

Application of Machine Learning Techniques in Insurance Fraud Detection

Khutso Mphelo

BScHons in Applied Mathematics
University of Johannesburg

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Outline

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- Insurance fraud poses significant financial and operational challenges.
- Traditional detection relies on audits, but machine learning offers advanced capabilities.

Introduction

- Objective: Enhance fraud detection in insurance claims using machine learning.
- Dataset: Vehicle claims fraud data (Bansal, 2021).



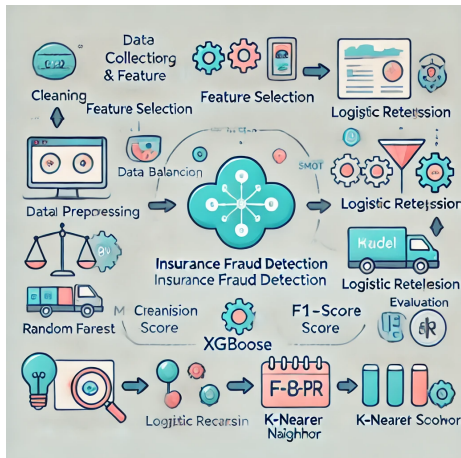
- Traditional methods: Audits and expert reviews.
- Machine learning in fraud detection: Logistic Regression, Random Forest, XGBoost.

Model Class	Methodology	Description
Clustering	K-means	Groups data points by similarity
Classification	Logistic Regression, Random Forest	Categorizes data based on labeled data
Outlier Detection	Isolation Forest	Identifies anomalous data points

Table: Overview of ML Models in Fraud Detection

Methodology

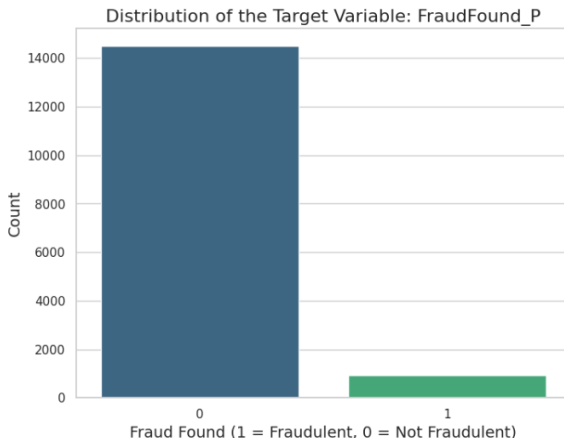
- **Data preprocessing:** Cleaning, encoding, standardization.
- **Class imbalance handling:** SMOTE and undersampling.
- **Models used:** Random Forest, Logistic Regression, XGBoost, and KNN.



- Before modeling, an exploratory data analysis (EDA) was conducted to understand key patterns and trends in the data.
- Insights from EDA guided the feature selection and informed the class balancing approach.

Class Imbalance Visualization

- The dataset shows a significant class imbalance, with a smaller proportion of fraudulent claims.
- To address this, techniques like SMOTE were applied to balance the classes.



Fraud Rate by Month Claimed

- A decrease in fraud rates is observed prior to November, possibly due to effective fraud prevention measures or reduced claims as the year ends.
- December shows an increase in fraud, potentially linked to holiday season factors.

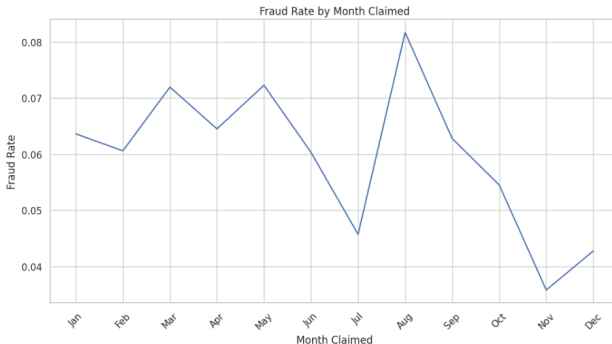


Figure: Fraud rate by month claimed

Correlation of Age of Policy Holder with Fraud Cases

- The most common fraudulent policy holders are middle aged, specifically in the 31-35 and 36-40 age group
- Likely due to more financial pressures, potentially leading to a greater number of bills and financial responsibilities.
- Understanding this relationship helps identify high-risk age groups in insurance claims.

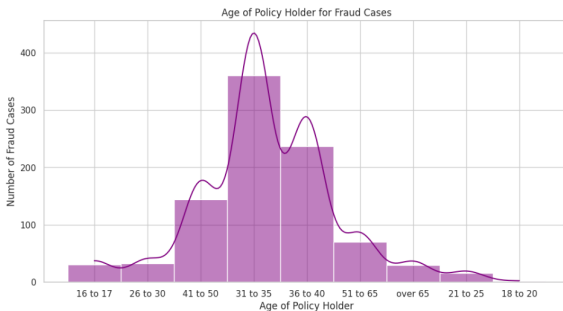


Figure: Correlation between Age of Policy Holder and Fraud Cases

Correlation of Age of Policy Holder with Fraud Cases

- Married individuals: Highest fraud cases (639), likely due to financial pressures.
- Single individuals: Moderate fraud cases (278).

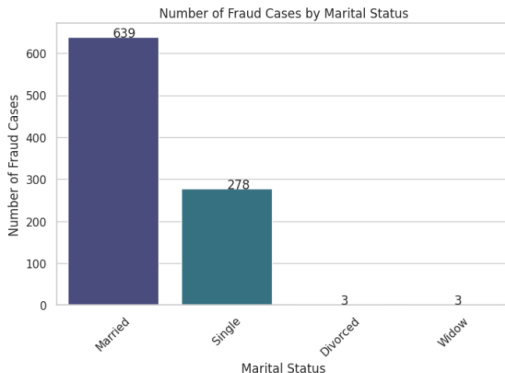


Figure: Number of Fraud Cases by Marital Status

Percentage of Fraud Cases by Accident Area

- Urban areas account for approximately 85.6% of fraud cases.
- Rural areas account only 14.4% of fraud cases.

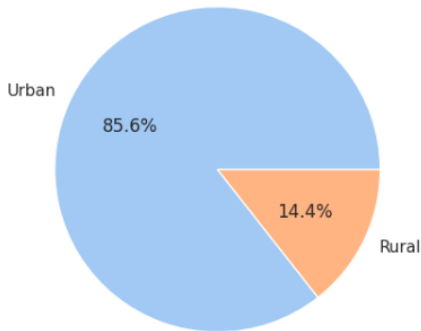


Figure: Correlation Heatmap of Key Features

- **Marital status & Age:** Higher fraud rates among married and middle-aged individuals.
- **Seasonal peaks:** Fraud cases peak in August and December, potentially due to financial or seasonal factors.
- **Geographic patterns:** Urban areas sees more fraud cases (85.6%), while rural areas have fewer.
- **Class imbalance:** Fraudulent claims are rare, requiring techniques like SMOTE for model balance.

XGBoost Model Performance - Precision and Recall

- Best performing model is XGboost with an accuracy of 76.5%.

```
Accuracy: 0.7659
Classification Report:
              precision    recall  f1-score   support

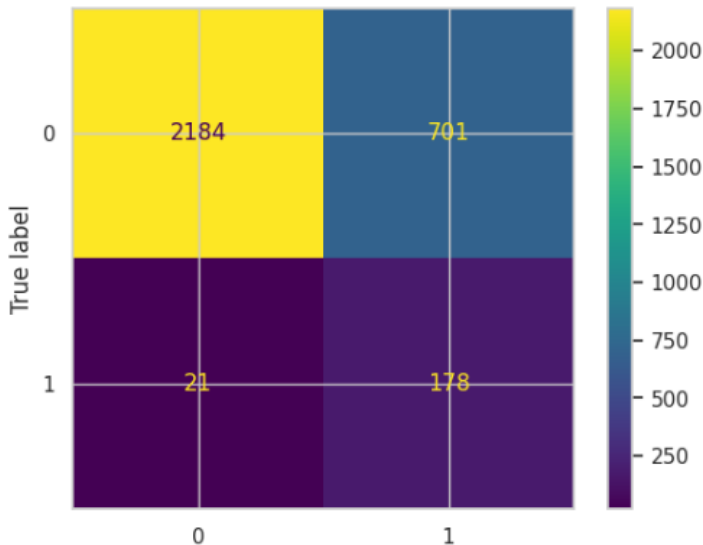
     0           0.99       0.76       0.86       2885
     1           0.20       0.89       0.33        199

 accuracy               0.77       3084
 macro avg           0.60       0.83       0.59       3084
 weighted avg        0.94       0.77       0.82       3084
```

Figure: Precision and Recall of Models

Confusion Matrix for XGBoost Model

- XGBoost model performance with SMOTE application.



- **Enhanced Detection:** Machine learning models enhance fraud detection accuracy.
- **Class Imbalance Challenge:** SMOTE helps address imbalance, boosting model effectiveness.
- **Key Risk Insights:** Higher fraud rates are seen among married, urban, and middle-aged groups, highlighting areas for targeted prevention.
- **Future Work:** Further explore ensemble models and advanced sampling techniques to refine detection capabilities.
- **Business Impact:** Effective fraud detection can significantly reduce losses and improve client trust in the insurance process.

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Thank you!
Questions?