**Machine Learning based Method for Insurance Fraud Detection on Class Imbalance Datasets with Missing Values**

**ABSTRACT:**

Insurance fraud, particularly within the automobile insurance sector, is a significant challenge faced by insurers, leading to financial losses and influencing pricing strategies. Fraud detection models are often impacted by class imbalance, where fraudulent claims are much rarer than legitimate claims, and missing data further complicates the process. This research tackles these issues by utilizing two car insurance datasets—an Egyptian real-life dataset and a standard dataset. The proposed methodology includes addressing missing data and class imbalance, and it incorporates the AdaBoost Classifier to enhance the model’s accuracy and predictive power. The results demonstrate that addressing class imbalance plays a crucial role in improving model performance, while handling missing data also contributes to more reliable predictions. The AdaBoost Classifier significantly outperforms existing techniques, improving prediction accuracy and reducing overfitting, which is often a challenge in fraud detection models. This study presents valuable insights into how improving data quality and using advanced algorithms like AdaBoost can enhance fraud detection systems, ultimately leading to more effective identification of fraudulent claims. These enhancements can significantly aid insurance companies in reducing financial losses, improving decision-making, and refining pricing models.

**INTRODUCTION**

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1.Introduction :

Insurance fraud, particularly in the automobile insurance sector, poses a significant challenge for insurance companies. Fraudulent claims not only result in substantial financial losses but also influence pricing strategies, ultimately leading to higher premiums for legitimate policyholders. One of the major hurdles in fraud detection is the class imbalance problem, where fraudulent claims are far less frequent than legitimate ones. This imbalance often leads to biased models that fail to correctly identify fraudulent claims. Furthermore, missing data exacerbates the issue by further complicating the training of effective predictive models. These challenges have prompted researchers to explore more sophisticated techniques to enhance fraud detection.

In response to these challenges, the proposed study utilizes two car insurance datasets—an Egyptian real-life dataset and a standard dataset—to develop a more robust fraud detection system. The methodology focuses on addressing both the class imbalance and missing data problems. Specifically, the research introduces the AdaBoost Classifier, a powerful machine learning algorithm that improves prediction accuracy by enhancing weak classifiers through ensemble learning. By applying AdaBoost, the model effectively handles both class imbalance and overfitting, common issues faced by traditional fraud detection models. The study demonstrates that addressing class imbalance significantly enhances the model’s performance, while the treatment of missing data ensures that the predictions remain reliable and accurate. The AdaBoost Classifier outperforms existing models, making it a promising approach for more effective fraud detection. This work provides valuable insights into how advanced machine learning algorithms, when combined with improved data quality handling techniques, can lead to more reliable and efficient fraud detection systems, ultimately helping insurance companies reduce financial losses and improve decision-making processes.

**SCOPE OF THE PROJECT**

The scope of this project focuses on addressing the challenges of insurance fraud detection within the automobile insurance sector. It aims to enhance the accuracy and efficiency of fraud detection models by utilizing advanced machine learning techniques, specifically addressing the class imbalance problem and missing data issues. The project involves working with real-life datasets, applying the AdaBoost Classifier, and evaluating the model's performance in comparison to existing systems. Additionally, the study explores how these enhancements can lead to better prediction accuracy, reduced overfitting, and more reliable fraud detection system

**OBJECTIVE**

The objective of this project is to develop an advanced and efficient insurance fraud detection system tailored for the automobile insurance industry. The project focuses on addressing key challenges such as class imbalance, where fraudulent claims are underrepresented compared to legitimate claims, and missing data, which often affects the model’s accuracy. By leveraging machine learning techniques, particularly the AdaBoost Classifier, the aim is to enhance prediction accuracy and reduce overfitting, ensuring the model generalizes better on unseen data. This project also seeks to provide a framework for improving the overall effectiveness of fraud detection systems, leading to more reliable identification of fraudulent claims and aiding in better decision-making and pricing strategies for insurance companies. Through this, the project aims to contribute to reducing financial losses for insurers and improving the overall integrity of the insurance system.

**EXISTING SYSTEM:**

Existing fraud detection models in the insurance industry typically rely on conventional machine learning algorithms like Logistic Regression, Decision Trees, and Random Forests. However, they face challenges when working with imbalanced datasets, where fraudulent claims are relatively rare compared to legitimate claims. This imbalance leads to poor model performance, as the classifiers are biased towards the majority class. Furthermore, missing data and inconsistencies in the dataset contribute to unreliable predictions, affecting the overall accuracy of these models. Despite their utility, traditional methods often suffer from overfitting, where models perform well on training data but fail to generalize to unseen data. Overfitting occurs because these models can become too complex when trying to fit noisy or incomplete data, resulting in reduced model robustness. While some approaches use sampling methods like under sampling or oversampling to address class imbalance, they do not always achieve optimal results, especially when the dataset contains many missing or noisy entries.

**EXISTING SYSTEM DISADVANTAGES:**

* Class Imbalance
* Handling Missing Data
* Overfitting
* Limited Performance with Complex Fraud Patterns
* Inefficient Fraud Detection

**LITERATURE SURVEY**

**Title:** Encoding High-Cardinality String Categorical Variables

**Author:** Patricio Cerda, G. Varoquaux

**Year:** 2022

**Description:** Statistical models usually require vector representations of categorical variables, using for instance one-hot encoding. This strategy breaks down when the number of categories grows, as it creates high-dimensional feature vectors. Additionally, for string entries, one-hot encoding does not capture information in their representation.Here, we seek low-dimensional encoding of high-cardinality string categorical variables. Ideally, these should be: scalable to many categories; interpretable to end users; and facilitate statistical analysis. We introduce two encoding approaches for string categories: a Gamma-Poisson matrix factorization on substring counts, and the min-hash encoder, for fast approximation of string similarities. We show that min-hash turns set inclusions into inequality relations that are easier to learn. Both approaches are scalable and streamable. Experiments on real and simulated data show that these methods improve supervised learning with high-cardinality categorical variables. We recommend the following: if scalability is central, the min-hash encoder is the best option as it does not require any data fit; if interpretability is important, the Gamma-Poisson factorization is the best alternative, as it can be interpreted as one-hot encoding on inferred categories with informative feature names. Both models enable autoML on the original string entries as they remove the need for feature engineering or data cleaning.

**Title:** Predicting Insolvency of Insurance Companies in Egyptian Market Using Bagging and Boosting Ensemble Techniques

**Author:** Ahmed A. Khalil , Zaiming Liu1 , Ahmad Salah , Ahmed Fathalla , And Ahmed Ali

**Year:** 2022.

**Description**: Insolvency is a crucial problem for several insurance companies that suffer from it. This problem has direct or indirect effects on both the people working in the financial business and normal citizens. Thus, in insurance companies, the ability to predict insolvency is in great demand. There are several efforts proposed to predict insurance company insolvency using computer science methods (e.g., support vector machine and fuzzy systems). Each country has its own data patterns due to interior matters. Thus, insurance companies from different countries may have different data patterns. Consequently, the utilized predictive model should adapt to the dataset at hand. To our best knowledge, despite there are several efforts to build an insolvency predictive model, none of these efforts explored the Egyptian market. In addition, even the existing efforts did not utilize the ensemble learning methods in the insolvency prediction problem. In this context, we have two main contributions to this work. First, we proposed the first public access dataset of Egyptian insurance companies. The collected dataset was gathered from 11 Egyptian insurance companies during the years 1999 to 2019. The dataset consists of a set of 22 ratios (21 input features and one output feature), e.g., retention and investment yield alongside the solvency ration (i.e., the target feature). In the second contribution, we proposed exploring the performance of the ensemble learning methods to address the insolvency prediction problem. Thus, we proposed building several insolvency predictive models using ensemble learning and classic machine learning models. Next, the proposed models are evaluated on different accuracy metrics, e.g., Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The experimental results revealed that the ensemble learning-based models outperformed the classic machine learning-based models. Moreover, the correlation analysis between the utilized 22 financial ratios revealed that the most significant ratios, for the task of predicting the solvency ratio, are the technical provisions to shareholders’ funds, insurance companies’ debit balances to shareholders, and earnings after taxes to shareholders’ funds.

**Title:** Enhancing Credit Card Fraud Detection: An Ensemble Machine Learning Approach

**Author:** by Abdul Rehman Khalid ,Nsikak Owoh ,ORCID,Omair Uthmani 1,Moses Ashawa ,Jude Osamor, John Adejoh

**Year:** 2024.

**Description:** In the era of digital advancements, the escalation of credit card fraud necessitates the development of robust and efficient fraud detection systems. This paper delves into the application of machine learning models, specifically focusing on ensemble methods, to enhance credit card fraud detection. Through an extensive review of existing literature, we identified limitations in current fraud detection technologies, including issues like data imbalance, concept drift, false positives/negatives, limited generalisability, and challenges in real-time processing. To address some of these shortcomings, we propose a novel ensemble model that integrates a Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF), Bagging, and Boosting classifiers. This ensemble model tackles the dataset imbalance problem associated with most credit card datasets by implementing under-sampling and the Synthetic Over-sampling Technique (SMOTE) on some machine learning algorithms. The evaluation of the model utilises a dataset comprising transaction records from European credit card holders, providing a realistic scenario for assessment. The methodology of the proposed model encompasses data pre-processing, feature engineering, model selection, and evaluation, with Google Colab computational capabilities facilitating efficient model training and testing. Comparative analysis between the proposed ensemble model, traditional machine learning methods, and individual classifiers reveals the superior performance of the ensemble in mitigating challenges associated with credit card fraud detection. Across accuracy, precision, recall, and F1-score metrics, the ensemble outperforms existing models. This paper underscores the efficacy of ensemble methods as a valuable tool in the battle against fraudulent transactions. The findings presented lay the groundwork for future advancements in the development of more resilient and adaptive fraud detection systems, which will become crucial as credit card fraud techniques continue to evolve.

**Title:**  Machine Learning Method for Return Direction Forecast of Exchange Traded Funds (ETFs) Using Classification and Regression Models

**Author:**  Raphael Paulo Beal Piovezan, Pedro Paulo de Andrade Junior & Sérgio Luciano Ávila

**Year:** 2023

**Description**: — This article aims to propose and apply a machine learning method to analyze the direction of returns from exchange traded funds using the historical return data of its components, helping to make investment strategy decisions through a trading algorithm. In methodological terms, regression and classification models were applied, using standard data sets from five reference markets, in addition to algorithmic error metrics. In terms of research results, they were analyzed and compared to those of the Naïve forecast and the returns obtained by the buy & hold technique in the same period of time. In terms of risk and return, the models mostly performed better than the control metrics, with emphasis on the linear regression model and the classification models by logistic regression, support vector machine (using the LinearSVC model), Gaussian Naive Bayes and K-Nearest Neighbors, where in certain data sets the returns exceeded by two times and the Sharpe ratio by up to four times those of the buy & hold control model.

**Title:** Machine Learning-Based Approaches for Real-Time Fraud Detection and Prevention

**Author**: Vikas R. Shetty, Pooja R, [Rashmi Laxmikant Malghan](https://researcher.manipal.edu/en/persons/rashmi-laxmikant-malghan)

**Year:** 2023**.**

**Description:** The proliferation of internet services in various industries, especially the financial sector, has increased financial fraud. Fraud detection and prevention are critical to protecting both individuals and organizations from significant financial loss. However, the lack of publicly available datasets containing fraud is a major challenge. This study aims to address these issues using advanced machine learning techniques. Known for their ability to provide insight into data, decision trees are used for real-time fraud detection. In addition, deep learning techniques and artificial neural networks (ANN) are used to detect complex fraud patterns, while logistic regression is used to model the probability of fraudulent events. The accuracy of these methods, including decision trees, logistic regression, and ANN, is fully evaluated, with accuracies of 99.8%, 99.9%, and 99.94%, respectively. These findings provide valuable guidance for companies on choosing effective anti-fraud strategies and shed light on the adaptability of algorithms to real financial contexts, contributing to machine learning-based fraud detection.

**PROPOSED SYSTEM**

The proposed system enhances insurance fraud detection by incorporating the AdaBoost Classifier, an ensemble technique that improves predictive performance by combining multiple weak classifiers to create a strong, accurate model. AdaBoost's ability to reduce overfitting makes it especially effective for handling noisy or incomplete datasets, ensuring that the model generalizes well to new data. This classifier is also integrated with techniques like SMOTE (Synthetic Minority Over-sampling Technique) to address the class imbalance problem, thereby improving the detection of fraudulent claims that are underrepresented in the dataset.

Furthermore, the proposed system employs more robust data preprocessing methods to handle missing data effectively. These preprocessing techniques ensure that the model works with cleaner, more complete datasets, improving overall prediction accuracy. The combination of AdaBoost with these advanced data handling methods makes the model more reliable, scalable, and efficient. By addressing both class imbalance and missing data, the proposed system outperforms traditional methods in terms of accuracy and robustness, providing a more effective solution for fraud detection in the insurance industry.

**PROPOSED SYSTEM ADVANTAGES:**

* Enhanced Fraud Detection
* Effective Missing Data Handling
* Optimized Model Performance
* Reduced Overfitting
* Increased Accuracy in Predictions

**Gathering The Dataset:**

The process of gathering data is a crucial and foundational step in any machine learning project, particularly when addressing complex problems like insurance fraud detection. A robust and diverse dataset ensures that the model can effectively learn patterns, identify anomalies, and make accurate predictions. For this project, the datasets selected must comprehensively represent the problem space, capturing both legitimate and fraudulent insurance claims to provide a balanced perspective for the model. In this study, two distinct datasets are used to enhance the diversity and comprehensiveness of the input data. The first dataset is sourced from a real-world Egyptian insurance company, offering practical insights into the specific challenges faced in the region’s insurance market. This dataset includes historical records of insurance claims, detailing various features such as claim amounts, policyholder demographics, claim types, and whether the claims are legitimate or fraudulent. The second dataset is a well-established, standardized dataset commonly used in fraud detection research, providing an additional layer of validation and allowing for benchmarking against other models in the field. By using a combination of real-world and standard datasets, the model benefits from a wider variety of data, covering both region-specific characteristics and more generalized fraud detection patterns. This approach not only ensures that the model is trained on a representative set of data but also helps in testing the model’s generalization capabilities across different scenarios. Ultimately, gathering diverse and relevant datasets is critical for training machine learning models that can accurately detect fraudulent claims, improving the efficiency and reliability of insurance fraud detection systems.

**Model Implementation**

The model implementation phase focuses on applying machine learning algorithms to the preprocessed dataset to generate accurate predictions. In this project, the AdaBoost Classifier is chosen as the core predictive model due to its effectiveness in handling complex classification problems, particularly in cases where the data is imbalanced. AdaBoost, or Adaptive Boosting, is an ensemble learning method that combines multiple weak classifiers, typically decision trees, to create a strong and robust model. The primary advantage of AdaBoost lies in its ability to improve the performance of weak classifiers by focusing more on the difficult-to-classify instances.

In the context of insurance fraud detection, class imbalance is a common issue, where fraudulent claims often represent a small proportion of the total claims. AdaBoost addresses this challenge by assigning higher weights to misclassified instances, especially fraudulent claims, during the learning process. This ensures that the model pays more attention to the fraudulent claims, improving its ability to detect them accurately and reducing the chances of false negatives. The first step in implementing the AdaBoost Classifier is to tune its hyperparameters to optimize its performance. This involves adjusting parameters like the number of estimators (weak classifiers) and the learning rate, which controls the contribution of each weak classifier to the final model. Once the hyperparameters are optimized, the model is trained on the preprocessed dataset, where it learns to differentiate between fraudulent and legitimate claims based on the features in the data. The trained AdaBoost model is then evaluated to assess its accuracy, precision, recall, and other metrics, ensuring that it performs well in identifying fraudulent claims while minimizing false positives.

**EXISTING TECHNIQUE:**

Traditional insurance fraud detection systems typically use machine learning algorithms like Logistic Regression, Decision Trees, and Random Forest. These algorithms, while effective for general classification tasks, struggle with imbalanced datasets where fraudulent claims are much fewer than legitimate ones. They are also limited by issues like overfitting, where the model learns noise from the training data, and missing values, which can degrade model performance. Despite using techniques like undersampling or oversampling to handle class imbalance, these models often fail to achieve optimal accuracy and robustness.

Additionally, many existing systems struggle with overfitting, where models memorize specific patterns in the training data, leading to poor generalization on unseen data. While Random Forest and similar algorithms are used, they still face challenges with large, imbalanced datasets, particularly when handling complex fraud patterns. The lack of advanced techniques to address both class imbalance and missing values diminishes the effectiveness of these systems, making it difficult to maintain a high fraud detection rate without sacrificing accuracy for legitimate claims.

**PROPOSED TECHNIQUE USED OR ALGORITHM USED:**

The proposed system leverages the AdaBoost Classifier, an ensemble method that combines weak learners to create a strong classifier, improving model robustness and accuracy. AdaBoost’s ability to reduce overfitting makes it especially useful for noisy and incomplete datasets. Additionally, techniques like SMOTE are used to address class imbalance, ensuring better performance in detecting fraudulent claims. The system also includes advanced data preprocessing methods to handle missing values, ensuring a more complete dataset and enhancing model performance, making it a more reliable solution for fraud detection.

In addition to AdaBoost, the proposed system employs the Synthetic Minority Over-sampling Technique (SMOTE) to address the class imbalance problem by generating synthetic samples for the minority class, which is critical for improving the fraud detection rate. The integration of advanced data preprocessing methods ensures that missing values are effectively handled, preventing data gaps from negatively impacting the model's performance. These combined strategies—AdaBoost for classification, SMOTE for data balancing, and advanced preprocessing for handling missing data—lead to a more accurate, reliable, and robust system for insurance fraud detection, significantly outperforming traditional methods in terms of both prediction accuracy and generalization.

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**SYSTEM REQUIREMENTS**

**HARDWARE REQUIREMENTS**

The hardware requirements may serve as the basis for a contract for the implementation of the system and should therefore be a complete and consistent specification of the whole system. They are used by software engineers as the starting point for the system design. It should what the system do and not how it should be implemented.

* PROCESSOR : DUAL CORE 2 DUOS.
* RAM : 4GB DD RAM
* HARD DISK : 500 GB

**SOFTWARE REQUIREMENTS**

The software requirements document is the specification of the system. It should include both a definition and a specification of requirements. It is a set of what the system should do rather than how it should do it. The software requirements provide a basis for creating the software requirements specification. It is useful in estimating cost, planning team activities, performing tasks and tracking the teams and tracking the team’s progress throughout the development activity.

* Operating System : Windows 10
* Platform : Spyder3
* Programming Language : Python
* Front End : Spyder3

**CONCLUSION**

The conclusion of this project highlights the significant advancements achieved in vehicle insurance fraud detection by implementing the AdaBoost Classifier. The proposed model effectively addresses challenges associated with class imbalance and missing data, which are common in insurance datasets. By leveraging AdaBoost, the system enhances the detection of fraudulent claims with greater accuracy and reduced overfitting, ensuring a robust predictive model that adapts to various fraud patterns. This approach not only improves the precision of identifying fraudulent activities but also contributes to minimizing financial losses for insurance companies.

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**Problem Statement**

Insurance fraud, particularly in the automobile insurance sector, is a critical challenge for insurers, leading to substantial financial losses and affecting pricing strategies. Fraudulent claims are often difficult to detect due to the inherent class imbalance in datasets, where fraudulent claims are much less frequent compared to legitimate claims. Additionally, missing data further complicates the development of accurate fraud detection models, as incomplete information can lead to unreliable predictions. These issues hinder the ability of traditional fraud detection models to effectively identify fraudulent claims, increasing the risk of false positives and false negatives. The lack of efficient and reliable fraud detection systems not only impacts insurers financially but also affects their decision-making processes and pricing models, making it essential to improve these systems to enhance the overall efficiency of the insurance industry.

**Problem Overcome**

This research addresses the key challenges of class imbalance and missing data in insurance fraud detection by employing a two-pronged approach. First, two datasets—an Egyptian real-life car insurance dataset and a standard dataset—are used to ensure diversity and comprehensiveness in the data. To tackle class imbalance, the AdaBoost Classifier is utilized, an ensemble learning method that improves model performance by focusing on misclassified instances, particularly fraudulent claims. Additionally, missing data is addressed through preprocessing techniques, ensuring that the dataset is complete and reliable for training.

The results of this study demonstrate that addressing class imbalance is essential for improving model performance, while handling missing data contributes to more accurate and trustworthy predictions. The AdaBoost Classifier outperforms traditional techniques, significantly improving prediction accuracy and reducing overfitting. This research highlights how enhancing data quality and utilizing advanced algorithms like AdaBoost can lead to more effective fraud detection systems, benefiting insurance companies by reducing financial losses, improving decision-making, and refining pricing strategies.