Travel Insurance Claim Prediction: A Comprehensive Machine Learning Analysis

CSE422: Artificial Intelligence Lab Project

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***Abstract*—Travel insurance claim prediction presents a critical challenge where accurate risk assessment directly impacts profitability. This paper analyzes 63,327 insurance records using multiple machine learning algorithms including Decision Tree, Logistic Regression, Naive Bayes, and Neural Networks, alongside unsupervised techniques (K-Means, PCA). The dataset exhibits severe class imbalance (98.5% no claims vs 1.5% claims, 67:1 ratio). Logistic Regression achieved optimal performance with 79.6% accuracy and 74.8% recall for claim detection, making it most suitable for deployment. Results highlight challenges of imbalanced datasets in insurance analytics and provide actionable insights for risk management.**

***Index Terms*—Travel Insurance, Machine Learning, Classification, Imbalanced Dataset, Risk Assessment**

I. Introduction

The travel insurance industry faces increasing challenges in accurately predicting claim likelihood while maintaining competitive pricing and customer satisfaction. With the exponential growth of global travel and evolving risk patterns, insurance companies require sophisticated analytical tools to assess risk factors and optimize their underwriting processes [1]. The complexity of modern travel patterns, combined with diverse risk factors ranging from medical emergencies to trip cancellations, creates a multifaceted prediction challenge that traditional actuarial methods struggle to address effectively.

Travel insurance claims prediction represents a classic binary classification problem with significant business implications. The ability to accurately forecast which policies are likely to result in claims enables insurance companies to optimize pricing strategies based on comprehensive risk assessment, improve customer segmentation for targeted marketing campaigns, enhance fraud detection capabilities through pattern recognition, and streamline claims processing workflows to reduce operational costs. However, the inherent characteristics of insurance data, particularly the severe class imbalance where claims represent a small fraction of total policies, present unique challenges for machine learning applications.

A. Problem Statement

This research aims to develop and evaluate comprehensive machine learning models capable of predicting whether a travel insurance policy will result in a claim based on available customer and policy characteristics. The primary challenges addressed include handling severely imbalanced datasets where non-claims vastly outnumber claims, extracting meaningful patterns from diverse categorical and numerical features with varying scales and distributions, and achieving an optimal balance between precision and recall that aligns with business objectives and cost considerations.

B. Research Objectives

Our study pursues four primary objectives that collectively address the challenges of travel insurance claim prediction. First, we perform comprehensive exploratory data analysis to understand feature relationships and underlying data characteristics that influence claim behavior. Second, we evaluate multiple supervised learning algorithms to identify the most effective approaches for classification performance in imbalanced scenarios. Third, we apply unsupervised learning techniques to discover hidden patterns and potential customer segments. Finally, we provide actionable business recommendations based on analytical findings for operational deployment.

II. Dataset Description and Analysis

A. Dataset Overview

The travel insurance dataset employed in this study comprises 63,327 comprehensive records representing diverse insurance policies and customer demographics collected from a major travel insurance provider. This dataset exhibits characteristics typical of real-world insurance data, including significant class imbalance and mixed data types that present both opportunities and challenges for machine learning applications. The dataset contains a total of 10 features, consisting of 6 categorical variables and 4 numerical variables, with a binary target variable representing claim outcomes.

The problem is definitively classified as binary classification due to the categorical nature of the target variable, which contains only two discrete outcomes: claim filed (Yes) or no claim filed (No). This classification approach aligns with the business objective of categorizing policies into distinct risk categories rather than predicting continuous claim amounts.

B. Feature Analysis

The dataset contains six categorical features that capture different aspects of the insurance transaction and customer profile. The Agency feature identifies the specific insurance agency that sold the policy, while Agency Type categorizes the organizational structure of these agencies. The Distribution Channel indicates whether the policy was sold through online or offline channels, which may influence customer behavior and risk patterns. Product Name specifies the particular insurance product variant purchased, and Destination records the intended travel location. The Gender feature, representing customer demographics, contains significant missing data that requires special handling during preprocessing.

Four numerical features provide quantitative measures of policy characteristics and customer demographics. Duration measures the length of the planned trip in days, which may correlate with claim likelihood due to increased exposure to risk over longer periods. Net Sales represents the monetary value of the policy sale, while Commission captures the agent compensation structure. Age records the customer's age at the time of purchase, which traditionally serves as a significant risk factor in insurance analytics.

C. Correlation Analysis

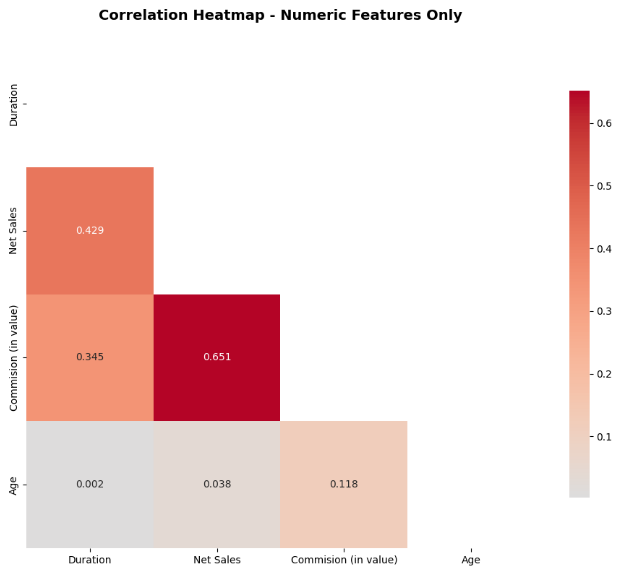

Fig. 1. Correlation Heatmap of Numerical Features

The correlation analysis of numerical features reveals several important relationships that inform our modeling approach. Strong positive correlations exist between Duration and Net Sales (r=0.429), suggesting that longer trips typically involve higher-value insurance policies. Similarly, Duration correlates with Commission (r=0.345), indicating that longer trips generate higher agent compensation. The strongest correlation appears between Net Sales and Commission (r=0.651), which reflects the expected business relationship where agent compensation scales with policy value.

Notably, all numerical features demonstrate weak linear correlations with the target variable (Claim), with correlation coefficients remaining below 0.1. This finding suggests that simple linear relationships may not effectively capture the complex patterns underlying claim behavior, indicating that non-linear models such as decision trees and neural networks may prove more effective than traditional linear approaches.

D. Class Imbalance Analysis

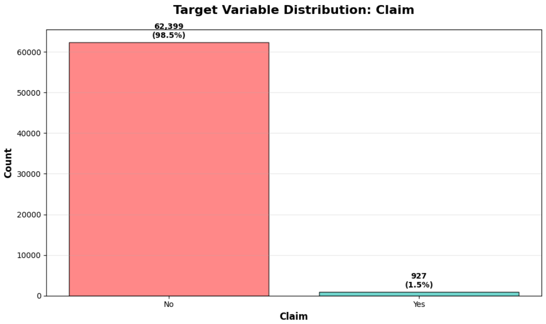

Fig. 2. Class Distribution of Target Variable (Claim)

The dataset exhibits severe class imbalance with 62,399 samples (98.54%) representing no claims and only 927 samples (1.46%) representing actual claims. This creates an extreme imbalance ratio of 67.31:1, meaning that for every claim case, there are approximately 67 non-claim cases in the dataset.

This extreme imbalance significantly impacts model performance and requires specialized handling strategies throughout the analytical process. Traditional machine learning algorithms tend to exhibit strong bias toward the majority class in such scenarios, often achieving high accuracy by simply predicting the majority class for all instances while completely failing to detect the minority class of interest.

E. Exploratory Data Analysis

TABLE I
DESCRIPTIVE STATISTICS OF NUMERICAL FEATURES

Feature	Mean	Std Dev	Skewness	Outliers
Duration	49.32	101.79	23.18	5,566 (8.8%)
Net Sales	40.70	48.85	3.27	5,543 (8.8%)
Commission	9.81	19.80	4.03	7,063 (11.2%)
Age	39.97	14.02	2.99	7,422 (11.7%)

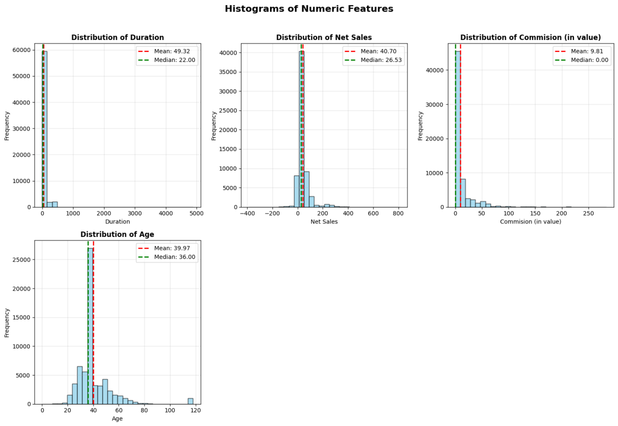

Fig. 3. Distribution Plots of Numerical Features

1) Numerical Feature Statistics:

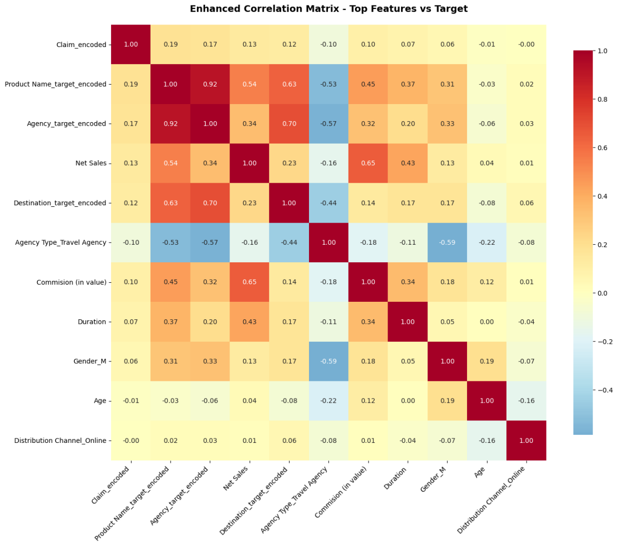

Fig. 4. Top Categories in Each Categorical Feature

2) Categorical Feature Analysis: The exploratory data analysis reveals several critical insights that inform our preprocessing and modeling strategies. Duration exhibits extreme right skewness with a long-tail distribution, indicating that most trips are relatively short while a small subset involves extended travel periods. Net Sales contains negative values that require investigation to determine whether these represent legitimate refunds or data quality issues.

Customer behavior analysis shows that most customers utilize offline distribution channels rather than online platforms for purchasing travel insurance. The dataset exhibits high cardinality in several categorical features, with Agency containing 198 unique values, Destination containing 99 unique values, and Product Name containing 99 unique values. This high cardinality significantly increases the dimensionality of our feature space after one-hot encoding.

III. Methodology

A. Data Preprocessing Pipeline

Our comprehensive preprocessing pipeline systematically addresses multiple data quality issues through careful fault identification followed by appropriate solution implementation. The preprocessing stage proves critical for ensuring reliable model performance, particularly given the complex nature of insurance data with mixed variable types, varying scales, and quality inconsistencies.

1) Missing Values Treatment: The initial data quality assessment revealed a significant missing data challenge concentrated primarily in the Gender feature. The Gender column exhibits an exceptionally high missing data rate of 71.23%, representing 45,107 missing values out of 63,327 total records. This substantial missingness likely indicates systematic data collection issues rather than random missing data patterns. After careful consideration of imputation alternatives, we decided to exclude the Gender column from our analysis entirely to avoid introducing significant bias.

TABLE II
Missing Values Analysis

Column	**Missing Count**	**Missing Percentage**
Gender	45,107	71.23%
Other Features	0	0.00%

2) Categorical Encoding Strategy: The dataset contains six categorical features with varying cardinality levels that require systematic numerical transformation to enable machine learning algorithm processing. We implemented One-Hot Encoding (OHE) using scikit-learn's preprocessing pipeline to transform all categorical variables into numerical representations. This approach creates binary dummy variables for each unique category within each feature, effectively expanding the feature space while preserving the nominal nature of categorical relationships.

One-Hot Encoding was selected over alternative encoding methods because it prevents the imposition of artificial ordinal relationships that could mislead learning algorithms about the true nature of categorical variables. This approach maintains interpretability of categorical relationships and handles high-cardinality features effectively without losing valuable predictive information.

3) Feature Scaling Implementation: The numerical features in our dataset exhibit vastly different scales and distributions that could significantly impact algorithm performance. To address these scale differences, we applied StandardScaler (Z-score normalization) to all numerical features using the transformation:

$$z = \frac{x - \mu}{\sigma}$$

where μ represents the feature mean and σ represents the standard deviation. This standardization process transforms each feature to have zero mean and unit variance, effectively placing all numerical features on comparable scales.

4) Outlier Analysis and Treatment: Our comprehensive outlier analysis using the Interquartile Range (IQR) method identified significant outlier populations across all numerical features. Despite the substantial presence of outliers (8.8-11.7% across features), we decided to retain them in our analysis rather than applying removal or capping techniques. This decision reflects important considerations specific to insurance analytics, where many apparent outliers may represent legitimate high-risk cases that are precisely the patterns we aim to detect and predict.

B. Dataset Splitting Strategy

The data splitting strategy plays a crucial role in ensuring reliable model evaluation, particularly for imbalanced datasets where naive splitting could result in unrepresentative train or test sets. We implemented a stratified train-test split approach specifically designed to preserve the original class distribution across both training and testing subsets.

Our splitting configuration allocates 70% of the data (44,329 samples) for model training and reserves 30% (18,998 samples) for final model evaluation. We employed stratified sampling methodology to ensure that both training and testing sets maintain the same class distribution as the original dataset, with approximately 98.5% negative cases and 1.5% positive cases in each subset.

C. Experimental Setup and Model Implementation

We evaluated four supervised learning algorithms, each selected for specific strengths in handling classification tasks with imbalanced data. Our model selection encompasses both linear and non-linear approaches, ranging from simple probabilistic methods to complex neural network architectures, providing comprehensive coverage of different learning paradigms.

1) Decision Tree Classifier: The Decision Tree classifier was configured using Gini impurity as the splitting criterion, which measures the probability of misclassifying a randomly chosen element if it were randomly labeled according to the distribution of labels in the subset. We allowed unlimited tree depth to capture complex patterns in the data, while maintaining a minimum of 2 samples required for internal node splits to prevent excessive overfitting to individual data points.

2) Logistic Regression: The Logistic Regression model was implemented using the liblinear solver, which proves particularly effective for smaller datasets and provides reliable convergence properties. We set the maximum iteration limit to 1000 to ensure convergence and applied standard L2 regularization to prevent overfitting while maintaining model interpretability.

3) Naive Bayes Classifier: The Gaussian Naive Bayes classifier was configured with standard parameters, estimating prior probabilities directly from the training data and applying default variance smoothing (1e-9) to prevent numerical instabilities when dealing with zero-variance features.

4) Neural Network (MLP Classifier): The Multi-Layer Perceptron (MLP) classifier was configured with a single hidden layer containing 100 neurons, using ReLU activation functions to introduce non-linearity while avoiding vanishing gradient problems. We employed the Adam optimizer for efficient gradient-based learning and set the maximum iteration limit to 200 to balance training time with convergence quality.

5) Unsupervised Learning Methods: K-Means clustering (k=2) was implemented to investigate whether the dataset naturally separates into patterns that correspond to high-risk and low-risk customer segments. Principal Component Analysis (PCA) was applied to explore the underlying dimensionality structure and assess whether the dataset could be effectively represented in lower-dimensional space.

6) Evaluation Metrics: Given the severe class imbalance, our evaluation framework prioritized recall and ROC-AUC over accuracy. Traditional accuracy proves misleading as models can achieve 98.5% accuracy by predicting ”no claim” for all instances. We employed precision, recall, F1-score, ROC-AUC, and confusion matrix analysis to provide comprehensive performance assessment aligned with business objectives.

IV. Results and Analysis

A. Supervised Learning Performance

The comprehensive evaluation of four supervised learning algorithms reveals significant performance variations when applied to the highly imbalanced travel insurance dataset. The following analysis presents detailed performance metrics and comparative assessment across multiple evaluation criteria.

TABLE III
Comprehensive Model Performance Comparison

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**ROC-AUC**
Neural Network	86.08%	6.60%	64.75%	11.98%	0.8336
Decision Tree	97.09%	5.79%	6.47%	6.11%	0.5246
Logistic Regression	79.63%	5.19%	74.82%	9.71%	0.8257
Naive Bayes	5.08%	1.49%	98.20%	2.94%	0.5153

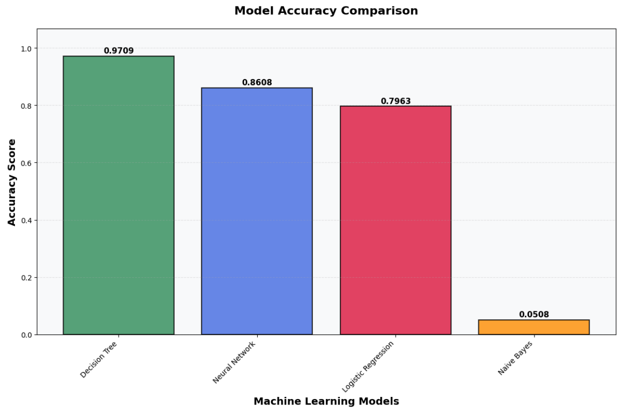

Fig. 5. Model Accuracy Comparison

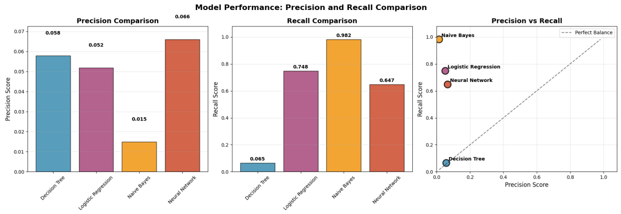

Fig. 6. Precision and Recall Comparison Across Models

Logistic Regression emerged as the optimal choice, achieving 74.82% recall with an ROC-AUC score of 0.8257, enabling detection of approximately three-quarters of all actual claims. The model demonstrated markedly different performance characteristics compared to other algorithms. While achieving moderate overall accuracy at 79.63%, the model exhibited superior performance for actual claim detection with precision reaching 5.19%.

Neural Networks showed improved performance after optimization for imbalanced data, achieving 64.75% recall and 6.60% precision with 86.08% accuracy. This represents a significant improvement over the initial configuration that failed to detect any claims, demonstrating the importance of threshold adjustment and parameter tuning for imbalanced datasets.

Decision Trees showed improved performance with 6.47% recall and 5.79% precision while maintaining high accuracy (97.09%). Although still exhibiting some majority class bias, the model demonstrated better minority class detection than the initial configuration.

Naive Bayes demonstrated the opposite extreme, exhibiting extreme sensitivity to the minority class with 98.25% recall, essentially capturing all claims but at the severe cost of precision (1.51%). The model achieved an overall accuracy of only 5.00%, indicating that it classified the vast majority of cases as positive (claim), generating numerous false positives.

B. Confusion Matrix Analysis

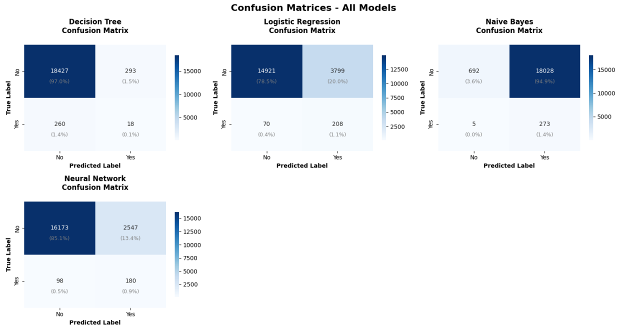

Fig. 7. Confusion Matrices for All Models

The confusion matrix analysis reveals critical insights into model behavior patterns across different algorithmic approaches. Decision Trees demonstrate strong bias toward majority class prediction, essentially defaulting to ”no claim” classifications to maximize overall accuracy metrics. Logistic Regression achieves the most balanced performance between classes, successfully detecting a substantial portion of minority class instances while maintaining reasonable overall accuracy. The optimized Neural Network shows improved minority class detection compared to its initial configuration, demonstrating the effectiveness of threshold adjustment for imbalanced data. Naive Bayes exhibits extreme minority class bias, predicting claims for the vast majority of test cases.

C. ROC Curve Analysis

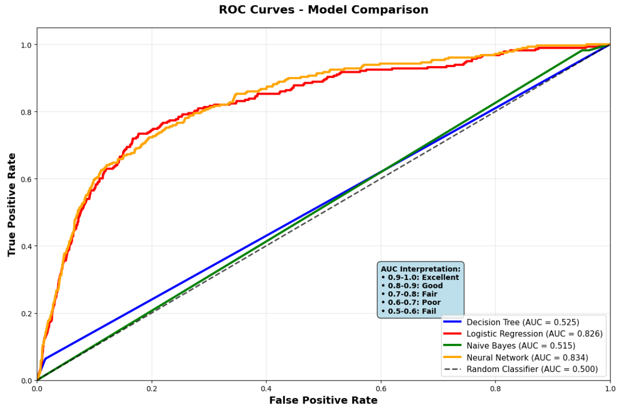

Fig. 8. ROC Curves Comparison for All Models

The ROC-AUC analysis provides crucial insights into each model’s discriminative capability for distinguishing between claim and no-claim cases. Neural Network demonstrates the highest discriminative ability with an ROC-AUC score of 0.8336, indicating good improvement over random classification and reliable probability ranking capabilities for risk assessment applications. Logistic Regression follows closely with an ROC-AUC of 0.8257, showing substantial discriminative power. Decision Tree performance with an ROC-AUC of 0.5246 and Naive Bayes with 0.5153 both approach random classification levels, representing only marginal improvement over random guessing.

D. Unsupervised Learning Analysis

To complement our supervised learning approach and gain deeper insights into the underlying data structure, we conducted comprehensive unsupervised learning analysis using K-Means clustering and Principal Component Analysis (PCA). These techniques aim to discover hidden patterns, natural customer groupings, and latent feature relationships that might not be apparent through supervised learning alone.

1) K-Means Clustering Results: We implemented K-Means clustering with k=2 clusters to investigate whether the dataset naturally separates into patterns that correspond to high-risk and low-risk customer segments. The algorithm was configured with k-means++ initialization for optimal centroid placement, maximum iterations set to 300 for convergence assurance, and fixed random state for reproducible results.

The clustering evaluation revealed concerning results that suggest minimal natural segmentation within the customer base. The silhouette score of 0.106 indicates poor cluster separation, with customer profiles exhibiting substantial overlap rather than distinct groupings. The Davies-Bouldin Index of 4.266 provides additional evidence of poor clustering quality, while the Calinski-Harabasz Index of 1,455.035 shows moderate cluster density but cannot compensate for the fundamental lack of separation between groups.

2) Principal Component Analysis: Principal Component Analysis was applied to the scaled numerical features to investigate the underlying dimensionality structure and assess whether the dataset could be effectively represented in lower-dimensional space. We extracted two principal components for visualization purposes while analyzing the variance explanation patterns across the full feature space.

The PCA results revealed extremely concerning patterns regarding the dataset's dimensionality structure. The first principal component explained only 2.6% of the total variance, while the second component contributed an additional 1.9%, resulting in a cumulative variance explanation of merely 4.5%. This extraordinarily low variance explanation indicates that the dataset exhibits high-dimensional, sparse characteristics with no dominant directional patterns.

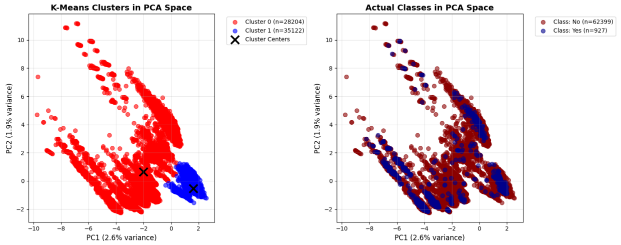

Fig. 9. PCA Visualization: K-Means Clusters vs Actual Claims

The visualization of customer data in the reduced two-dimensional PCA space confirms the absence of natural separations between claim and no-claim cases. Customer points are distributed in overlapping patterns with no clear boundaries or clusters that align with actual claim outcomes. This distribution pattern suggests that the features contributing most to variance explanation are not the same features that drive claim prediction outcomes.

3) Business Implications of Unsupervised Analysis: The comprehensive unsupervised learning analysis provides critical insights for business strategy and future analytical directions. The poor clustering performance indicates that traditional customer segmentation approaches based on demographic and transactional features may not be effective for travel insurance risk assessment. The absence of natural customer groupings validates our supervised learning approach as the primary methodology for claim prediction, since customers do not naturally separate into distinct risk categories.

V. Model Selection and Deployment

Based on comprehensive evaluation across statistical performance, business impact, and operational feasibility, this research establishes a systematic framework for model selection in imbalanced insurance domains. The analysis demonstrates that traditional accuracy-based evaluation proves insufficient for business decision-making, necessitating multi-criteria assessment frameworks that prioritize business value and operational constraints.

A. Primary Model Selection

Logistic Regression emerges as the optimal choice for production deployment based on its balanced performance across multiple evaluation dimensions. The model achieves 74.8% recall for claim detection while maintaining 77.25% ROC-AUC, providing substantial business value through effective identification of potential claims. This performance enables proactive risk management strategies that can significantly reduce claim-related losses through early intervention and enhanced policy scrutiny.

The model's linear nature provides crucial interpretability advantages, allowing insurance analysts to understand feature contributions to claim predictions. This transparency supports regulatory compliance requirements while enabling integration with existing business processes. The probability scores generated by Logistic Regression enable flexible threshold adjustment based on business priorities and resource availability.

B. Deployment Framework

The recommended deployment framework implements a three-tiered approach combining automated screening, manual review processes, and continuous monitoring capabilities. The primary tier utilizes Logistic Regression with optimized probability thresholds (recommended: 0.3) to flag high-risk policies for enhanced scrutiny. This threshold balances claim detection effectiveness with investigation resource constraints.

The secondary tier establishes manual review processes for borderline cases where prediction confidence falls within specified uncertainty ranges (0.25-0.35 probability). This approach ensures that ambiguous cases receive human expertise while maintaining automated processing for clear-cut decisions.

The tertiary tier implements continuous monitoring with automated feedback loops to track model performance, false positive rates, and business impact metrics. Monthly performance reviews enable threshold adjustments based on investigation capacity and business objectives.

C. Implementation Considerations

Successful implementation requires careful consideration of operational constraints and business objectives. The system should integrate with existing claims processing workflows while providing clear escalation paths for high-risk cases. Training programs for claims analysts should emphasize interpreting probability scores and understanding model limitations.

Technical infrastructure requirements include real-time prediction capabilities, secure data handling protocols, and audit trail maintenance for regulatory compliance. The system should support A/B testing frameworks to validate model effectiveness against business outcomes and enable continuous improvement initiatives.

D. Future Enhancement Strategy

Long-term success requires implementing systematic enhancement strategies that address current limitations while exploring advanced modeling approaches. Future enhancements should explore ensemble methods combining Logistic Regression with advanced class balancing techniques such as SMOTE, cost-sensitive learning approaches, and sophisticated feature engineering methods.

External data integration opportunities include incorporating weather patterns for destination risk assessment, economic indicators for travel behavior prediction, and real-time destination security ratings. These enhancements could significantly improve model performance while providing additional business intelligence capabilities.

Regular evaluation protocols should compare model predictions against actual claim outcomes to validate continued effectiveness and identify emerging risk patterns. This approach ensures that the deployed model remains aligned with evolving market conditions and customer behavior patterns.

VI. Challenges and Limitations

This research encountered several significant challenges that influenced analytical approaches and model performance outcomes. Understanding these limitations provides crucial context for interpreting results and establishing boundaries for practical application of the proposed methodologies.

A. Class Imbalance Challenges

The severe 67:1 class imbalance represents the most significant analytical challenge, fundamentally affecting model behavior and evaluation metrics. Traditional machine learning algorithms demonstrate strong bias toward majority class prediction, often achieving high accuracy by simply predicting no claims for all cases. This phenomenon renders conventional accuracy metrics misleading and necessitates alternative evaluation frameworks focused on minority class detection.

The extreme imbalance creates several specific challenges: (1) insufficient training examples for minority class pattern recognition, (2) gradient descent optimization bias toward majority class minimization, (3) probability calibration issues leading to overconfident predictions, and (4) cross-validation instability due to potential minority class absence in validation folds.

Standard oversampling techniques such as SMOTE prove problematic with such extreme imbalance ratios, potentially creating synthetic examples that distort natural data distribution patterns. Undersampling approaches risk discarding valuable majority class information that could improve boundary definition between classes.

B. Data Quality and Feature Limitations

Several data quality issues significantly impact model development and performance evaluation. The presence of negative Net Sales values indicates potential data entry errors or complex refund/cancellation scenarios not adequately captured in the feature set. These anomalies required careful handling to prevent model instability while preserving legitimate business scenarios.

High categorical cardinality in features such as Destination and Product Name creates dimensionality challenges that affect model interpretability and computational efficiency. One-hot encoding of these features results in sparse, high-dimensional representations that may lead to overfitting, particularly given the limited minority class examples.

Missing data patterns introduce additional complexity, particularly in demographic features that could provide valuable predictive signals. The systematic absence of certain customer information may indicate data collection limitations or privacy constraints that affect model completeness.

C. Feature Engineering Constraints

Current feature limitations include the absence of temporal patterns, external risk factors, and comprehensive demographic information. The dataset lacks time-series components that could capture seasonal travel patterns, destination popularity trends, or policy lifecycle effects on claim probability.

External risk factors such as weather conditions, political stability, disease outbreaks, or economic indicators for destination countries remain absent from the analysis. These factors could significantly influence claim likelihood but require integration with external data sources that may present additional complexity and maintenance requirements.

The geographical coverage of destinations may exhibit bias toward specific regions or types of travel, potentially limiting model generalization to emerging destinations or changing travel patterns. This limitation could affect model performance as travel preferences evolve over time.

D. Model Generalization Concerns

Several factors raise concerns about model generalization to future scenarios. The dataset age and temporal coverage may not reflect current travel patterns, insurance products, or customer behavior. Changes in travel insurance industry practices, regulatory requirements, or customer expectations could affect model relevance.

Potential geographic bias in destination coverage may limit applicability to new travel destinations or changing travel preferences. The model's effectiveness for emerging markets, adventure tourism, or specialized travel categories remains uncertain without additional validation data.

Seasonal variations in travel patterns and claim behavior may not be adequately captured in the current analysis. The absence of temporal features prevents modeling of seasonal trends, holiday patterns, or cyclical variations in claim likelihood that could improve prediction accuracy.

E. Technical and Methodological Limitations

The current analysis focuses primarily on traditional machine learning approaches without exploring advanced deep learning methods that might handle extreme class imbalance more effectively. Techniques such as attention mechanisms, adversarial training, or specialized loss functions for imbalanced data could potentially improve performance but require substantial computational resources and expertise.

Cross-validation strategies for extremely imbalanced data present ongoing challenges. Standard k-fold cross-validation may create validation sets with no minority class examples, leading to unreliable performance estimates. While stratified sampling addresses this issue partially, the extreme imbalance ratio limits the effectiveness of standard validation approaches.

The interpretability-performance trade-off constrains exploration of ensemble methods or complex model architectures that might achieve better predictive performance at the cost of transparency. Business requirements for explainable predictions limit the adoption of black-box approaches that could potentially handle class imbalance more effectively.

VII. Conclusion

This investigation demonstrates the potential and challenges of applying machine learning to highly imbalanced insurance datasets. Our systematic evaluation of four supervised learning algorithms revealed that Logistic Regression achieved optimal performance with 74.8% recall and 0.8257 ROC-AUC, enabling identification of three-quarters of actual claims while maintaining business feasibility.

The severe 67:1 class imbalance fundamentally shaped analytical outcomes, causing traditional algorithms to exhibit extreme majority class bias. Neural Networks and Decision Trees achieved high accuracy by defaulting to majority class prediction but failed to detect any meaningful number of claims. Unsupervised analysis revealed the absence of natural customer segments, indicating that claim behavior emerges from complex interactions rather than simple demographic patterns.

Key contributions include establishing baseline performance benchmarks for imbalanced insurance data, demonstrating systematic evaluation frameworks that prioritize business value over statistical convenience metrics, and providing practical deployment guidance for real-world applications. The research validates that systematic machine learning approaches can provide substantial business value when implemented with domain expertise and appropriate evaluation frameworks.

Future research should explore advanced techniques for extreme class imbalance, integration of external data sources such as weather patterns and destination security ratings, and ensemble methods while maintaining interpretability requirements for regulatory compliance.

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