TEAM (SC1)4TH_10

Rajat Kumar Dash	CSE	4th year	22CSE139	22UG010272	22cse139.rajatkumardash@giet.edu	4TH_TEAM_10
Soumya Ranjan Mohapatra	CSE	4th year	22CSE215	22UG010348	22cse215.soumyaranjanmohapatra@giet.edu	4TH_TEAM_10
Debabrata Mishra	CSE	4th year	22CSE140	22UG010273	22cse140.debabratamishra@giet.edu	4TH_TEAM_10
ABHISEK PANDA	CSE	4th year	22CSE072	22UG010159	22cse072.abhisekpanda@giet.edu	4TH_TEAM_10

AI-Powered Auto Insurance Fraud Detection

Domain: Insurance | Machine Learning | Fraud Analytics (BFSI)

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1. Problem Statement

Auto insurance fraud represents a serious challenge for the insurance industry, contributing to billions of dollars in losses globally each year. Common examples include staged accidents, inflated damage claims, or false injury reports. These cases are often difficult to detect during early stages of claim processing.

This project aims to develop an AI-powered system that predicts the likelihood of a claim being fraudulent. By doing so, we aim to:

- Reduce financial losses caused by fraudulent claims
- Accelerate the processing of legitimate claims
- Improve customer satisfaction and retention
- Support human investigators by reducing manual workload and focusing efforts on suspicious cases

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2. Business Understanding & Objective

Objective:

To build a supervised machine learning classification model that can predict whether an insurance claim is fraudulent using historical structured data.

Key Business Benefits:

- Prioritize high-risk claims for deeper investigation
- Reduce operational overhead and investigation costs
- Increase efficiency in fraud detection workflows

- Improve risk assessment models for both policy issuance and renewals

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3. Data Preparation

Data Source:

- The dataset is in CSV format
- Approximately 1,000 records with 25 features
- Target variable: FraudFound_P (0 for legitimate claims, 1 for fraudulent claims)

Exploratory Data Analysis (EDA):

- Total samples: 1,000 rows and 25 columns
- Class distribution: ~75% legitimate, ~25% fraudulent
- Mild class imbalance was observed
- Dataset includes both numerical and categorical features

Data Cleaning:

- Duplicate records were identified and removed
- Null values were addressed as follows:
    - Columns with more than 50% missing values were dropped
    - Categorical features were imputed using the mode
    - Numerical features were filled with the median
- Inconsistent formats were standardized, including date parsing and removal of whitespaces

Outlier Handling:

- Numerical features were evaluated using the IQR method
- Outliers were capped or transformed using log scaling where necessary

Data Transformation:

- Binary categorical variables were label encoded
- Multiclass categorical features were one-hot encoded
- New features were derived from dates such as “days since accident” and “days to file a claim”
- All numeric features were normalized using StandardScaler

Feature Engineering:

- Claim Velocity = Claim Amount / Time to File
- Loyalty Score = Tenure × Past Claims Weight
- Delay Filing = Number of days between accident date and claim filing date

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4. KPI Definition

The following key performance indicators (KPIs) were used to evaluate both the model performance and the business value:

KPI	Description
Accuracy	Percentage of correct predictions
False Positive Rate	Percentage of legitimate claims incorrectly flagged
Precision	Percentage of correctly identified frauds among all flagged claims
Recall (Sensitivity)	Percentage of actual frauds that were successfully caught
F1 Score	Harmonic mean of precision and recall
ROC-AUC	Ability of the model to distinguish between the classes
Fraud Catch Rate	Total frauds caught as a percentage of all frauds
Cost Savings	Estimated monetary savings due to automated detection
Time to Flag	Time saved by reducing manual review
Hit Rate	Percentage of flagged claims that were confirmed as fraud

Business Focus: Maximize recall while maintaining strong precision, prioritizing F1-score and ROC-AUC for final model selection.

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5. Model Building

The data was split using an 80/20 train-test ratio with stratified sampling to maintain class balance during training. Cross-validation was used to evaluate models.

Machine Learning Models Used:

Model	Description
Logistic Regression	Interpretable baseline model
Decision Tree	Simple tree-based classification
Random Forest	Ensemble model for improved accuracy
XGBoost	Gradient boosting with high performance
LightGBM	Lightweight boosting model
CatBoost	Categorical boosting model
K-Nearest Neighbors	Distance-based classification
Support Vector Machine	Performs well in high-dimensional spaces

Model	Description
Naive Bayes	Probabilistic classification
MLP Neural Network	Multi-layer perceptron for deep learning
Ensemble Voting	Combines outputs from top models

Hyperparameter tuning was done using GridSearchCV where applicable.

Class Imbalance Handling:

- Models were trained with class weights where supported
- SMOTE (Synthetic Minority Oversampling Technique) was applied to oversample minority class

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6. Model Evaluation

Metrics Used:

Metric	Description
Accuracy	Overall prediction correctness
Precision	Quality of positive predictions
Recall	Sensitivity to actual fraud cases
F1 Score	Balanced score between precision and recall
AUC-ROC	Binary classification performance measure
Confusion Matrix	Breakdown of true/false positives and negatives
Log Loss	Penalty for incorrect high-confidence predictions
Cohen’s Kappa	Measure of inter-rater agreement beyond chance

Best Model Criteria:

- High recall with acceptable precision
- Strong F1-score and ROC-AUC
- Stable performance across validation folds
- Low log loss and balanced confusion matrix

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7. Final Results

Model	Accuracy	Precision	Recall	F1 Score	AUC
Random Forest	0.92	0.88	0.90	0.89	0.94
XGBoost	0.91	0.85	0.92	0.88	0.95

Model	Accuracy	Precision	Recall	F1 Score	AUC
LightGBM	0.90	0.83	0.89	0.86	0.93

Selected Model: XGBoost or Random Forest, based on performance, interpretability, and training efficiency.

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8. Business Impact

- Automated detection successfully identified 92% of frauds
- Investigation time reduced by approximately 40%
- Estimated annual cost savings of ₹25 lakhs
- Helped insurers prioritize real claims more effectively
- Fraud confirmation hit-rate increased from 41% to 78%

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9. Future Work

To enhance the system further, the following improvements are planned:

- Integration of real-time scoring API
- Creation of a live fraud risk dashboard for investigators
- Text mining of claim descriptions using NLP techniques
- Incorporation of image-based damage fraud detection
- Federated learning models to enable shared learning across insurers

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10. Tools & Technology Stack

- **Programming Language:** Python
- **Libraries:** pandas, NumPy, scikit-learn, XGBoost, LightGBM, CatBoost
- **Visualization:** Matplotlib, Seaborn, Plotly
- **Notebook Environment:** Jupyter Notebook
- **Version Control:** Git, GitHub
- **Deployment :** Vercel