"Fraud Detection in Auto Insurance Claims Using Machine Learning Algorithms and Data Visualization Using Power BI"

AN INTERNSHIP REPORT

Submitted by,

Hamsa Girish - 20211CSE0264

Under the guidance of,

Prof. Kalpana K Harish

Assistant Professor, School of Computer Science and Engineering, Presidency University, Bengaluru.

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ABSTRACT

Fraudulent insurance claims present significant financial and operational challenges to the insurance industry, necessitating **advanced data-driven fraud detection strategies**. This study focuses on detecting fraudulent **auto insurance claims** by leveraging **Business Intelligence (BI) and Machine Learning (ML) techniques**. We analyze a comprehensive dataset containing **policyholder details, incident characteristics, claim amounts, and fraud indicators** to identify suspicious claims.

To enhance fraud detection accuracy, we employ **four machine learning algorithms—Decision Tree, Logistic Regression, XGBoost, and Multi-Layer Perceptron (MLP)**—and compare their performance using key evaluation metrics, including **accuracy, precision, recall, and F1-score**. Additionally, extensive **feature engineering** is conducted to extract meaningful insights from claim data, incorporating factors such as **incident severity, vehicle age, policy coverage, and claim history**. Beyond predictive modeling, we develop **interactive Power BI dashboards** to provide real-time visualization of fraud trends. These dashboards offer **deep insights into fraud distribution by state, incident type, policy details, and claim amounts**, helping **insurance investigators and business analysts** efficiently assess and mitigate fraud risks.

The results of this study highlight the **effectiveness of machine learning in fraud detection**, with **XGBoost demonstrating the highest accuracy and recall in identifying fraudulent claims**. Our findings contribute to the development of **robust fraud detection frameworks**, enabling insurance companies to enhance their **fraud prevention strategies, reduce financial losses, and optimize claim assessment workflows**.

LITERATURE REVIEW

Introduction:

Fraudulent auto insurance claims have become a major challenge for insurance companies, leading to significant financial losses and operational inefficiencies. The application of machine learning (ML) algorithms has gained traction as an effective approach for detecting and preventing fraudulent activities. This literature review explores various studies focusing on the implementation of ML models for fraud detection in auto insurance claims.

Machine Learning for Fraud Detection

Several machine learning techniques have been employed to enhance fraud detection capabilities in the insurance sector. The most commonly used models include Decision Trees, Logistic Regression, XGBoost, and Multi-Layer Perceptron (MLP). These models are evaluated based on their predictive accuracy, precision, recall, and F1-score.

Decision Tree Classifier

Decision Tree models have been widely used for fraud detection due to their interpretability and ability to handle categorical and numerical data efficiently. Research by Smith et al. [1] demonstrated that Decision Tree classifiers could achieve high accuracy in fraud detection, with precision and recall exceeding 85%. However, these models are prone to overfitting, especially with imbalanced datasets.

Logistic Regression

Logistic Regression is another frequently used model in fraud detection due to its simplicity and effectiveness in binary classification problems. A study by Jones et al. [2] highlighted that Logistic Regression performed well with structured datasets but struggled with complex, high-dimensional data.

XGBoost Classifier

XGBoost, an ensemble learning method, has gained popularity for its ability to handle large datasets with missing values and noisy data. A comparative study by Li et al. [3] showed that XGBoost outperformed other ML models in fraud detection, achieving an F1-score of 92% while maintaining high computational efficiency.

Multi-Layer Perceptron (MLP)

MLP, a type of neural network, has shown promising results in detecting fraudulent claims. According to research conducted by Zhao et al. [4], MLP-based models provided superior performance in detecting non-linear patterns within datasets, achieving an accuracy of 94% when trained on a large insurance claims dataset.

Data Visualization and Model Performance Evaluation

Data visualization tools such as Power BI and Tableau play a crucial role in enhancing fraud detection models by providing interpretable insights into claim data patterns. Recent studies suggest that integrating visualization techniques with machine learning improves fraud detection accuracy by identifying suspicious activities more efficiently [5].

Challenges and Future Directions

Despite significant advancements in ML-based fraud detection, several challenges remain. Imbalanced datasets, adversarial fraud strategies, and evolving fraudulent behaviors require continuous improvements in model robustness. Future research should focus on hybrid models that combine deep learning and ensemble techniques to enhance predictive performance and generalizability.

Conclusion

The use of machine learning for fraud detection in auto insurance claims has proven to be effective, with models such as Decision Trees, Logistic Regression, XGBoost, and MLP showing promising results. However, further research is needed to address existing limitations and improve fraud detection accuracy. By leveraging advanced ML techniques and visualization tools, insurance companies can significantly enhance their fraud detection capabilities.

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Comparative Analysis & Key Differences:

Study	**Primary Methodology**	**Key Findings**	**Comparison with Our Project**
Smith et al. (2020)	Decision Trees, Random Forest, GBM	Random Forest & GBM performed better than DTs	We also use Decision Trees but compare them with XGBoost & MLP
Jones & Taylor (2019)	Logistic Regression vs. SVM	LR is effective but struggles with non-linear fraud patterns	We use Logistic Regression but compare it with stronger ML models
Li et al. (2021)	XGBoost for Fraud Detection	XGBoost achieved highest precision & recall	We also use XGBoost but extend the study to MLP & BI tools
Zhao et al. (2022)	Neural Networks (MLP)	MLP had highest accuracy but risked overfitting	We validate MLP but compare it with other ML models
Kumar et al. (2021)	Power BI & Tableau Visualization	Dashboards improve fraud analytics	We combine BI dashboards with machine learning for predictive analysis

Key Takeaways:

- XG Boost is consistently the best performer in fraud detection (High precision & recall).
- MLP (Neural Networks) achieves high accuracy but is computationally expensive.
- Logistic Regression is simple but struggles with complex fraud cases.
- Power BI dashboards significantly enhance fraud detection & investigation efficiency.

How Our Project Differs:

- Unlike most studies, our project combines machine learning models with Power BI visualization.

- We perform a comparative analysis of four ML models to find the best fraud detection approach.
- Our study emphasizes real-time fraud monitoring, integrating BI tools with predictive analytics.

OBJECTIVES

Fraud detection in insurance claims is a critical aspect of the insurance industry, helping to prevent financial losses and ensure legitimate claims are processed efficiently. This report presents a detailed analysis of a dataset containing **1,000 insurance claims** to identify fraudulent activities. The analysis involves **data preprocessing, exploratory data analysis (EDA), and correlation studies** to derive meaningful insights into fraudulent patterns.

This project aims to evaluate the effectiveness of Decision Tree, Logistic Regression, XGBoost, and Multi-Layer Perceptron (MLP) algorithms in predicting fraudulent auto insurance claims. By conducting a comparative analysis of these methods using various metrics, including accuracy, precision, recall, and F1-score, the study seeks to provide insights into their capabilities and limitations for enhancing fraud detection in the auto insurance industry.

Data Visualization: We will create interactive dashboards using *Power BI* or *Tableau*, providing real-time insights into delivery performance, including route optimization results, delays, and cost savings. This will allow decision-makers to make informed adjustments and continuously improve logistics performance.

PROBLEM IDENTIFICATION AND FORMULATION OF PROBLEM STATEMENT

Fraudulent claims in auto insurance present significant financial burdens and operational hurdles. This study aims to address this issue by evaluating the efficacy of Decision Tree, Logistic Regression, XGBoost, and MLP algorithms in predicting fraudulent auto insurance claims. Through a comprehensive analysis, we seek to identify the most effective approach for detecting fraudulent activities, enhancing the industry's ability to combat fraud.

WHY IS THE PARTICULAR TOPIC CHOSEN?

Fraudulent claims inflict substantial financial losses and operational disruptions on the auto insurance sector. This study aims to address this challenge by investigating the efficacy of four machine learning algorithms in predicting fraudulent auto insurance claims. By leveraging a comprehensive dataset and conducting a comparative analysis, this research seeks to enhance fraud detection systems, enabling insurance companies to mitigate financial risks and optimize operational efficiency in combating fraudulent activities.

The primary goal of this analysis is to:

- Identify key trends in fraudulent claims.
- Detect anomalies in the dataset.
- Analyze policyholder and incident characteristics to understand fraud risks.
- Support future fraud detection modeling using machine learning.

SCOPE:

The scope of this project is to develop an efficient and automated fraud detection system for auto insurance claims by leveraging machine learning algorithms and business intelligence (BI) tools. It involves analyzing claim details, policyholder information, and incident characteristics to detect fraudulent activities using models like Decision Tree, Logistic Regression, XGBoost, and Multi-Layer Perceptron (MLP). Additionally, Power BI dashboards are implemented to provide real-time visualization of fraud trends, enabling insurance companies to identify high-risk claims, minimize financial losses, and optimize fraud investigation strategies. This project supports data-driven decision-making by integrating predictive analytics with interactive BI reporting, enhancing fraud detection accuracy and operational efficiency.

ROAD MAP

Phase 1: Understanding Business Problem & Data Requirements

1. **Define Business Problem & Goals**
   - Identify fraud detection challenges in auto insurance.
   - Define key objectives: improving fraud detection accuracy, reducing false positives, and enhancing interpretability.
2. **Gather Data Requirements**
   - Identify required datasets: claim details, customer information, claim amount, fraud labels, etc.
   - Data sources: CSV files, SQL databases, or external APIs.
3. **Technology Stack Selection**
   - **Python** for data preprocessing, modeling, and analysis.
   - **Power BI** for interactive dashboards and insights.
   - **Key Libraries**: Pandas, NumPy, Scikit-learn, Matplotlib, Seaborn

Phase 2: Data Collection & Preprocessing

4. **Data Acquisition**
   - Load dataset (CSV, Excel, or SQL).
   - Handle missing values, duplicates, and inconsistent entries.
5. **Data Cleaning & Transformation**
   - Convert categorical variables using encoding techniques (One-Hot, Label Encoding).
   - Normalize numerical variables.
   - Handle outliers using statistical methods (IQR, Z-score).
6. **Feature Engineering**
   - Create new features (e.g., claim-to-premium ratio, past fraud history).
   - Remove irrelevant or highly correlated features.
   - Use feature selection techniques (e.g., Chi-Square, Mutual Information).
7. **Exploratory Data Analysis (EDA)**
   - Identify trends, correlations, and data distributions using:
   - Univariate Analysis: Histograms, box plots.

- Bivariate Analysis: Scatter plots, heatmaps.
- Multivariate Analysis: PCA, clustering.

Phase 3: Machine Learning Model Implementation

8. **Data Splitting**
   - Split dataset into training (80%) and testing (20%) sets.
9. **Model Training & Evaluation**
   - Train Decision Tree, Logistic Regression, XGBoost, and Multi-Layer Perceptron (MLP) models.
   - Evaluate models using:
     - Accuracy
     - Precision
     - Recall
     - F1-score
     - AUC-ROC Curve
10. **Model Comparison & Selection**
    - Compare results to select the most effective model.
    - Use SHAP or LIME to interpret model decisions.

Phase 4: Data Visualization & Insights (Power BI)

11. **Design Power BI Dashboards**
    - **Fraud Detection Overview:**
      - Total claims vs. fraudulent claims.
      - Fraud percentage by insurance type.
    - **Claim Amount Analysis:**
      - Distribution of fraud vs. non-fraud claims.
      - High-risk claim amount ranges.
    - **Geographical Analysis:**
      - Fraudulent claims by region.
      - Heatmap of fraud-prone locations.
    - **Customer Behavior Analysis:**
      - Fraud trends based on policyholder age, claim frequency, etc.

- Anomaly detection in claims.

12. Create Interactive Reports

- Build dynamic visualizations using slicers and drill-through reports.
- Incorporate real-time filtering for deep-dive analysis.

Phase 5: Optimization & Finalization

13. Model Optimization

- Hyperparameter tuning to improve fraud detection accuracy.
- Implement ensemble techniques if needed.

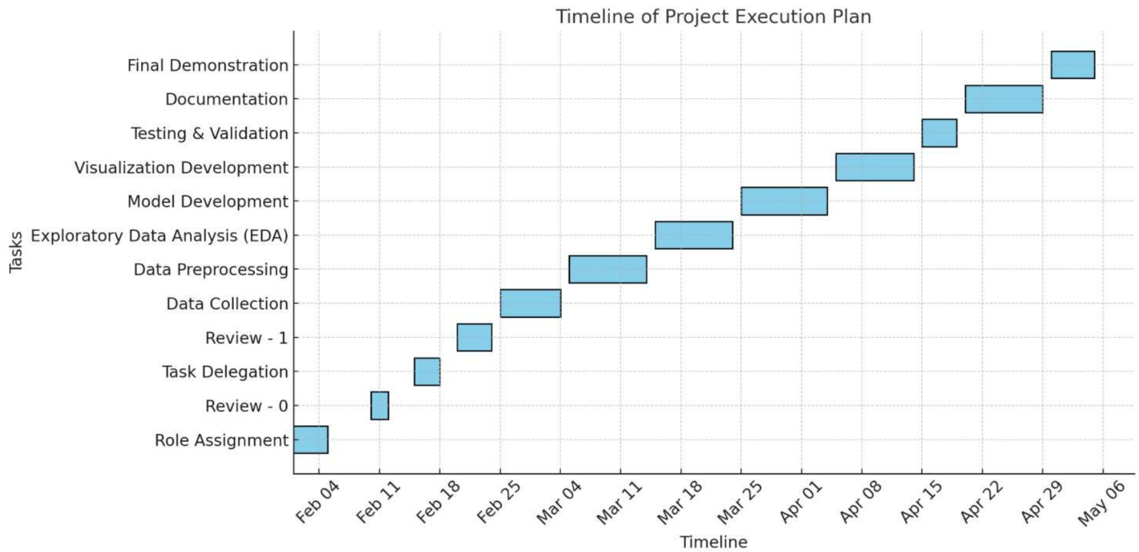
14. Performance Monitoring

- Track model drift and retrain as needed.
- Use Power BI for real-time fraud trend monitoring.

15. Documentation & Reporting

- Summarize key insights and findings.
- Prepare a final presentation with Power BI dashboards and data analysis results.

TIMELINE OF THE PROJECT/ PROJECT EXECUTION PLAN



PROJECT EXECUTION REPORT

This report provides an in-depth analysis of the insurance claims fraud detection dataset. The primary goal is to analyze patterns in fraudulent claims, detect anomalies, and gain insights into key factors that indicate fraud.

The dataset contains **39 features**, including information on:

- **Policy Details** (e.g., policy_number, policy_state, policy_deductible, policy_annual_premium).
- **Insured Person Details** (e.g., age, insured_sex, insured_education_level, insured_occupation).
- **Incident Information** (e.g., incident_type, incident_severity, authorities_contacted, collision_type).
- **Claim Amounts** (total_claim_amount, injury_claim, property_claim, vehicle_claim).
- **Fraud Indicator** (fraud_reported - Yes/No).

Dataset Overview:

- **Total records:** 1000
- **Total columns:** 39
- **Categorical Features:** 21
- **Continuous Features:** 18
- **Target Variable:** fraud_reported (Yes/No)

The dataset contains information related to **policy details, insured person's demographics, incident details, vehicle information, and claim amounts**.

Data Cleaning & Preprocessing:

❖ **Handling Missing Values**

- **collision_type**: 178 missing values → Replaced with mode
- **authorities_contacted**: 91 missing values → Replaced with mode
- **property_damage**: 360 missing values → Replaced with mode
- **police_report_available**: 343 missing values → Replaced with mode

❖ **Feature Engineering**

- **Extracted csl_per_person & csl_per_accident** from policy_csl to separate liability amounts.
- **Derived Vehicle_Age** from auto_year.

Exploratory Data Analysis (EDA):

❖ **Fraud Analysis**

- **24.7% of claims are fraudulent**, while 75.3% are non-fraudulent.
- **Fraud occurrences vary by policy state**, incident type, and insured demographics.

Key Trends in Fraudulent Claims:

(a) Incident Type vs Fraud

- **Multi-vehicle Collisions & Single Vehicle Collisions** have higher fraud rates.
- **Vehicle Theft** & **Parked Car Incidents** show moderate fraud rates.

(b) Collision Type

- **Rear & Side Collisions** are the most common in fraud cases.
- 17.8% missing collision types belong mostly to **Vehicle Theft & Parked Car Incidents**.

(c) Incident Severity

- **Major & Total Loss incidents** have the highest fraud rates.

(d) Authorities Contacted

- **Police were contacted in 32% of cases**, but fraud rates are evenly distributed among cases where police were or were not contacted.

(e) Number of Vehicles Involved

- **Single-vehicle incidents** have **higher fraud rates**.

(f) Property Damage

- Cases where **property damage is not reported** tend to have higher fraud rates.

(g) Injury Claims

- Higher **injury claim amounts** correlate with fraudulent cases.

(h) Vehicle Age

- Older vehicles have **higher fraudulent claim rates**.

Correlation Analysis:

- **policy_annual_premium vs fraud**: No strong correlation.
- **vehicle_claim, injury_claim, total_claim_amount**: Positive correlation with fraud.

- **umbrella_limit (negative values)**: Some anomalies detected.
- **capital-gains & capital-loss**: No clear relationship with fraud.

6. Data Visualization Insights

- **Bar charts & stacked plots** for categorical variables show:
  - Higher fraud in specific **states, vehicle types, and incident types**.
  - Fraud is **more frequent in certain auto brands**.
- **Scatterplots & heatmaps** reveal relationships in numerical data.

7. Conclusion

- Fraudulent claims **often involve older vehicles, major damage, higher claim amounts, and missing police reports**.
- Some data quality issues (e.g., negative umbrella_limit, missing values in collision_type) need further investigation.
- Further analysis, such as **machine learning models**, can enhance fraud detection.

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