FRAUDULENT CLAIM DETECTION A MACHINE LEARNING APPROACH TO IDENTIFYING INSURANCE FRAUD Submitted by:-1. Shreya Singh 2. Ayush Saraswat 3. Ashish Shrivastava

Problem Statement

- Insurance fraud causes significant financial loss.
- Goal: Predict whether a claim is fraudulent (Y) or not (N).
- Challenge: Detect rare fraudulent events accurately.

Methodology Overview

- Data Preparation: Cleaning, encoding, handling missing values.
- Model Selection: Random Forest Classifier
- Evaluation Metrics: AUC-ROC, Accuracy, Precision, Recall, F1-Score
- Visualization Tools: Confusion Matrix, ROC Curve, Feature Importance Plot

Class Imbalance Problem

- Majority class: Non-fraudulent ('N')
- Minority class: Fraudulent ('Y')
- Significant imbalance affects model performance on 'Y' class

Model Performance Metrics

• AUC-ROC Score: 0.772

• Accuracy: 0.75

• **Precision (Y):** 0.40

• **Recall (Y):** 0.03

• **F1-Score (Y):** 0.05

Confusion Matrix Insights

- High number of True Negatives
- Very low True Positives
- Model struggles with identifying fraudulent claims

Feature Importance

- Top 10 features identified by Random Forest
- Useful for feature selection and model optimization
- Can be used to understand key drivers of fraud

Visualizations

- Confusion Matrix Heatmap
- ROC Curve
- Feature Importance Bar Plot

Key Insights

- Model performs well on majority class
- Poor recall and F1-score on minority class
- Current model not suitable for automated fraud flagging

Actionable Outcomes

- Class Imbalance Handling: Use SMOTE or class weighting
- Algorithm Testing: Try XGBoost or LightGBM
- Threshold Tuning: Lower probability threshold
- Feature Engineering: Use top features for new variable creation
- Manual Review Strategy: Flag high-risk claims for further investigation

Conclusion

- Good baseline model with potential for improvement
- Requires enhanced strategies to effectively detect fraudulent claims
- Future work: Address imbalance, optimize recall, improve business value

