FRAUDULENT CLAIM DETECTION

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INTRODUCTION

Fraudulent insurance claims pose a significant challenge for insurers, resulting in substantial financial losses and inefficiencies. As claim volumes grow, traditional manual detection methods fall short. Data-driven approaches offer a more effective solution for identifying and preventing fraud.

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)

DATA PREPARATION & CLEANING

Missing Values

- Identified and dropped columns with excessive missingness.
- Imputed or removed rows for remaining nulls as appropriate.

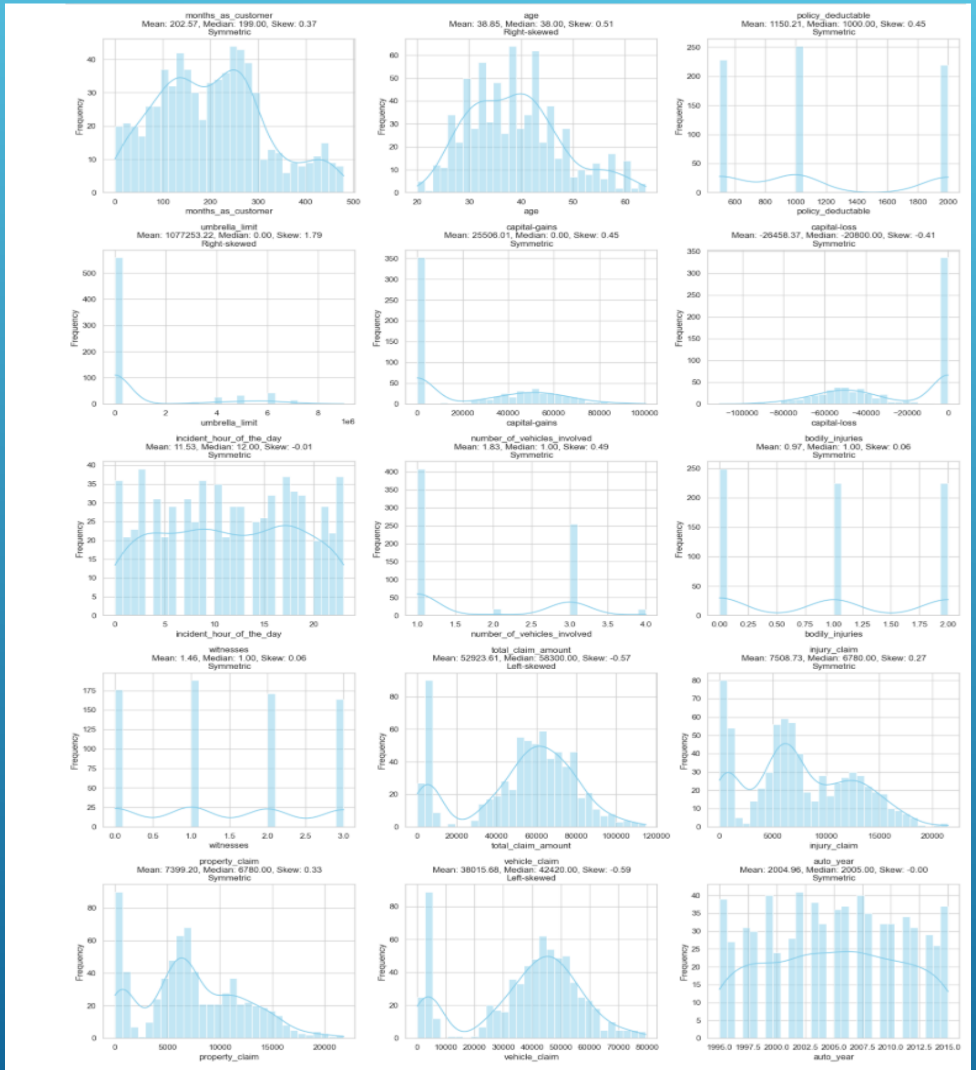
Redundant & Illogical Entries

- Removed duplicate records.
- Dropped features with constant or near-constant values.
- Ensured numeric fields (e.g., policy durations, claim amounts) were non-negative.

Data Types

- Converted date fields to datetime objects.
- Cast categorical columns to category dtype.

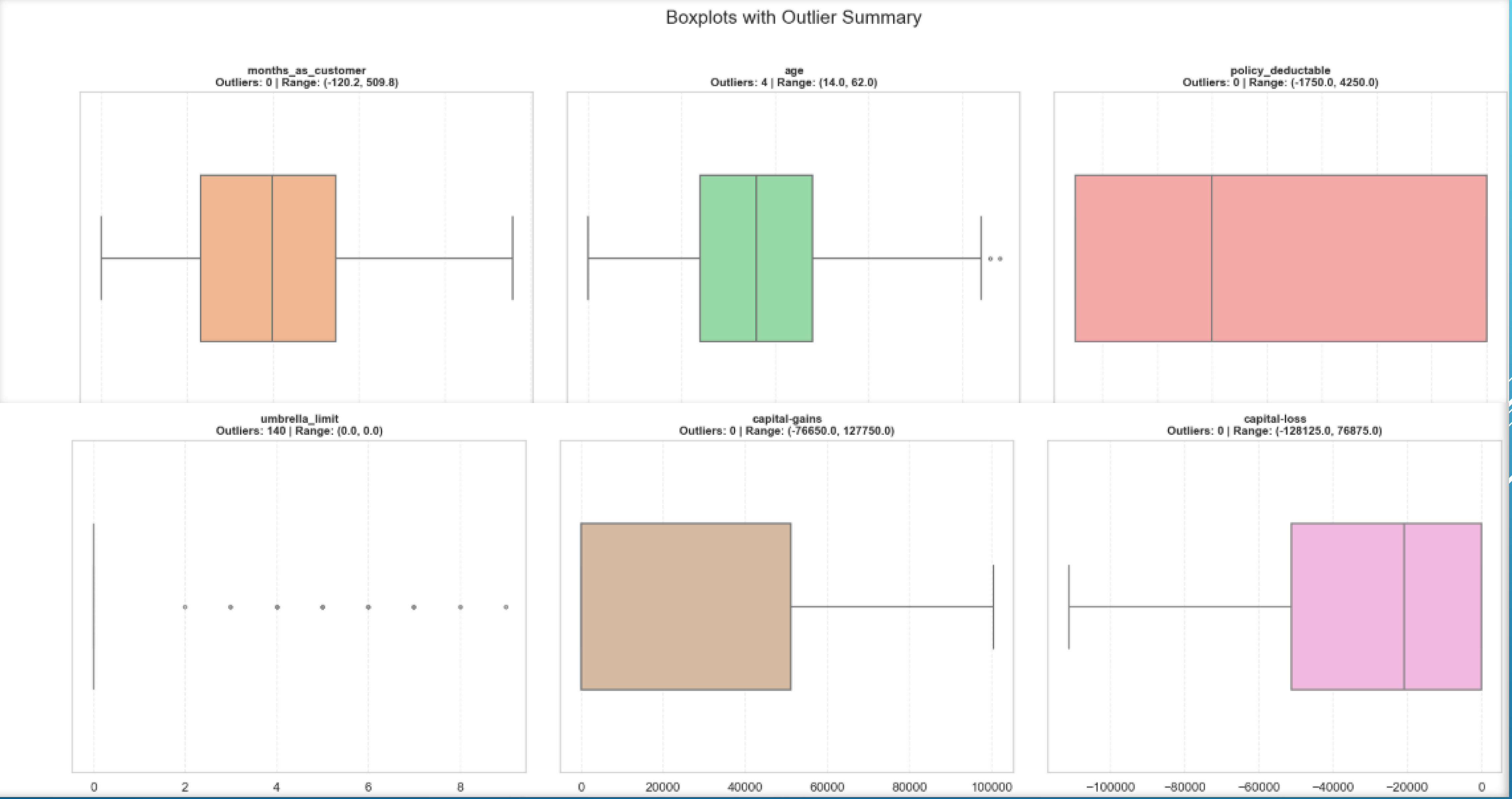
EDA – UNIVARIATE ANALYSIS



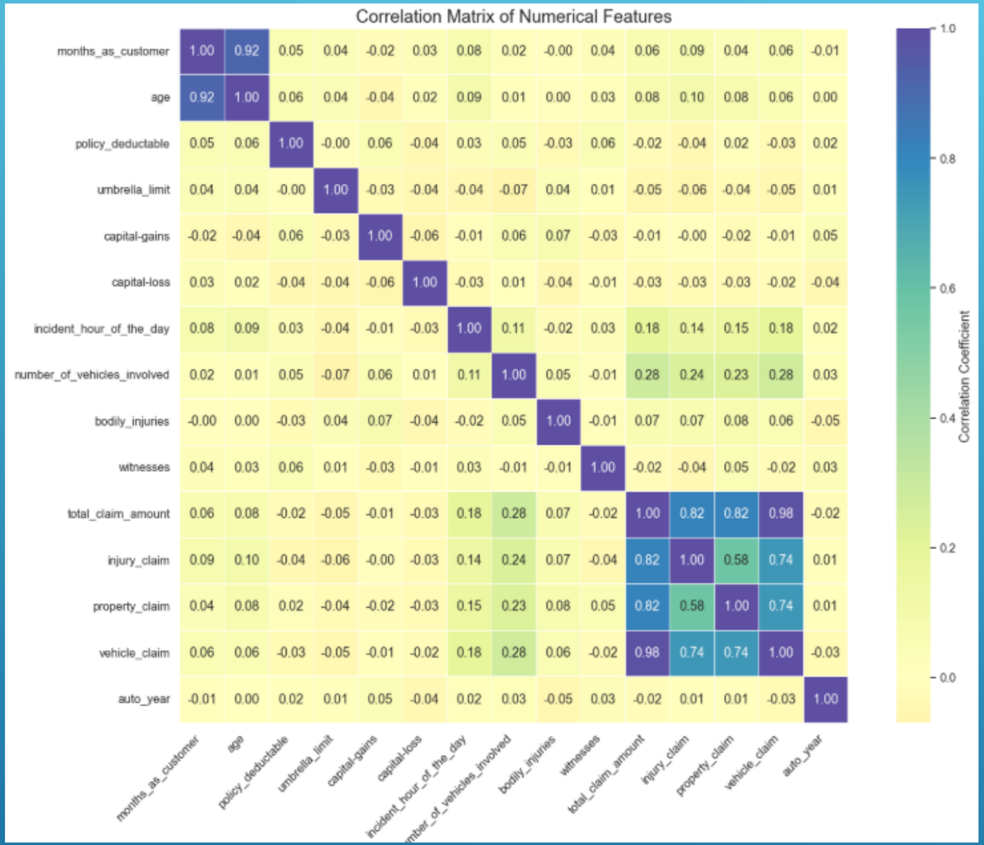
Observations from histogram plots:
months_as_customer:
- Mean: 202.57, Median: 199.00
- Skewness: 0.37
- Distribution appears approximately symmetric
age:
- Mean: 38.85, Median: 38.00
- Skewness: 0.51
- Distribution is positively skewed (right-tailed)
policy_deductable:
- Mean: 1150.21, Median: 1000.00
- 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

Observations from histogram plots:
- 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

EDA – UNIVARIATE ANALYSIS



CORRELATION MATRIX



Highly correlated feature (|correlation| > 0.7):

age vs months_as_customer: 0.920

injury_claim vs total_claim_amount: 0.818

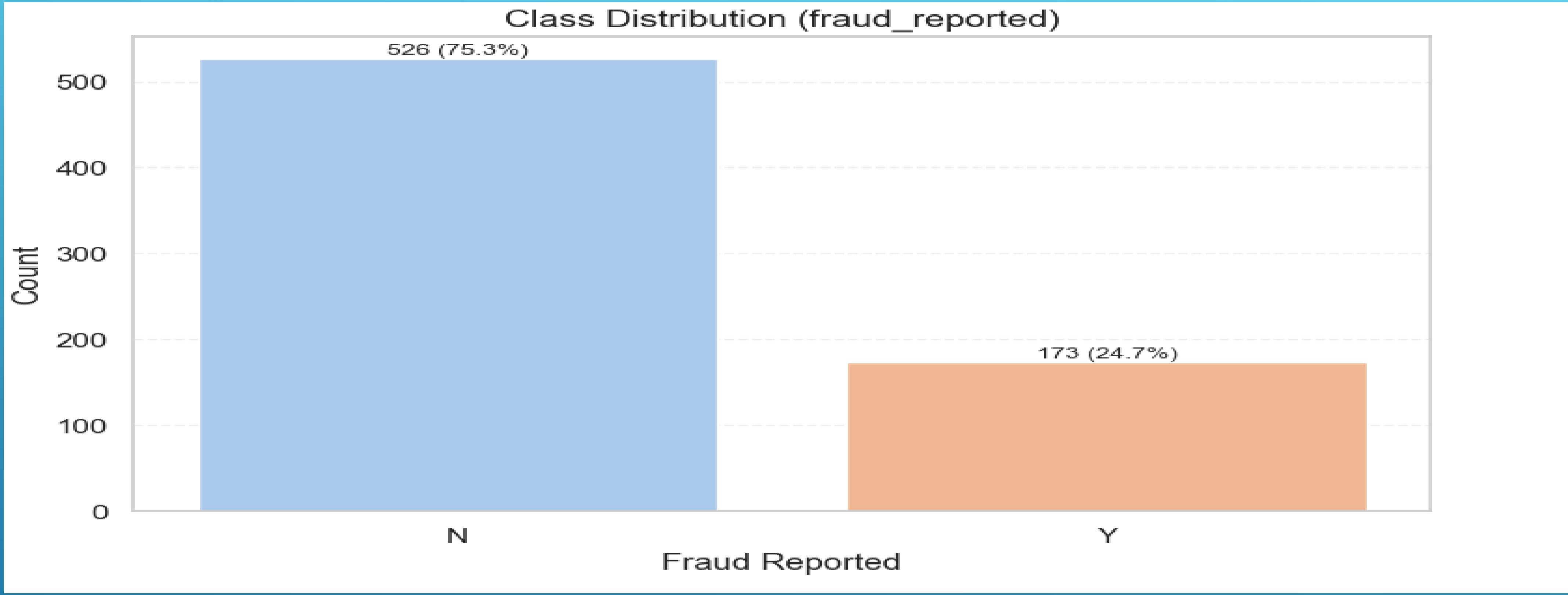
property_claim vs total_claim_amount: 0.815

vehicle_claim vs total_claim_amount: 0.984

vehicle_claim vs injury_claim: 0.743

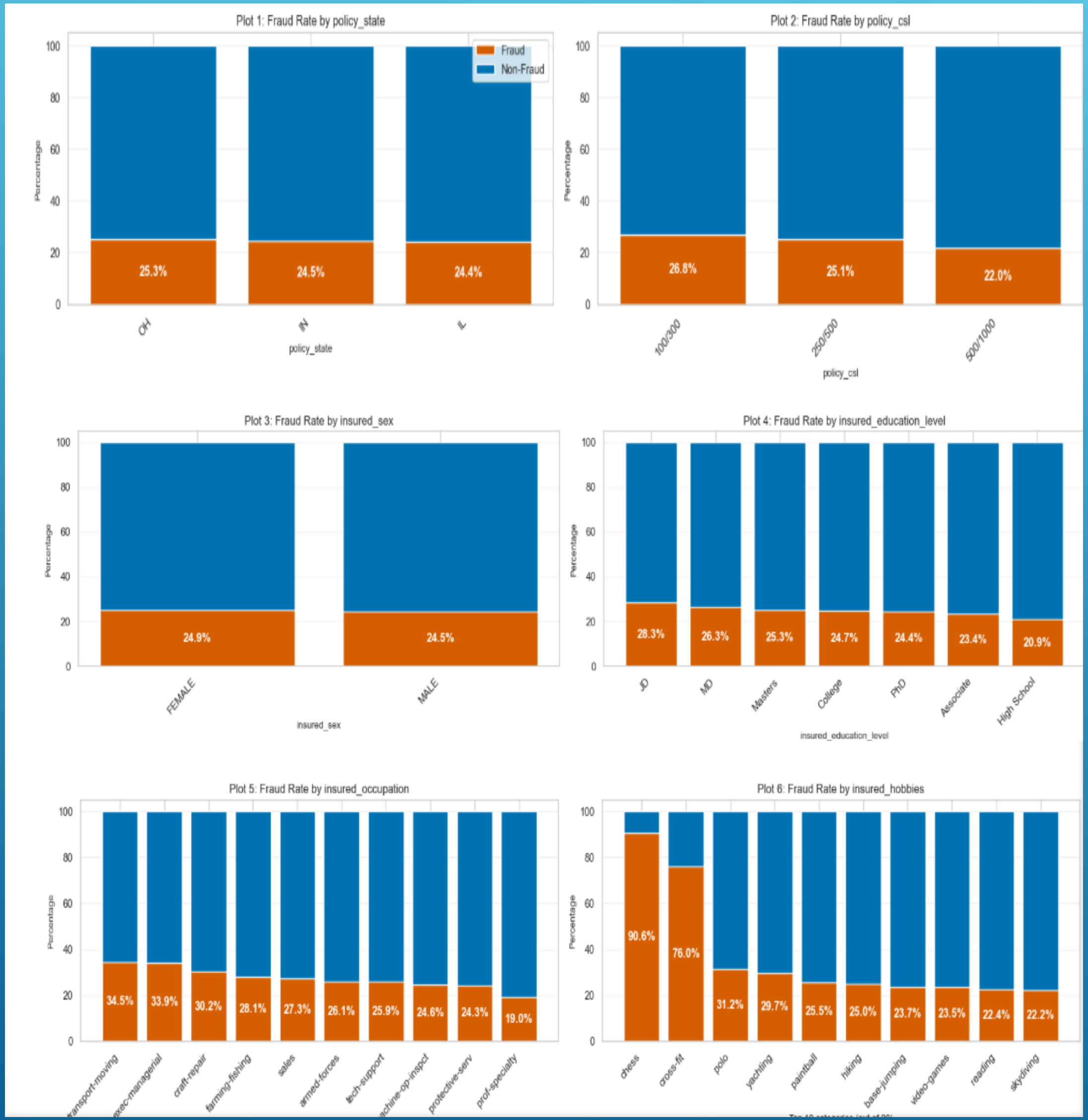
vehicle_claim vs property_claim: 0.742

CLASS IMBALANCE ANALYSIS



Imbalance Ratio: 3.04:1 (N vs Y)
Significant class imbalance detected. This may affect model performance.
Consider: resampling, class weights, or specialized metrics (F1, AUC, etc.)

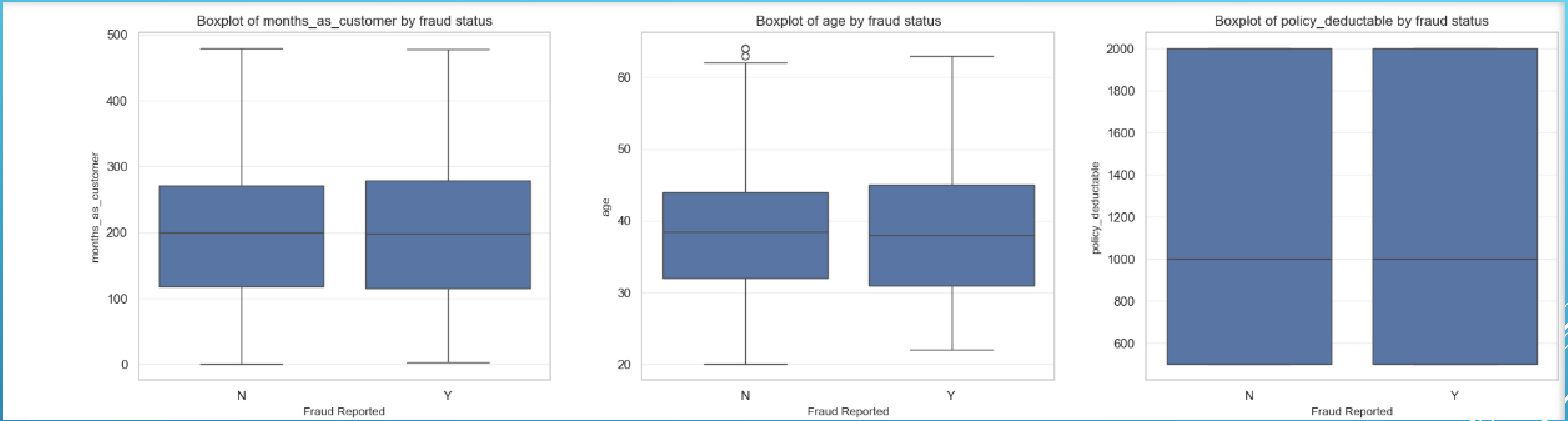
EDA – BIVARIATE ANALYSIS

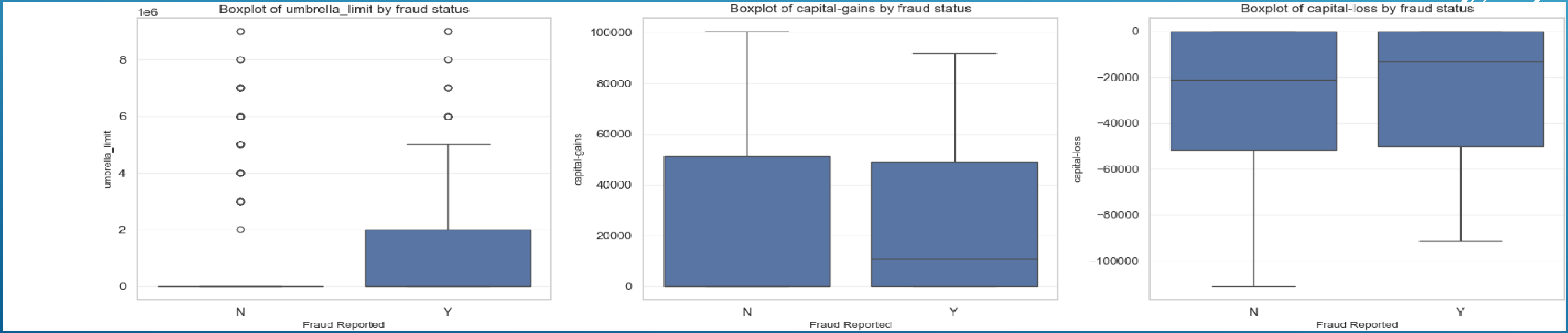


Feature importance based on variance in fraud rates:
incident_severity: 655.5417
insured_hobbies: 437.9118
auto_model: 138.9059
incident_type: 127.9124
collision_type: 97.4883
incident_state: 73.1274
property_damage: 39.8805
insured_occupation: 39.3522
auto_make: 27.8186
insured_relationship: 24.6759
authorities_contacted: 23.6709
incident_city: 14.4581
policy_csl: 6.0253
insured_education_level: 5.3411
police_report_available: 2.1569
policy_state: 0.2506
insured_sex: 0.0773

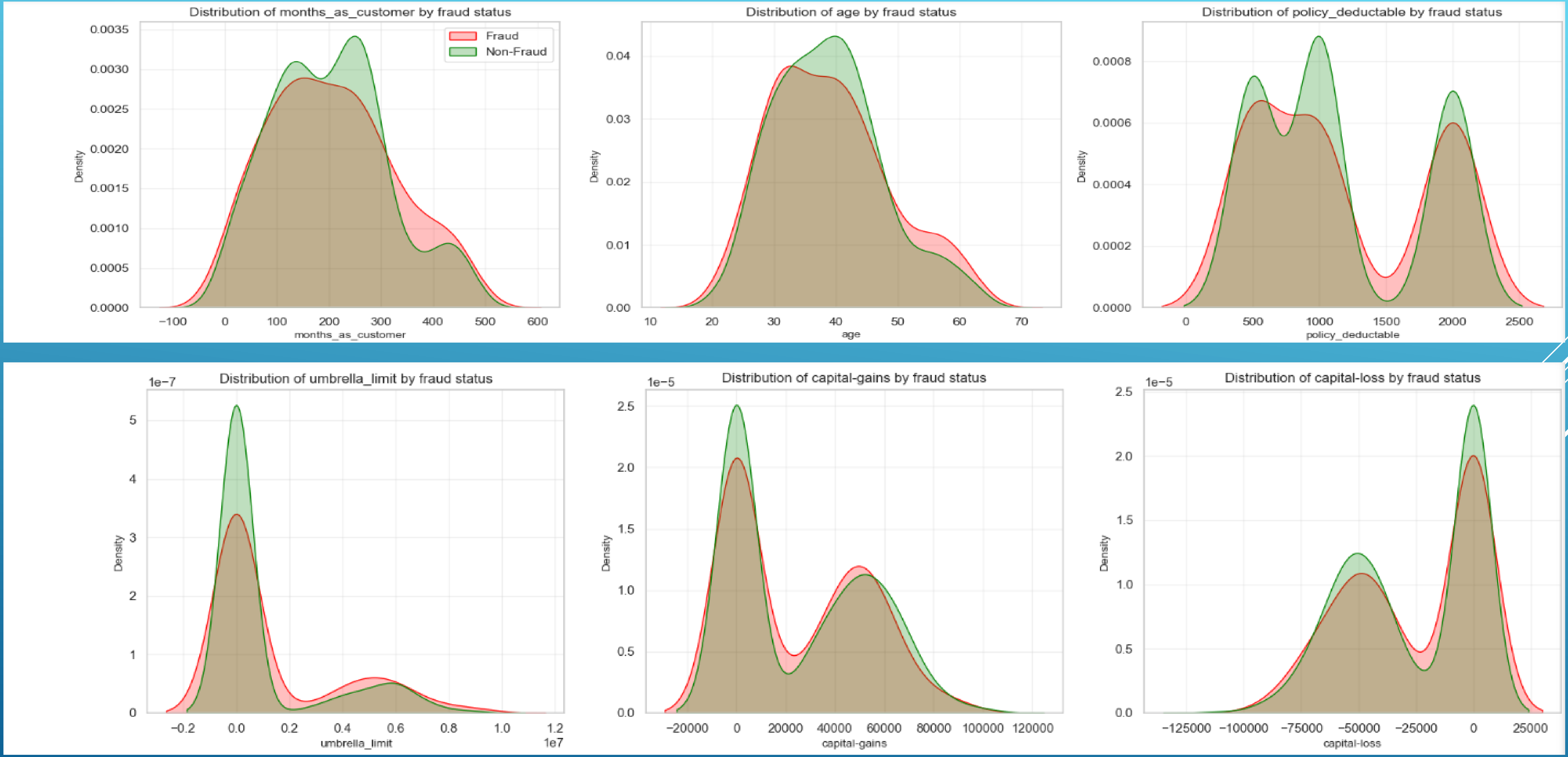
Categorical features with low variance may not contribute much to explaining fraud.

EDA –RELATIONSHIP B/W NUMERICAL FEATURES AND TARGET VARIABLE

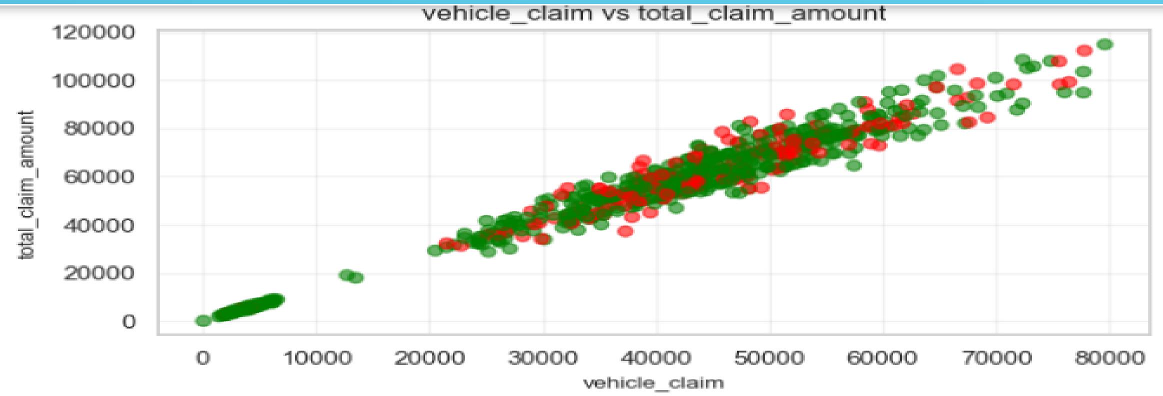


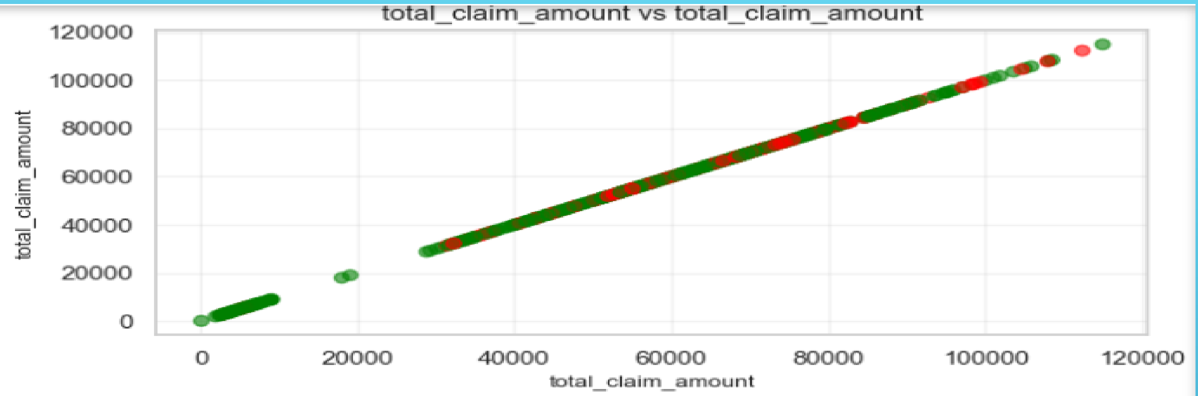


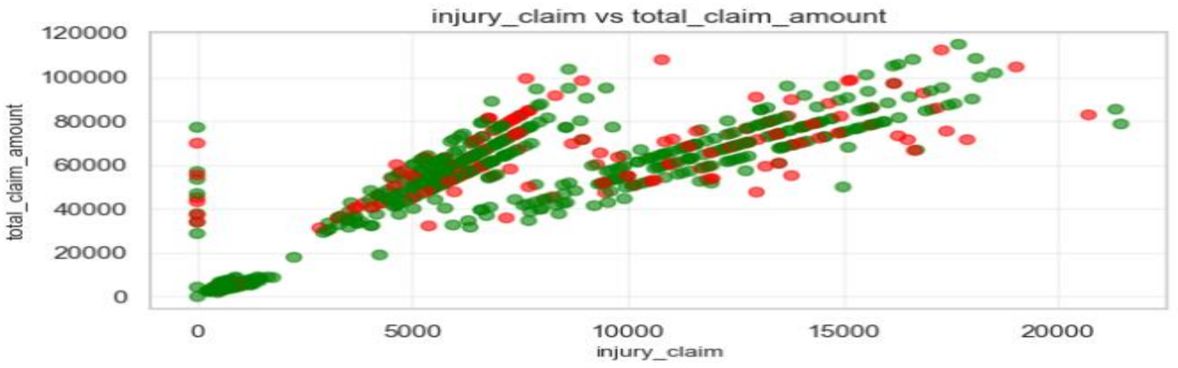
EDA –RELATIONSHIP B/W NUMERICAL FEATURES AND TARGET VARIABLE

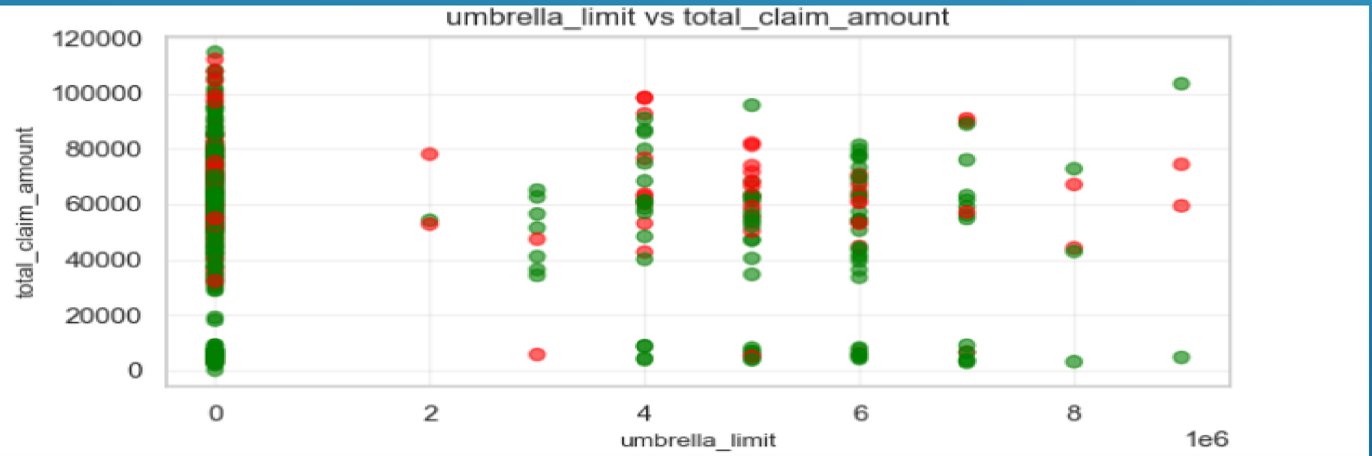


EDA –RELATIONSHIP B/W NUMERICAL FEATURES AND TARGET VARIABLE









MODEL SELECTION

Models

- Logistic Regression
- Random Forest Classifier

LOGISTIC REGRESSION+RFECV

Number of selected features: 52
Selected features:
['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']

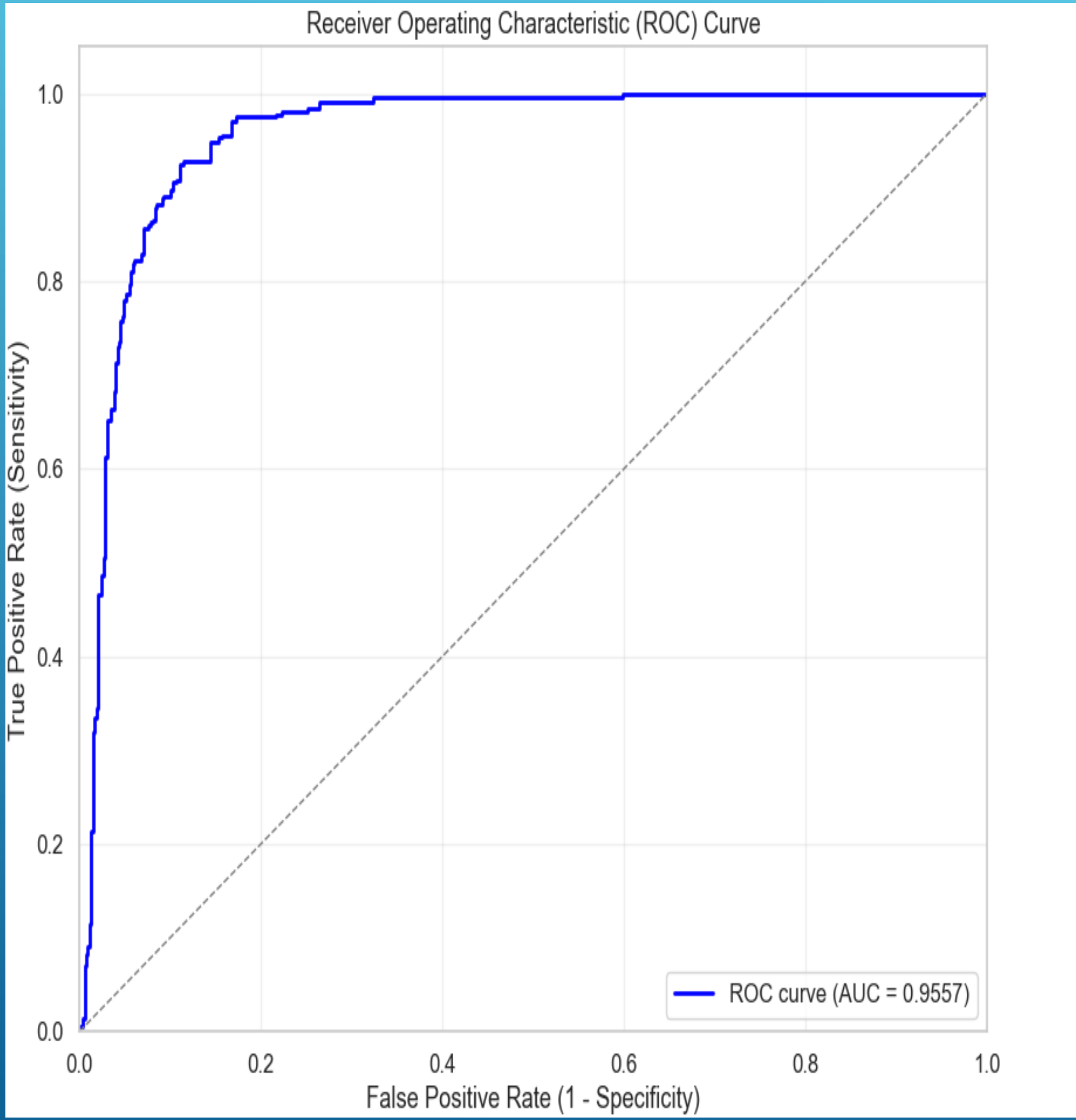
LOGISTIC REGRESSION

```
Optimization terminated successfully.
         Current function value: 0.270871
         Iterations 8
                           Logit Regression Results
==============================================================================
Dep. Variable:         fraud_reported   No. Observations:                 1052
Model:                          Logit   Df Residuals:                      999
Method:                           MLE   Df Model:                           52
Date:                Sun, 11 May 2025   Pseudo R-squ.:                  0.6092
Time:                        18:51:35   Log-Likelihood:                -284.96
converged:                       True   LL-Null:                       -729.19
Covariance Type:            nonrobust   LLR p-value:                 1.247e-152
==================================================================================================
                                         coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------------------------
const                                  1.7477      0.400      4.373      0.000       0.964       2.531
policy_csl_250/500                     0.7082      0.247      2.872      0.004       0.225       1.192
insured_education_level_JD             0.8216      0.336      2.449      0.014       0.164       1.479
insured_education_level_MD             1.2077      0.344      3.511      0.000       0.533       1.882
insured_education_level_PhD            0.9790      0.361      2.709      0.007       0.271       1.687
insured_occupation_exec-managerial     0.5662      0.429      1.320      0.187      -0.274       1.407
insured_occupation_farming-fishing    -1.3002      0.613     -2.120      0.034      -2.502      -0.098
insured_occupation_handlers-cleaners  -2.1783      0.632     -3.447      0.001      -3.417      -0.940
insured_occupation_other-service      -1.4148      0.512     -2.763      0.006      -2.418      -0.411
insured_occupation_priv-house-serv    -1.2779      0.499     -2.562      0.010      -2.255      -0.300
insured_hobbies_camping               -0.9977      0.579     -1.724      0.085      -2.132       0.137
insured_hobbies_chess                  7.0837      0.721      9.819      0.000       5.670       8.498
insured_hobbies_cross-fit              4.5590      0.639      7.134      0.000       3.307       5.811
insured_hobbies_dancing               -1.9433      0.784     -2.478      0.013      -3.480      -0.406
insured_hobbies_golf                  -0.1594      0.558     -0.286      0.775      -1.253       0.935
insured_hobbies_movies                -0.9588      0.639     -1.500      0.134      -2.211       0.294
insured_hobbies_sleeping              -1.7921      0.547     -3.275      0.001      -2.865      -0.720
insured_hobbies_video-games            1.9492      0.450      4.330      0.000       1.067       2.832
insured_relationship_not-in-family     1.1859      0.332      3.572      0.000       0.535       1.837
insured_relationship_own-child        -0.3911      0.346     -1.131      0.258      -1.069       0.287
insured_relationship_unmarried         0.5995      0.343      1.748      0.080      -0.073       1.272
incident_type_Vehicle Theft           -0.4552      0.738     -0.617      0.537      -1.902       0.991
collision_type_Side Collision         -1.0720      0.280     -3.835      0.000      -1.620      -0.524
collision_type_Unknown                 0.4954      0.629      0.787      0.431      -0.738       1.728
incident_severity_Minor Damage        -5.4462      0.448    -12.143      0.000      -6.325      -4.567
incident_severity_Total Loss          -4.3645      0.358    -12.175      0.000      -5.067      -3.662
incident_severity_Trivial Damage      -5.8056      0.863     -6.731      0.000      -7.496      -4.115
incident_state_NY                     -0.6497      0.301     -2.157      0.031      -1.240      -0.059
incident_state_OH                      0.8415      0.756      1.112      0.266      -0.641       2.324
incident_state_PA                     -1.2445      0.855     -1.455      0.146      -2.920       0.431
incident_state_WV                     -1.1661      0.326     -3.579      0.000      -1.805      -0.528
incident_city_Northbrook              -1.0728      0.459     -2.339      0.019      -1.972      -0.174
property_damage_Unknown                0.9624      0.289      3.330      0.001       0.396       1.529
property_damage_YES                    0.8091      0.311      2.600      0.009       0.199       1.419
auto_make_Audi                         0.9949      0.557      1.786      0.074      -0.097       2.087
auto_make_BMW                          2.1325      0.712      2.995      0.003       0.737       3.528
auto_make_Chevrolet                   -1.6916      0.662     -2.554      0.011      -2.990      -0.394
auto_make_Nissan                      -0.9644      0.690     -1.398      0.162      -2.316       0.388
auto_model_A5                          0.3517      0.726      0.485      0.628      -1.071       1.774
auto_model_Camry                      -1.3952      0.909     -1.536      0.125      -3.176       0.386
auto_model_Civic                       2.5883      0.722      3.585      0.000       1.173       4.003
auto_model_F150                        0.8345      0.693      1.205      0.228      -0.523       2.192
auto_model_Fusion                     -1.6368      0.833     -1.965      0.049      -3.269      -0.005
auto_model_Grand Cherokee              1.3517      0.681      1.984      0.047       0.017       2.687
auto_model_Legacy                     -2.1517      0.943     -2.282      0.022      -3.999      -0.304
auto_model_MDX                        -1.6200      0.612     -2.648      0.008      -2.819      -0.421
auto_model_Other                      -1.4888      0.431     -3.458      0.001      -2.333      -0.645
auto_model_Pathfinder                 -3.7078      1.187     -3.124      0.002      -6.034      -1.382
auto_model_Silverado                   2.1133      0.927      2.280      0.023       0.297       3.930
auto_model_Ultima                      1.2015      0.974      1.233      0.218      -0.708       3.111
auto_model_Wrangler                   -1.2062      0.705     -1.711      0.087      -2.588       0.175
```

```
VIF values for detecting multicollinearity:
                                 Feature        VIF
0                                  const  13.036403
23                collision_type_Unknown   3.132409
37                      auto_make_Nissan   2.879380
26      incident_severity_Trivial Damage   2.299748
34                        auto_make_Audi   2.282747
35                         auto_make_BMW   2.282130
38                         auto_model_A5   2.257321
51                         auto_model_X5   2.059363
49                     auto_model_Ultima   1.924383
36                   auto_make_Chevrolet   1.882268
47                 auto_model_Pathfinder   1.871605
21           incident_type_Vehicle Theft   1.870257
48                  auto_model_Silverado   1.772085
24        incident_severity_Minor Damage   1.692725
46                      auto_model_Other   1.644159
32               property_damage_Unknown   1.562649
33                   property_damage_YES   1.549599
25          incident_severity_Total Loss   1.388979
11                 insured_hobbies_chess   1.305639
30                     incident_state_WV   1.300934
41                      auto_model_F150   1.277417
27                     incident_state_NY   1.270492
29                     incident_state_PA   1.255231
18    insured_relationship_not-in-family   1.251663
39                      auto_model_Camry   1.227242
20        insured_relationship_unmarried   1.223582
2             insured_education_level_JD   1.218897
28                     incident_state_OH   1.217091
19        insured_relationship_own-child   1.185366
3             insured_education_level_MD   1.180762
4            insured_education_level_PhD   1.164540
22         collision_type_Side Collision   1.153783
5     insured_occupation_exec-managerial   1.143442
12             insured_hobbies_cross-fit   1.141175
15                insured_hobbies_movies   1.133120
44                     auto_model_Legacy   1.132341
42                     auto_model_Fusion   1.130494
17           insured_hobbies_video-games   1.130119
45                        auto_model_MDX   1.129547
14                  insured_hobbies_golf   1.125835
40                      auto_model_Civic   1.117335
6     insured_occupation_farming-fishing   1.114497
50                   auto_model_Wrangler   1.109286
7   insured_occupation_handlers-cleaners   1.109146
1                     policy_csl_250/500   1.107126
31              incident_city_Northbrook   1.101857
52                       age_group_Young   1.099676
43             auto_model_Grand Cherokee   1.095855
13               insured_hobbies_dancing   1.095049
16              insured_hobbies_sleeping   1.094537
9     insured_occupation_priv-house-serv   1.092637
10               insured_hobbies_camping   1.080957
8       insured_occupation_other-service   1.079876

Features with high multicollinearity (VIF > 5):
  Feature        VIF
0   const  13.036403
```

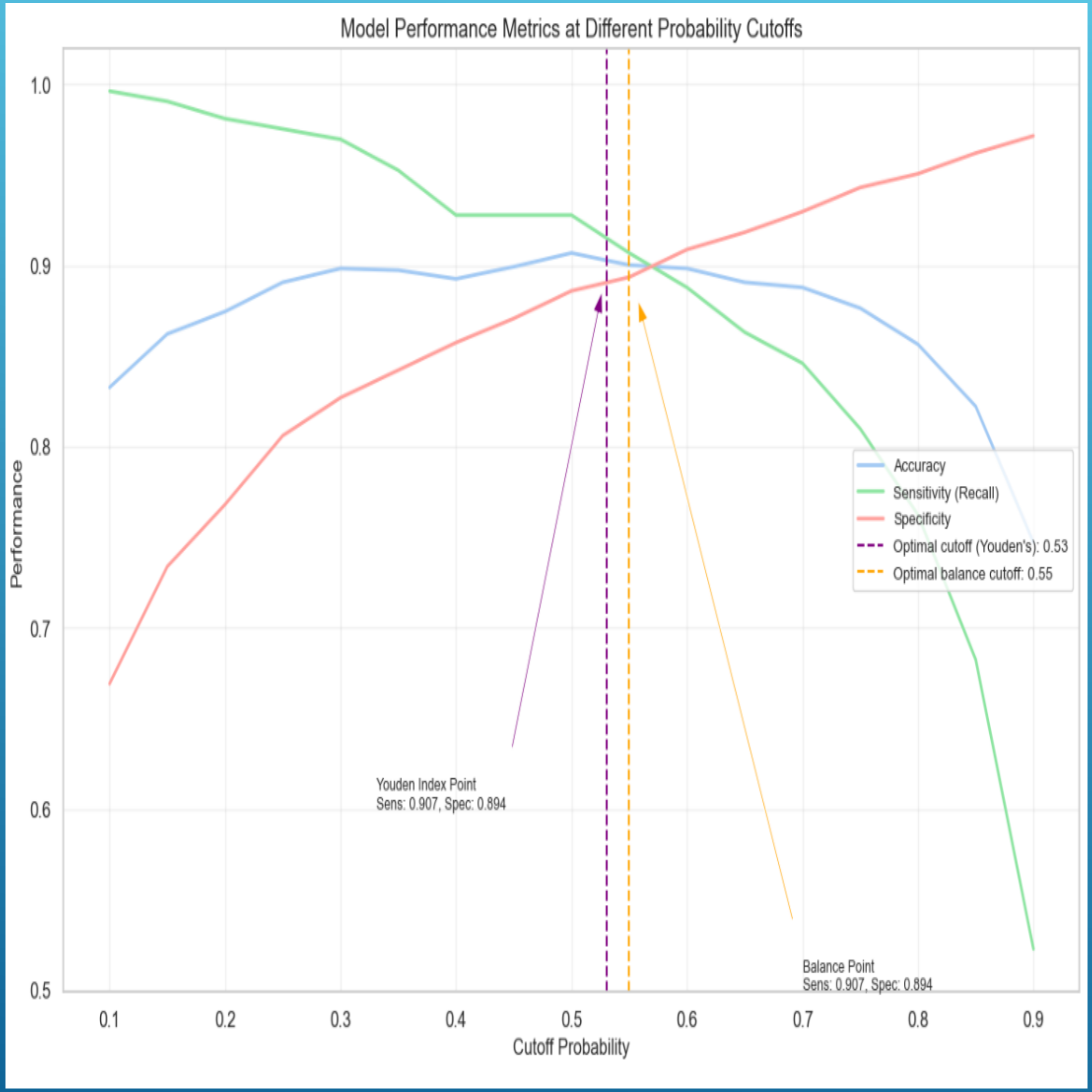
LOGISTIC REGRESSION – ROC CURVE



Optimal threshold based on Youden's index: 0.5309
At this threshold - Sensitivity: 0.9240, Specificity: 0.8897

Optimal cutoff value: 0.5309

LOGISTIC REGRESSION – ROC CURVE

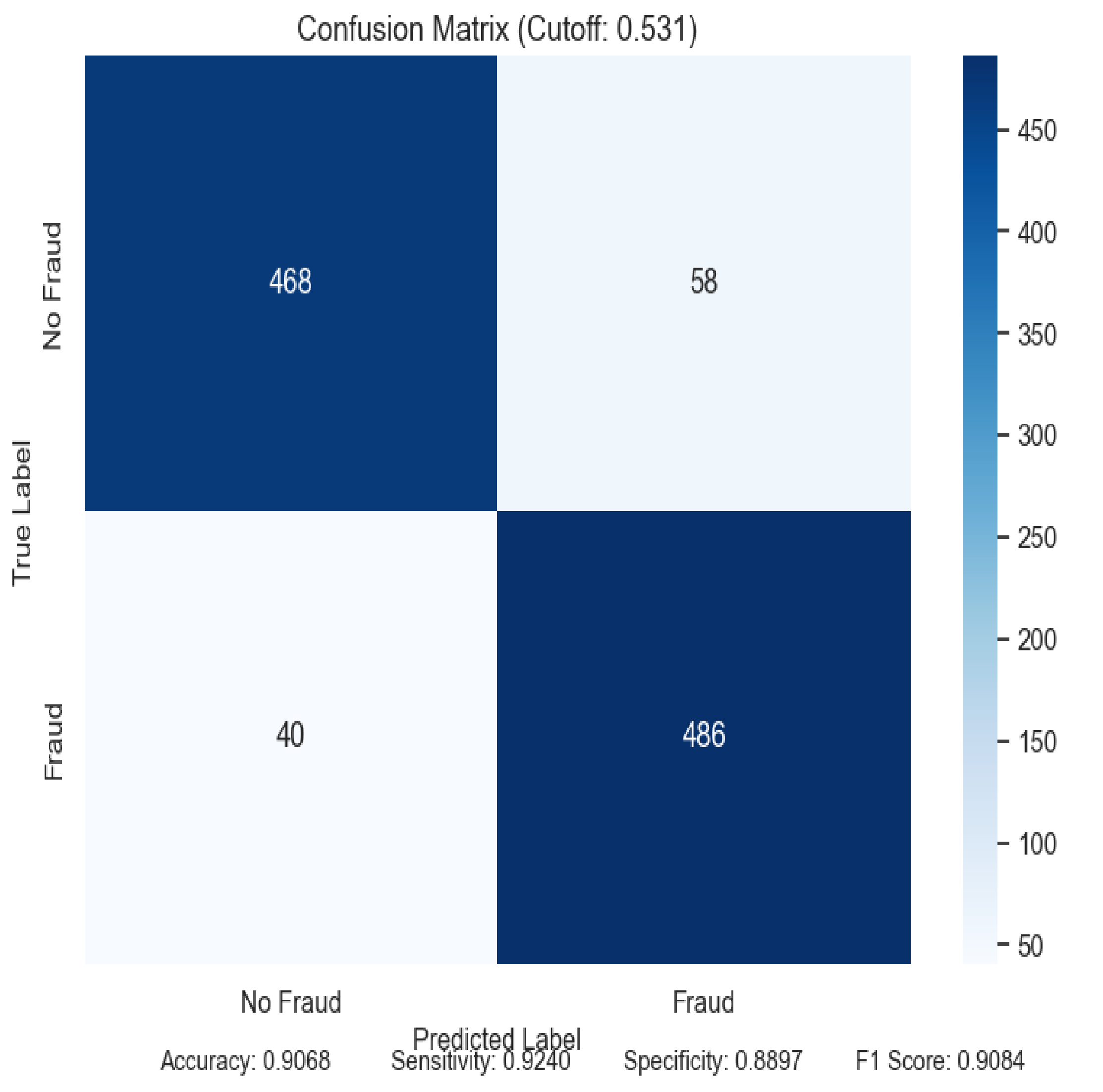


Optimal cutoff where sensitivity and specificity are closest: 0.5500

At this cutoff - Sensitivity: 0.9068, Specificity: 0.8935

Accuracy at this cutoff: 0.9002

LOGISTIC REGRESSION – CONFUSION ATRIX



Confusion Matrix using optimal cutoff:
[[468 58]
 [40 486]]

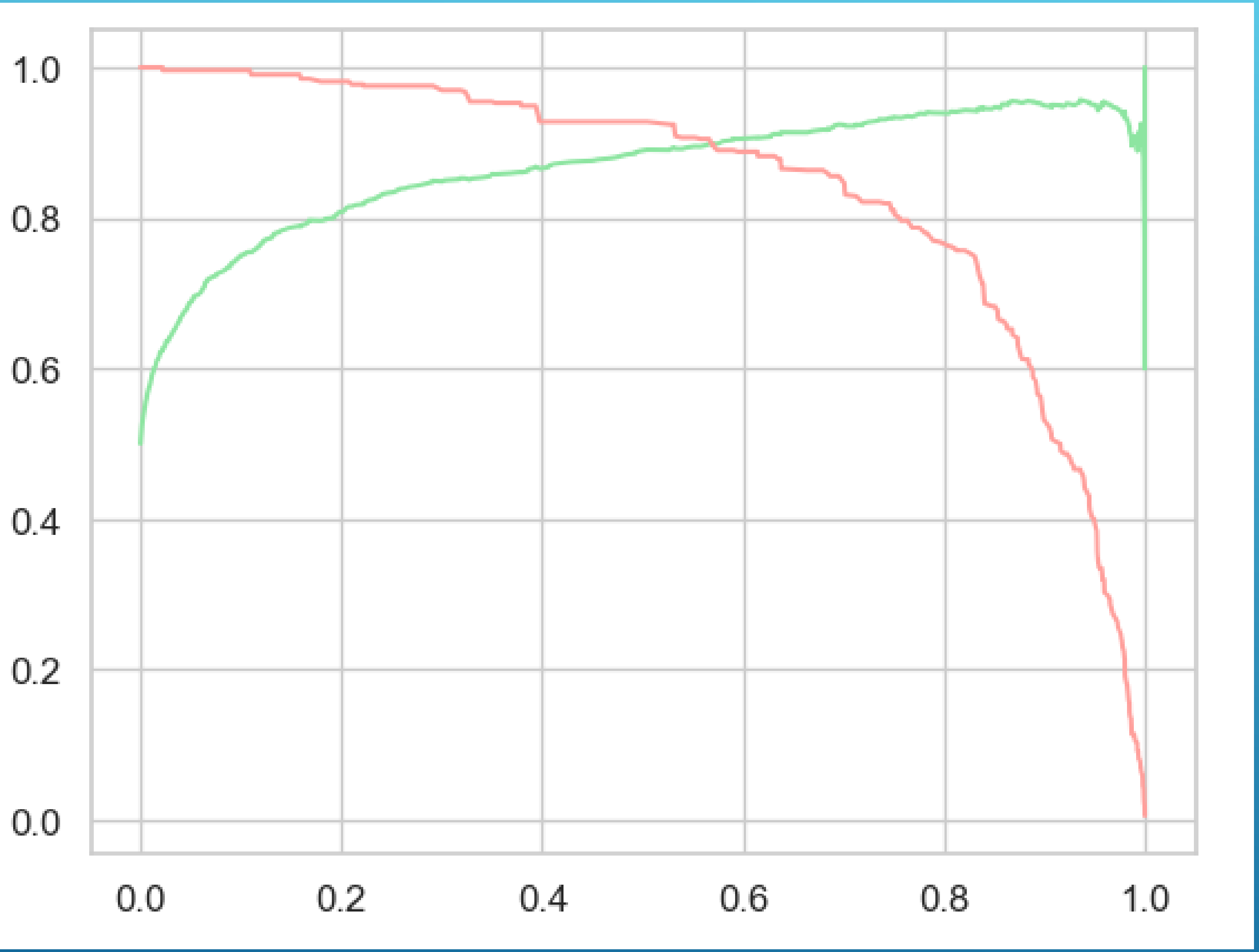
Model performance metrics using optimal cutoff (0.5309):
Accuracy: 0.9068

Sensitivity (True Positive Rate): 0.9240

Specificity (True Negative Rate): 0.8897

Precision: 0.8934
Recall: 0.9240
F1 Score: 0.9084

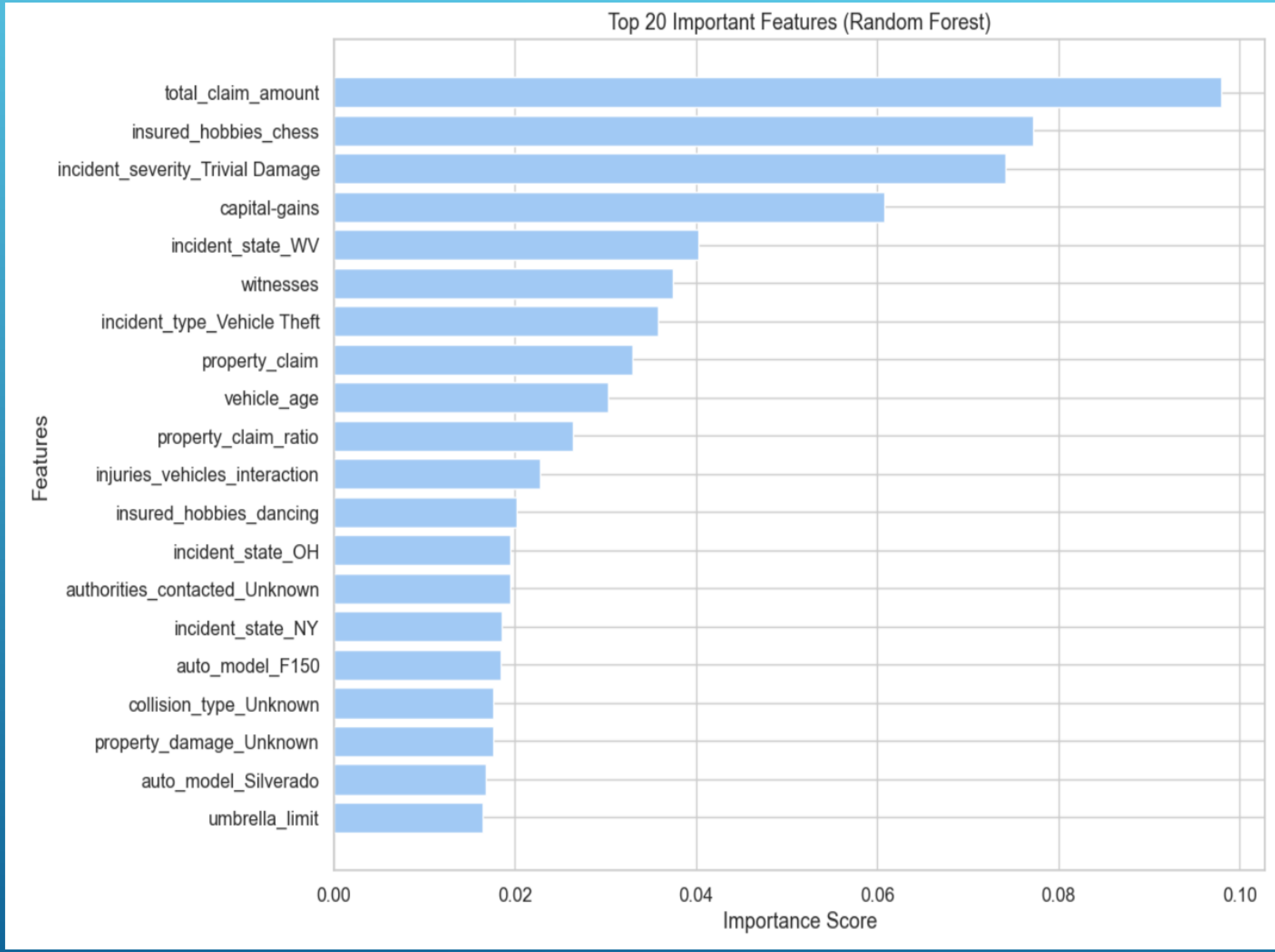
LOGISTIC REGRESSION – PRECISION – RECALL CURVE



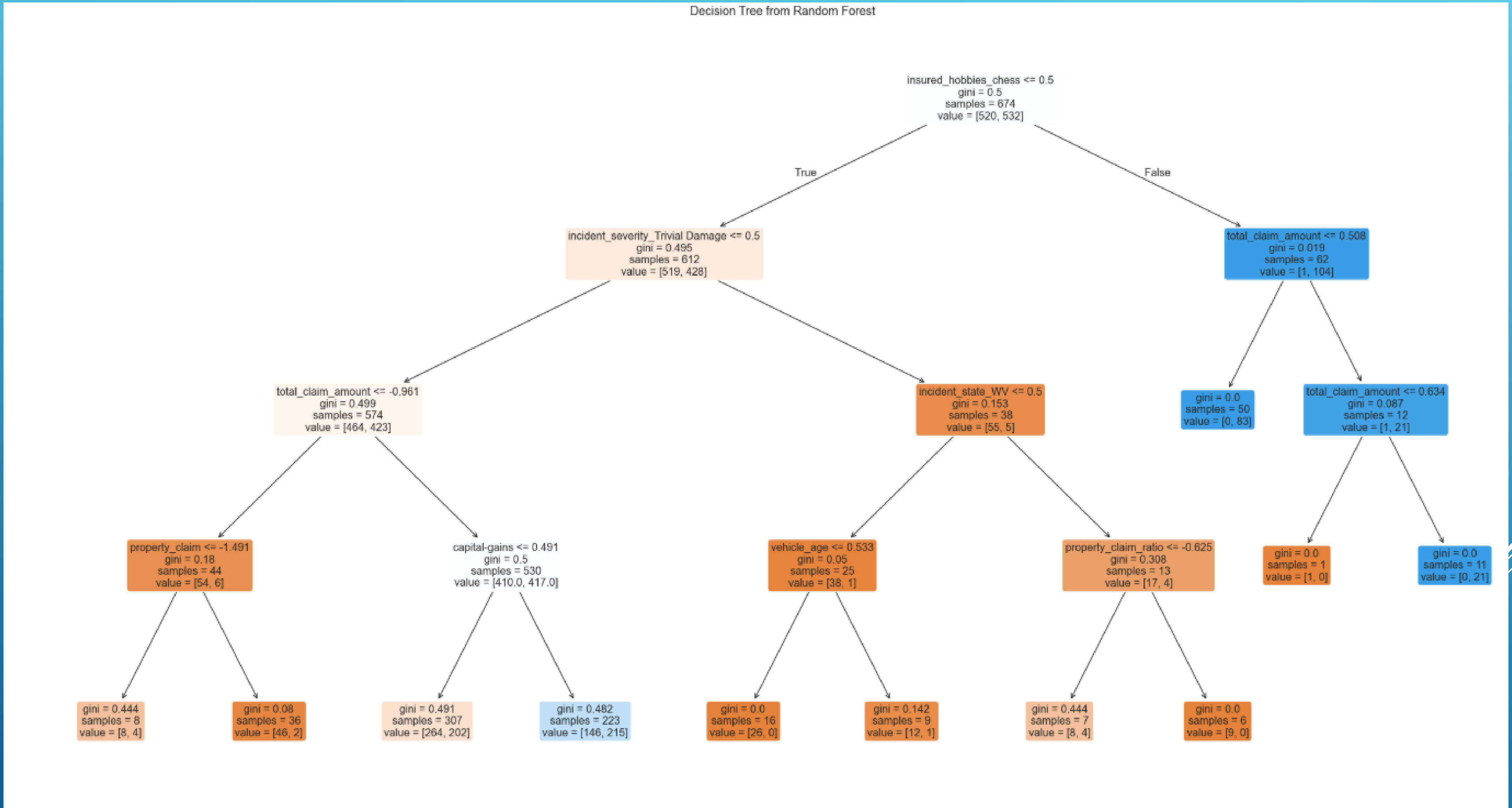
RANDOM FOREST

Number of selected features based on importance threshold (0.01): 28
Selected features based on importance threshold:
['total_claim_amount', 'insured_hobbies_chess', 'incident_severity_Trivial Damage', 'capital-gains', 'incident_state_WV', 'witnesses', 'incident_type_Vehicle Theft', 'property_claim', 'vehicle_age', 'property_claim_ratio', 'injuries_vehicles_interaction', 'insured_hobbies_dancing', 'incident_state_OH', 'authorities_contacted_Unknown', 'incident_state_NY', 'auto_model_F150', 'collision_type_Unknown', 'property_damage_Unknown', 'auto_model_Silverado', 'umbrella_limit', 'capital-loss', 'insured_hobbies_board-games', 'auto_model_95', 'incident_city_Riverwood', 'policy_deductable', 'insured_hobbies_movies', 'incident_day_of_week', 'insured_hobbies_bungie-jumping']

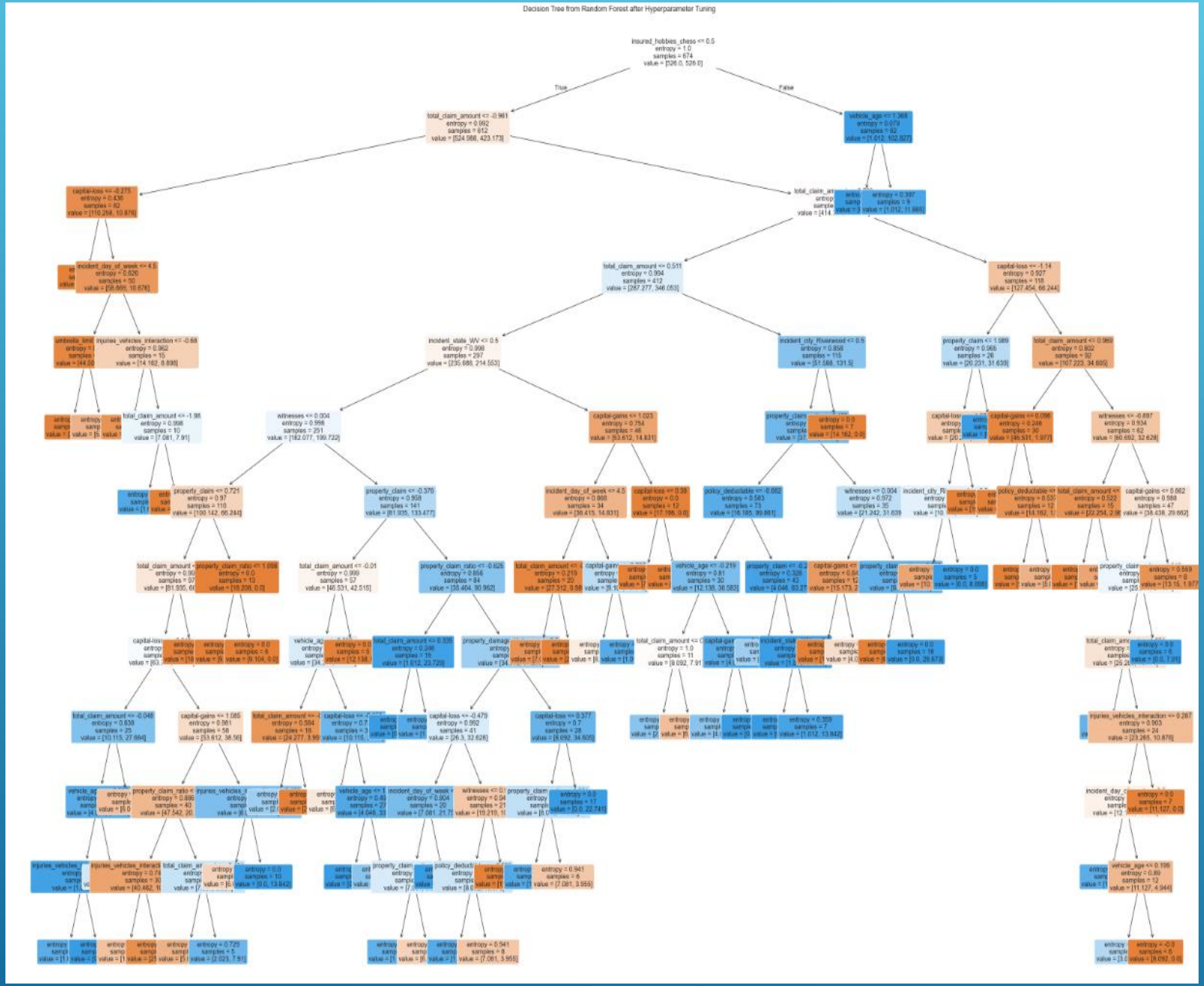
RANDOM FOREST – FEATURE IMPORTANCE



RANDOM FOREST – DECISION TREE BASED ON FEATURE

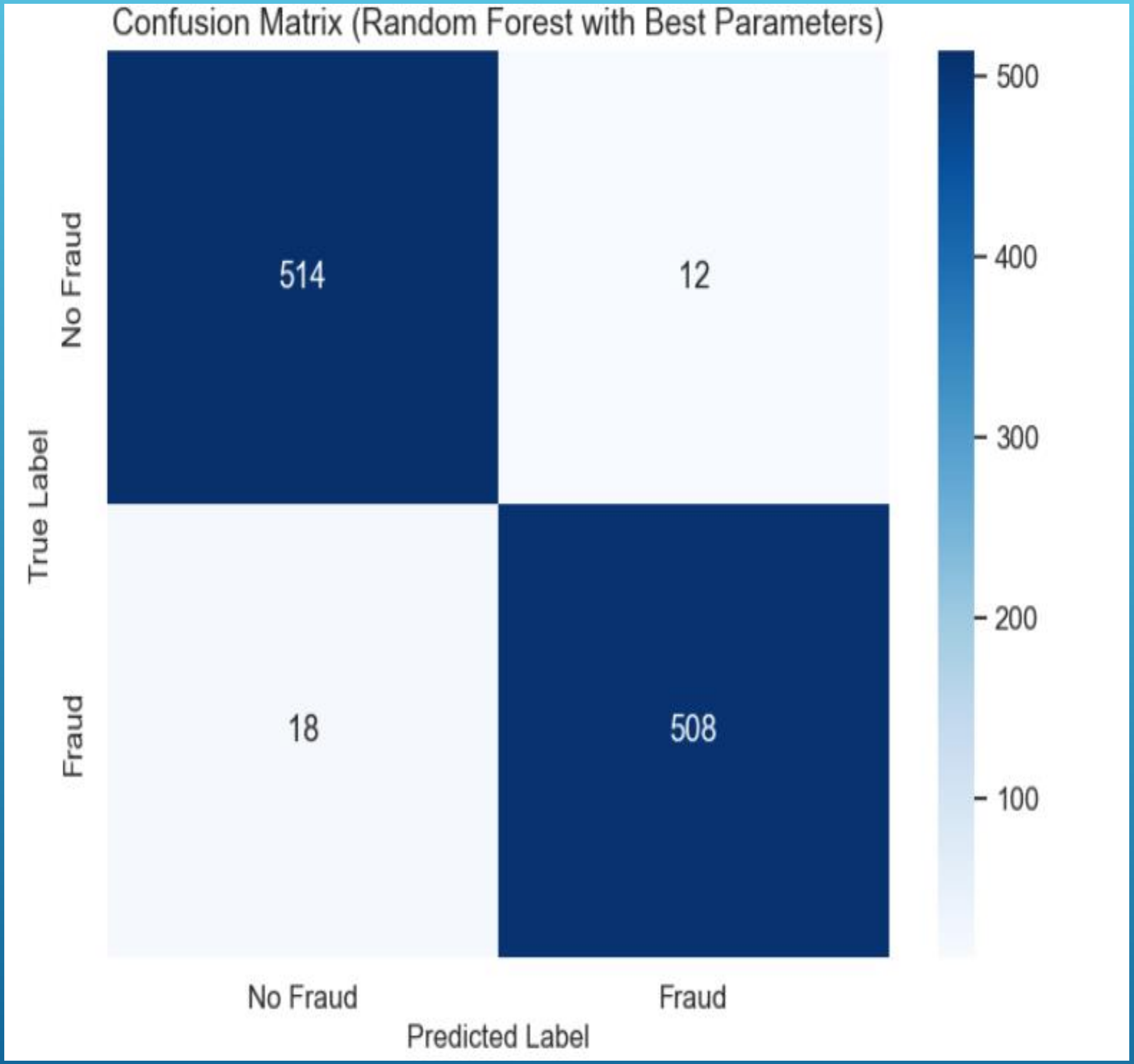


RANDOM FOREST – HYPERPARAMETER TUNING



Starting grid search for 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

RANDOM FOREST – CONFUSION MATRIX



Confusion Matrix:
[[514 12]
[18 508]]
Random Forest Model with Best Parameters:
Accuracy: 0.9715
Sensitivity (True Positive Rate): 0.9658
Specificity (True Negative Rate): 0.9772
Precision: 0.9769
Recall: 0.9658
F1 Score: 0.9713

PREDICTION AND MODEL EVALUATION

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

Achieves 80.00% validation accuracy Shows good sensitivity/recall at 67.57% (effectively captures true positives) Maintains high specificity at 84.07% (effectively identifies true negatives) Delivers precision of 58.14% (moderate confidence in positive predictions) Results in F1-Score of 62.50% (balanced performance between precision and recall) Random Forest
Reaches 72.33% validation accuracy Demonstrates poor sensitivity at only 33.78% (misses many positive cases) Maintains high specificity at 84.96% (slightly better than Logistic Regression) Shows lower precision at 42.37% (less confidence in positive predictions)

QUESTIONS

1. What methods can be used to analyze historical insurance claims data for identifying potential fraud patterns?

- EDA to uncover variable relationships and trends linked to fraud.
- Feature engineering to create derived metrics like claim-to-premium ratios and claim frequency.
- Outlier detection using statistical or unsupervised methods to flag anomalies.
- Predictive modeling (e.g., logistic regression, random forest) to detect complex fraud patterns.
- ROC curve analysis to find optimal fraud detection thresholds.
- Model evaluation using sensitivity, specificity, and precision-recall metrics to handle class imbalance effectively.

QUESTIONS

2. Which factors most strongly indicate potential fraudulent behavior in insurance claims?

- Total Claim Amount – Higher claim amounts are often associated with increased fraud risk.
- Customer Demographics – Certain hobbies (e.g., chess, dancing) may correlate with specific fraud patterns.
- Incident Severity – Minor or trivial damage claims show a higher likelihood of being fraudulent.
- Capital Gains/Losses – Claimants with notable financial fluctuations may present higher fraud risks.
- Geographic Location – States like West Virginia (WV), New York (NY), and Ohio (OH) exhibit elevated fraud rates.
- Vehicle Type – Models such as the Ford F-150 and Chevy Silverado are more frequently involved in suspicious claims.
- Incident Type – Claims involving vehicle theft or unspecified collision types tend to raise red flags.
- Property Damage Reporting – Delayed or inconsistent property damage reporting can signal fraudulent intent.

QUESTIONS

3. Is it possible to predict the likelihood of fraud in new insurance claims using historical data?

- Logistic Regression Performance – Achieved 80% validation accuracy with a sensitivity of 67.57%, indicating strong performance in identifying actual fraud cases.
- Probability Threshold Optimization – An optimal cutoff of approximately 0.55 was identified to balance false positives and false negatives.
- Fraud Probability Scores – The model generates a probability score for each claim, indicating the likelihood of fraud.
- Random Forest Benchmark – Offers an alternative model with slightly lower sensitivity (33.78%) but useful for comparison and ensemble strategies.
- Deployment Capability – These models can be integrated into claim processing systems to automatically score and flag suspicious claims in real time.

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QUESTIONS

4. What actionable insights from the model can enhance the fraud detection strategy?

- Optimize Probability Thresholds – A fixed 0.5 threshold is suboptimal for imbalanced datasets; tuning cutoffs improves detection without overwhelming false positives.
- Prioritize High-Risk Claim Attributes – Claims involving minor damage or specific vehicle models should receive heightened scrutiny.
- Leverage Geographic Trends – Certain states consistently show higher fraud risk, suggesting the need for regional fraud flags.
- Balance Sensitivity and Customer Experience – Cutoff adjustments can strike a balance between catching fraud and minimizing disruption for genuine claimants.
- Implement Tiered Reviews – Use model-generated probability scores to route claims into different levels of manual or automated review.
- Model Selection Matters – Logistic regression with optimized thresholds outperforms more complex models in terms of practical fraud detection effectiveness.
- Use Demographics with Caution – Patterns in hobbies or occupations should be considered carefully to avoid bias or unfair profiling.