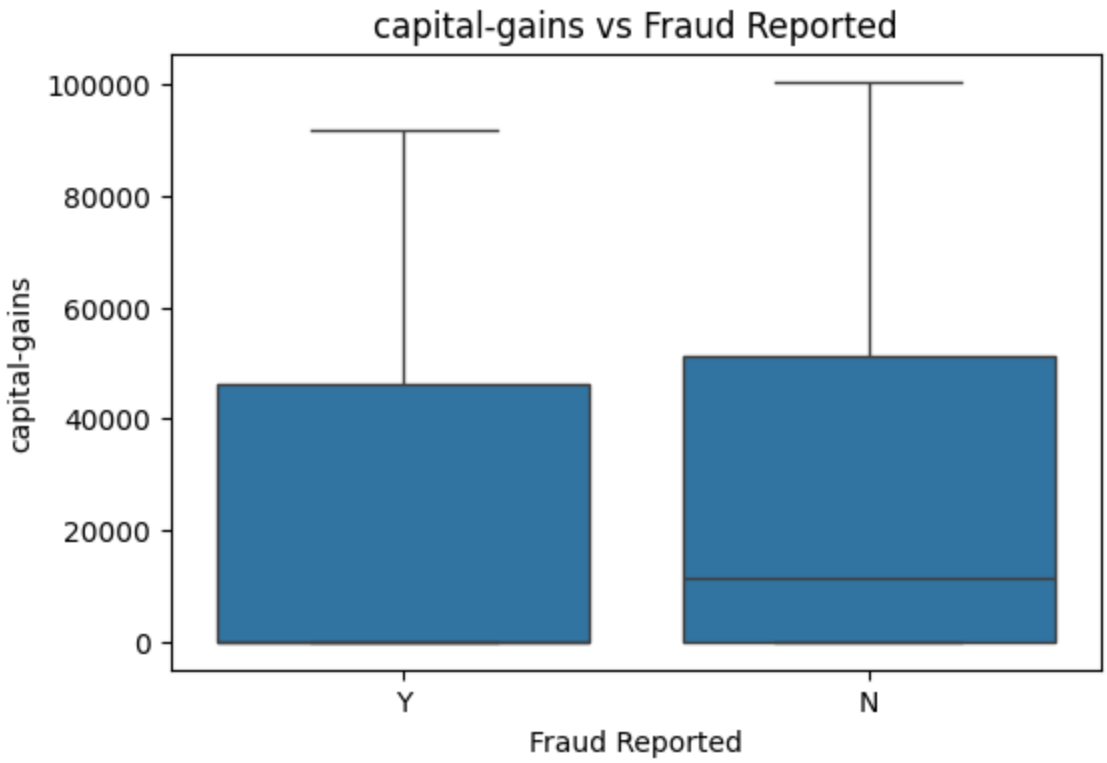

age vs Fraud Reported
age
60
50
40
30
20
Y
N
Fraud Reported

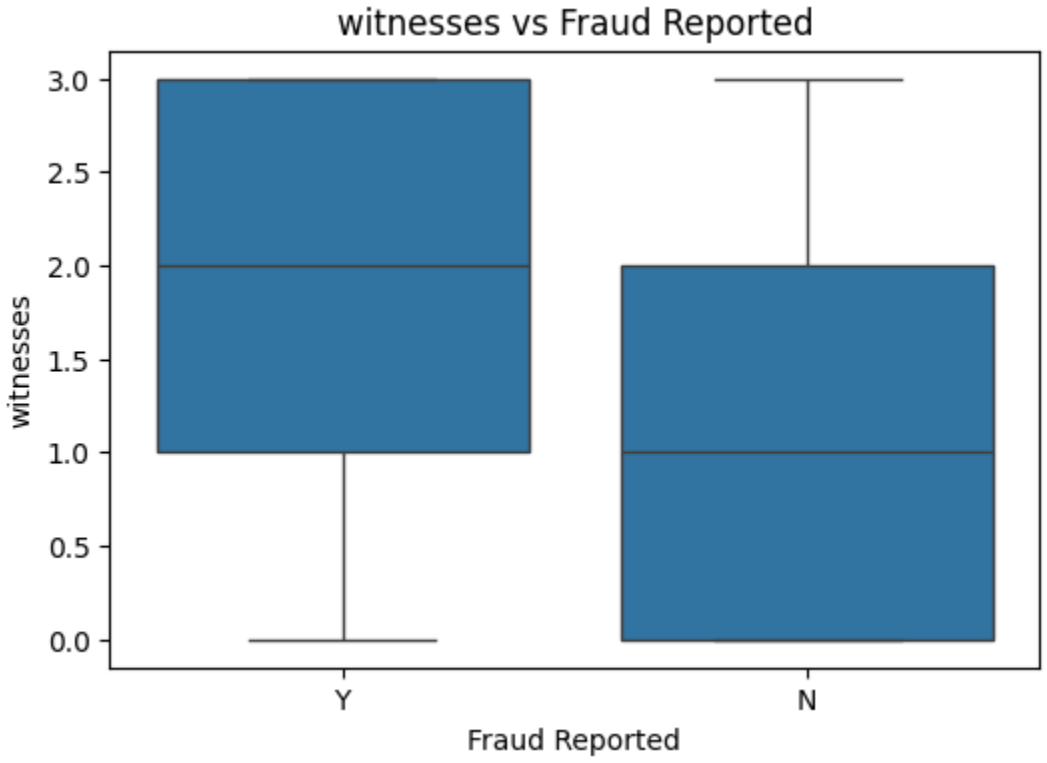

months_as_customer vs Fraud Reported
months_as_customer
500
400
300
200
100
0
Y
N
Fraud Reported

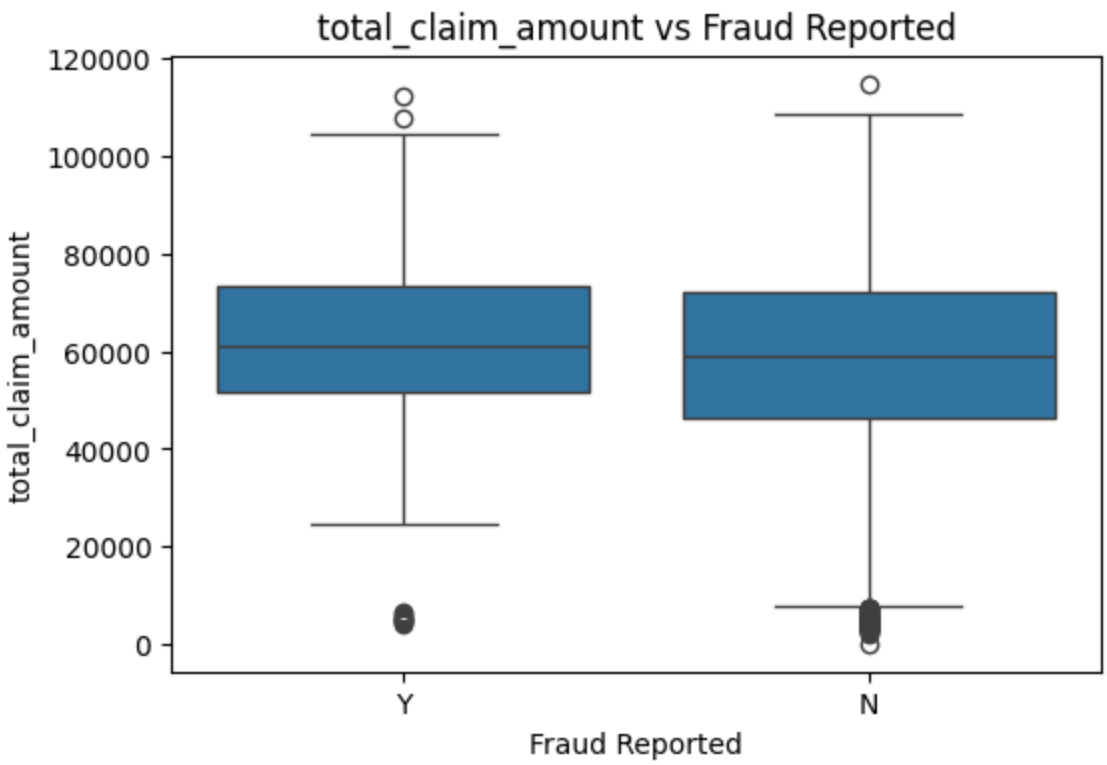

policy_annual_premium vs Fraud Reported
policy_annual_premium
2000
1800
1600
1400
1200
1000
800
600
Y
N
Fraud Reported


capital-loss vs Fraud Reported
capital-loss
0
−20000
−40000
−60000
−80000
−100000
Y
N
Fraud Reported


number_of_vehicles_involved vs Fraud Reported
number_of_vehicles_involved
4.0
3.5
3.0
2.5
2.0
1.5
1.0
Y
N
Fraud Reported

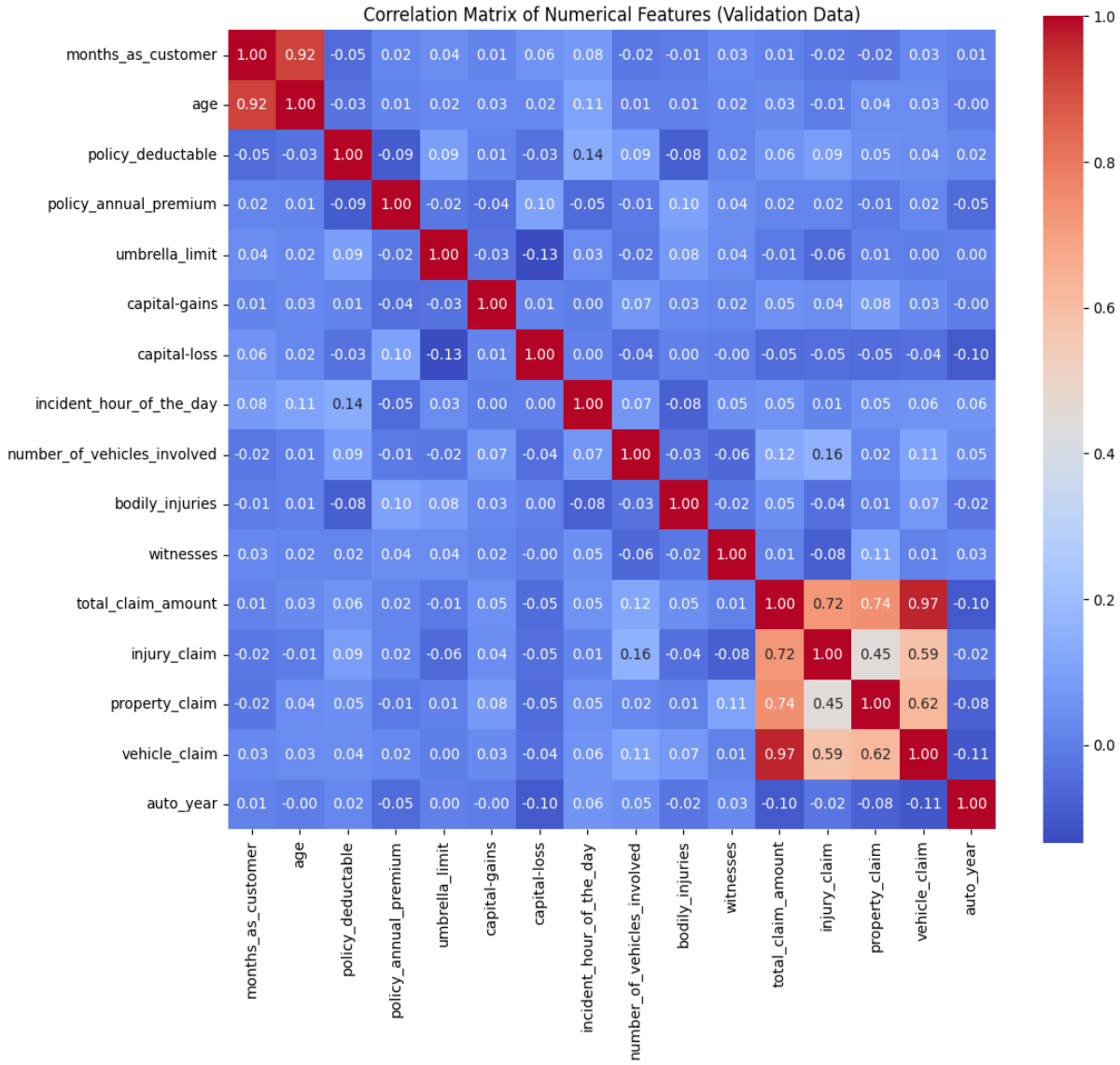

capital-gains vs Fraud Reported
capital-gains
100000
80000
60000
40000
20000
0
Y
N
Fraud Reported


witnesses vs Fraud Reported
witnesses
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Y
N
Fraud Reported



5. Model Building & Evaluation

5.1 Lgistic Regression



Feature Selection: RFECV selected optimal features.

Training Accuracy: 80.9%

Validation Accuracy (optimal cutoff 0.2): 31.5%

Validation Sensitivity: 98.6%

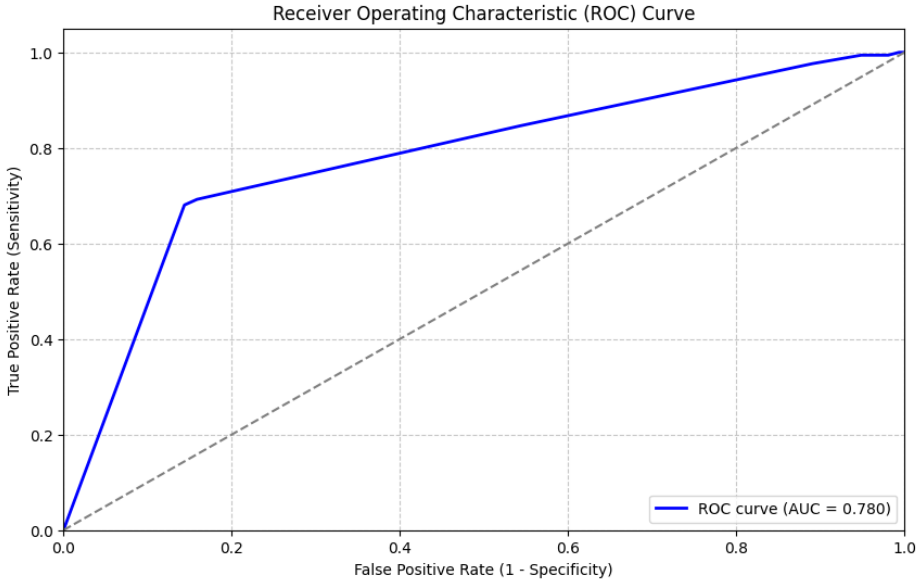
Validation Specificity: 7.5%

Confusion Matrix (Validation):

Precision: 56.3%

Recall (Sensitivity): 98.6%

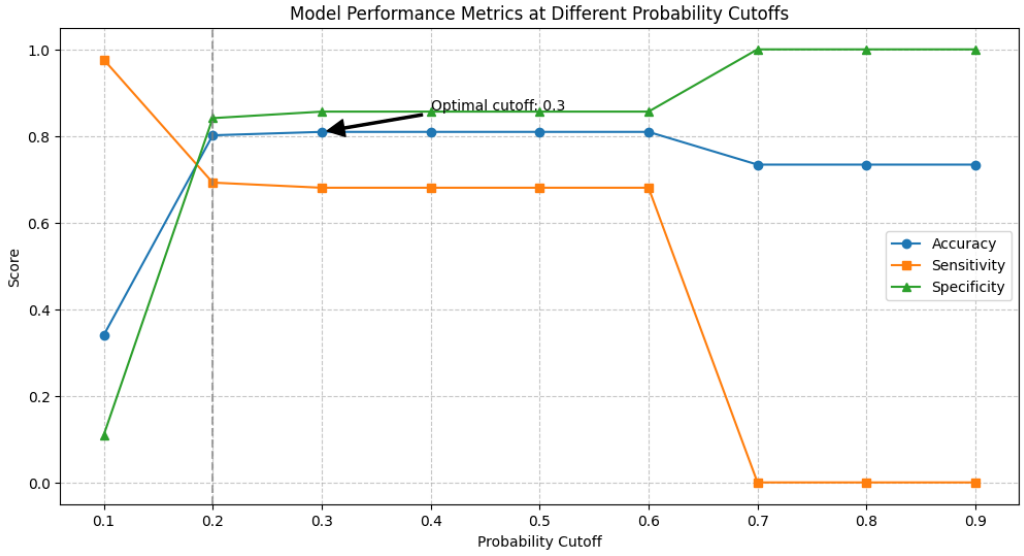
F1 Score: 71.7%



ROC Curve:

AUC is moderate, but the model is biased toward the positive class.

Cutoff Analysis:



Cutoff Metrics

At cutoff 0.2, sensitivity is maximized but specificity is very low.

5.2 Random Forest

Feature Importance: Top predictors identified (e.g., total_claim_amount, incident_severity).

Training Accuracy: 100%

Validation Accuracy: 77.7%

Validation Sensitivity: 31.9%

Validation Specificity: 94.0%

Validation Precision: 71.9%

Validation F1 Score: 44.2%

Confusion Matrix (Validation):

Classification Report (Validation):

6. Key Insights

Overfitting in Logistic Regression: High sensitivity but very poor specificity on validation data.

Random Forest Generalizes Better: Balanced metrics and higher validation accuracy.

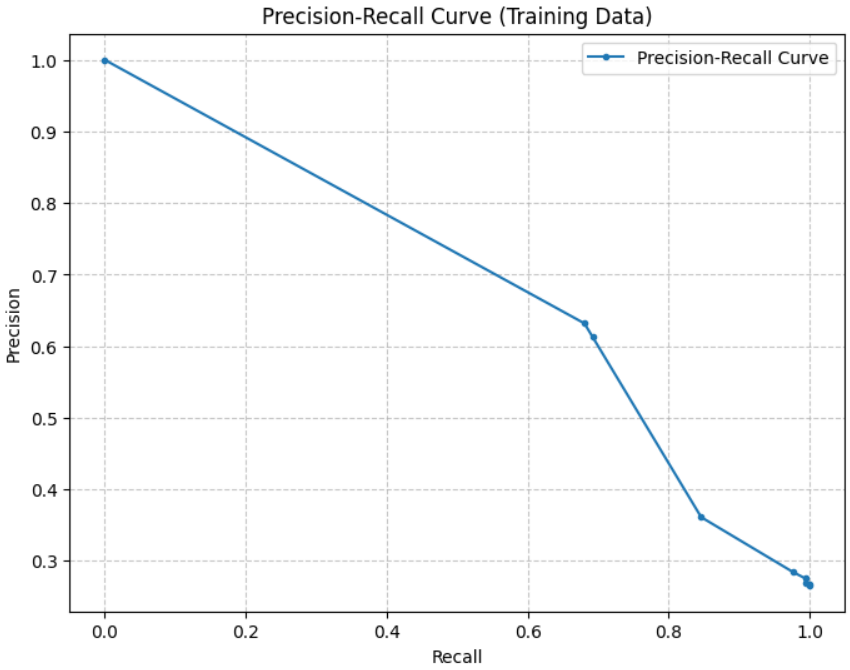
Feature Importance: Random forest highlights actionable predictors for fraud.

Threshold Tuning: Adjusting cutoffs impacts sensitivity/specificity tradeoff.

Precision-Recall Tradeoff: Business priorities should guide metric selection.

7. Visual Summary

Precision-Recall Curve (Logistic Regression):



Shows the tradeoff between precision and recall.

8. Conclusion

GitHub Copilot

Conclusion and Insights

After building and evaluating both logistic regression and random forest models for fraudulent claim detection, the following conclusions and insights were observed:

Model Performance

Logistic Regression:

High sensitivity (recall) but very low specificity on validation data.

Significant drop in accuracy from training to validation, indicating overfitting.

The model tends to classify most claims as fraudulent, leading to many false positives.

Random Forest: Much better balance between sensitivity and specificity.

Higher validation accuracy and F1-score compared to logistic regression.

Demonstrated better generalization and less overfitting.

Key Insights

Random Forest Outperforms Logistic Regression:

Random forest provided more reliable and balanced results, making it a better choice for this fraud detection problem.

Feature Importance:

Random forest highlighted the most predictive features, which can guide business teams to focus on key risk indicators for fraud.

Class Imbalance Handling:

Using resampling techniques like RandomOverSampler helped address class imbalance, improving the model's ability to detect minority (fraudulent) cases.

Cutoff Selection Matters:

Adjusting the probability cutoff based on ROC and precision-recall analysis is crucial for balancing sensitivity and specificity according to business needs.

Precision-Recall Tradeoff:

There is a tradeoff between catching more frauds (recall) and avoiding false alarms (precision). The optimal balance depends on the business context and cost of errors.

Recommendations

Use Random Forest for Deployment:

Given its superior performance, random forest should be the preferred model for production use.

Monitor and Update Models:

Regularly retrain and validate models as fraud patterns and data distributions may change over time.

In summary:

A data-driven approach using random forest significantly improves the early detection of fraudulent claims, helping the business reduce losses and streamline claim processing.