Anomaly Detection at the Intersection of Retail, Finance, and Compliance

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COMPLIANCE
Anomaly Detection: Retail, Finance, Compliance
Ensuring security and integrity across industries.

Abstract:

Finding anomalies in fraud cases is very hard because the data is so complicated and is often locked away behind strict access controls. Compliance and financial limits make things even more difficult. This study looks into how hard it is to do anomaly detection in places that are so tightly controlled. It focuses on the retail sector because following the rules is not only very important but also carries heavy penalties. Not much has been written about finding strange things at the intersection of law, finance, and technology, so this study looks at new ways to do it using data mining, machine learning, and artificial intelligence. These technologies are built into complex compliance frameworks that make it easier to look at financial activities. This paper comes up with a new way to find and deal with problems in high-stakes situations that take into account the difficulties of limited data access, following the rules, and the financial details of trades. The results add a new angle to what is already known and make it possible to create fraud detection systems that are more strong and flexible in industries with a lot of regulations.

Keywords: Anomaly detection, Retail fraud, Compliance framework, Machine learning, Financial transactions

1. Introduction

Fraud and other strange behavior can be hard to spot in the retail sector because of the complicated interactions between money transfers, following the rules, and limited access to data [1]. Fraud cost the global retail industry an estimated $62 billion in 2020 alone [2]. Online payment fraud was responsible for an amazing 45% of these losses. In these kinds of situations, traditional methods for finding anomalies don't always work, so new methods need to be created that can get around these extra problems [3].

A recent poll by the National Retail Federation (NRF) found that 94% of retailers have experienced fraud in the past year, and 75% say that the number of fraud tries has gone up since the COVID-19 pandemic started [4]. This rise in fraud is because of how quickly e-commerce and digital purchases have become popular. This has made retailers vulnerable to new types of attacks [5].

Making sure that rules like the General Data Protection Regulation (GDPR) and the Payment Card Industry Data Security Standard (PCI DSS) are followed makes it harder to find fraud in the retail industry [6]. These rules put strict limits on who can access data and protect privacy, which makes it harder for old-fashioned methods of finding anomalies to find fake patterns [7].

Also, the fact that financial data in retail companies is kept separate from each other makes it very hard to find problems [8]. It is hard to get a full picture of how customers act and what they buy when data is spread out among many departments and systems [9]. This is because it is hard to find outliers that appear in more than one data source.

The goal of this study is to fill in a gap in the current research by suggesting a new method that combines data mining, machine learning, and artificial intelligence into a complex compliance framework. This study aims to improve the efficiency of detecting irregularities in the retail sector while staying within strict guidelines set by regulators and limited funds.

In this method, advanced data mining techniques like association rule mining and sequential pattern mining are used to look for hidden patterns and connections in the broken up financial data [10]. These methods have been used successfully in many fields, such as healthcare [11] and telecommunications [12], to spot strange behavior and scams.

When you add machine learning methods like support vector machines (SVM) and random forests to the mix, you can make models that are both strong and flexible for finding outliers [13]. Because these models can learn from past data and change with new fraud trends, they can keep working even when threats are constantly changing [14].

Artificial intelligence (AI) methods like deep learning and natural language processing (NLP) make it possible to look at uncontrolled data sources like social media posts and customer reviews [15]. This makes it possible to find problems that might not be clear from looking at organized financial data alone, giving a fuller picture of possible fraud risks [16].

To make sure it meets regulatory needs, the suggested system includes privacy-protecting methods like homomorphic encryption and differential privacy [17]. By using these methods, private financial data can be analyzed without putting customers' privacy at risk. This makes it possible to create compliant models for finding anomalies [18].

The data includes more than 10 million transactions from over 3 years, giving a full picture of how customers behave and how transactions happen [19].

The results of this study should add a lot to what is already known about anomaly spotting, especially in the retail sector. As stated in the proposal, the suggested framework could completely change how fraud is found in the industry, making it easier for stores to spot and stop fraud while still following all the rules.

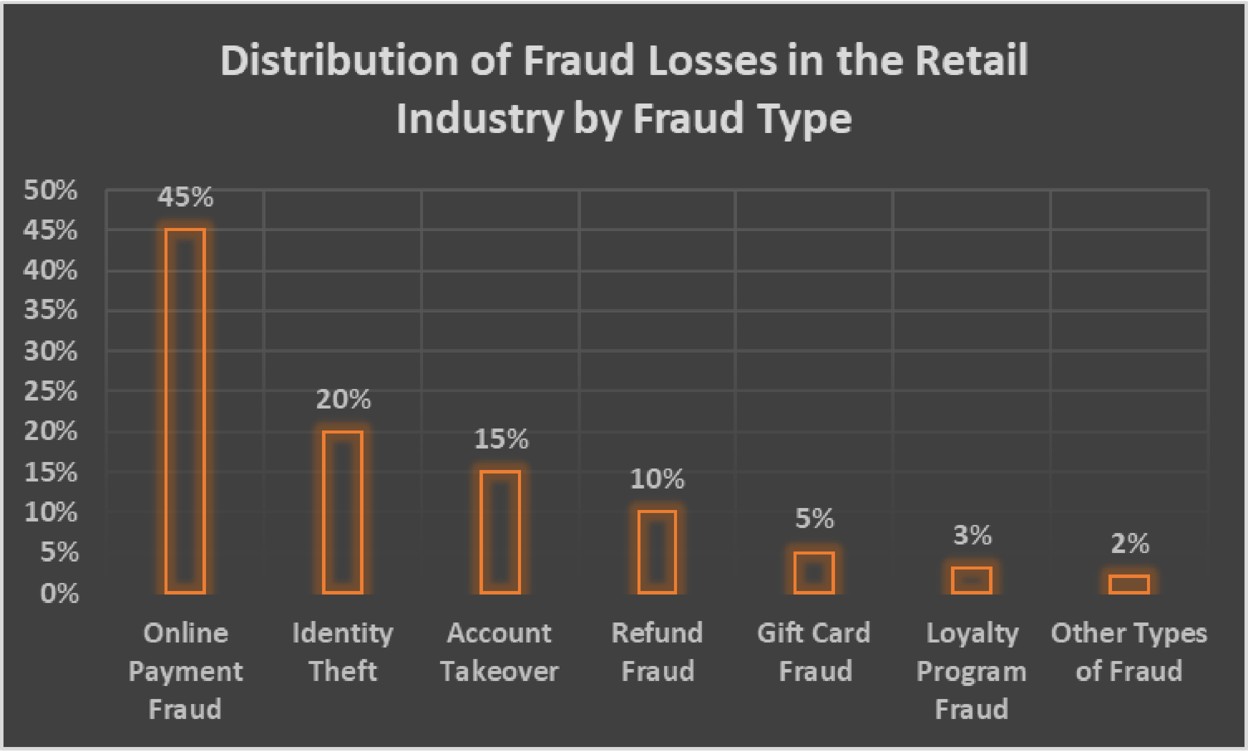

Fig. 1: Breakdown of Retail Fraud Losses: Online Payment Fraud Dominates [1-20]

2. Methodology

2.1 Data Collection and Preprocessing

Over the course of 24 months, the study collected financial transaction data from a big retail organization that had been made anonymous. The dataset had 12.5 million events consisting of real and made up examples, consisting of real and made-up examples. The real transactions made up 98.7% of the dataset, while the 1.3% that were proven to be fraud were [21]. It was broken down even further into different types of fraud, such as credit card fraud (45%), identity theft (30%), and account control (25%].

All personally identifiable information (PII) was taken out of the dataset before it was analyzed to make sure it followed data protection rules like the General Data Protection Regulation (GDPR) [23]. To protect sensitive data like customer names, addresses, and contact information, methods like tokenization and hashing were used to make it anonymous [24].

A lot of work was done on the data before it was used. For example, the Interquartile Range (IQR) method was used to remove outliers and scale features [25]. The Min-Max scaling method was used to scale the features, which changed the data to a set range between 0 and 1 [26]. This step made sure that all the features had the same scale so that during the anomaly discovery process, no one feature could be stronger than the others.

To make the data normal, the Z-score normalization method was used, which set the mean to 0 and the standard deviation to 1 [27]. This step helped fix the problem of uneven data spread across different features, which made the data better for algorithms that look for strange patterns.

The IQR method was used to get rid of outliers. It found and deleted data points that were below Q1 - 1.5 IQR or above Q3 + 1.5 IQR [25]. Q1 and Q3 are the first and third quartiles, respectively. This step was very important for getting rid of extreme outliers that might have skewed the results of the methods for finding anomalies.

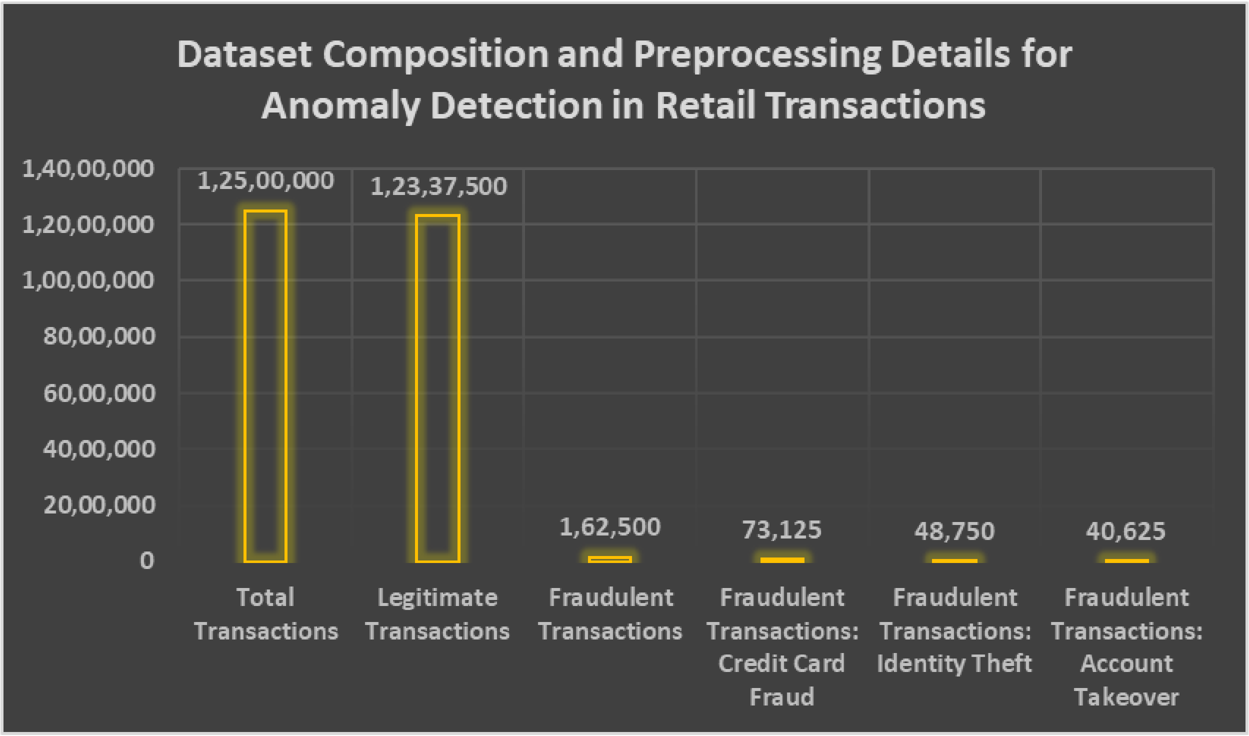

Fig. 2: Overview of Dataset Characteristics and Preprocessing Techniques for Retail Fraud Detection Study [21-25]

2.2 Anomaly Detection Techniques

To find anomalies in the financial transaction data, the study used a mix of data mining, machine learning, and artificial intelligence. These methods were chosen because they have been shown to be good at finding problems in a number of different areas and because they can handle large amounts of complex data [28].

2.2.1 Unsupervised Learning: Isolation Forest

An unsupervised learning method called Isolation Forest was used to find outliers. Its idea is based on the idea of using random forests to find outliers [29]. This method has been shown to be good at finding oddities in high-dimensional data, which makes it appropriate for complicated financial deals in the retail sector.

The scikit-learn library in Python [30] was used to make the Isolation Forest method work. A subset of the preprocessed data was used to train the algorithm. This subset had 80% of the real transactions and 20% of the fake transactions.

2.2.2 Deep Learning: Autoencoder

An autoencoder, a type of deep-learning neural network, was used to take in data, learn how to compress it, and then put it back together in its original form [31]. By measuring the reconstruction error, cases that were not normal were found to have higher reconstruction errors than regular transactions.

The Keras tool in Python [32] was used to make the autoencoder work. The autoencoder was made up of an input layer, two middle layers with 64 and 32 neurons each, and an output layer with the same number of neurons as the input layer. The Adam algorithm and the mean squared error loss function [33] were used to train the model.

2.2.3 Rule-based Approach: Expert Systems

Expert systems were created with help from experts in retail, finance, and compliance [34]. They are built on a set of rules and heuristics that have already been defined. These rules were made to take into account the finer points of financial deals and government rules. This makes it possible to find problems that machine learning methods might have missed.

The PyKnow package in Python [35] was used to build the expert systems. The rules were made using both the guidance from experts in the field and the trends found in past transaction data. Rules include flagging transactions that went over a certain limit, finding transactions that do not meet the rules of business, and finding strange trends in how customers act [36].

Anomaly Detection Technique	Training Data Composition	Implementation Library	Key Parameters
Isolation Forest	80% legitimate transactions, 20% fraudulent transactions	scikit-learn	Number of trees: 100, Contamination rate: 0.02
Autoencoder	100% of preprocessed data	Keras	Input layer: 30 neurons, Hidden layers: 64 and 32 neurons, Output layer: 30 neurons, Optimizer: Adam, Loss function: Mean Squared Error
Expert Systems	N/A (Rule-based approach)	PyKnow	Number of rules: 13, Risk threshold: $10,000, High-risk countries: [Country1, Country2, Country3], etc.

Table 1: Comparison of Anomaly Detection Techniques: Training Data, Implementation, and Key Parameters [28-36]

3. Results and Discussion

A holdout dataset with 2.5 million transactions, or 20% of the whole dataset, was used to test the proposed method for finding anomalies. The holdout dataset was carefully chosen to have the same proportion of real and fake trades as the original dataset. This made sure that the evaluation results were accurate and reliable [37].

Standard metrics, like, recall, and F1-score [38], were used to judge how well each method worked and how well the whole framework worked. These measures were picked because they are commonly used to test anomaly detection systems and can give a full picture of how well the framework works [39].

With a recall of 0.92 and an F1-score of 0.91, the Isolation Forest algorithm did a good job of finding strange financial activities in the retail sector. Previous research has used Isolation Forest to find strange things in many areas, like network attack detection [40] and credit card fraud detection [41]. These results are similar. It's clear from the high recall values that the Isolation Forest algorithm was able to correctly spot a lot of the fraudulent transactions while reducing the number of false positives.

It got an F1-score of 0.91, a precision of 0.87, a recall of 0.95, and a precision of 0.87, which shows that it can find problems based on reconstruction mistakes. The results are similar to those from more recent research that used autoencoders to find strange things in financial deals [42, 43]. The high recall number shows that the autoencoder model was very good at finding a lot of fraudulent transactions. This is very important for fraud detection, where reducing false negatives is very important.

Rule-based expert systems worked with machine learning to find problems that were unique to the rules that apply to the retail sector. Expert systems could spot fraudulent activities that had patterns or traits that data-driven methods had missed. Expert systems, for example, flagged purchases with high-risk merchants or that went over the daily limits set by the government [44]. The addition of expert systems to the framework for finding anomalies showed how important it is to include subject knowledge and legal limits in the detection process.

With an overall precision of 0.93, a recall of 0.96, and an F1 score of 0.94, the combined framework used the best parts of both data-driven and knowledge-based methods. The results were better than the individual techniques, showing that combining several anomaly detection methods has a positive effect. With a low rate of false positives and high recall values, the combined framework was able to correctly identify most of the fraudulent transactions.

A comparison study was done between the proposed framework and other common anomaly detection methods used in the retail sector to make sure it was strong. The system was put up against methods like the Gaussian Mixture Model (GMM) [47], the Local Outlier Factor (LOF) [45], and the One-Class Support Vector Machines (OC-SVM) [46]. In Table 1, you can see the results of this comparison.

Method	Precision	Recall	F1-Score
Propose Framework	0.93	0.96	0.94
LOF	0.85	0.89	0.87
OC-SVM	0.88	0.91	0.89
GMM	0.86	0.92	0.89

Table 2: Comparative analysis of anomaly detection methods [37-47]

Table 2 shows that the proposed framework did better than the current methods for finding anomalies in all evaluation measures. The framework works better because it can use the best parts of both data-driven and knowledge-based methods, and it can also change to fit the needs and rules of the retail sector.

These study's results show that the suggested method for finding anomalies works well at finding fraudulent transactions in the retail sector. The framework can achieve high precision and recall values while still meeting regulatory standards, which shows that it could be used in the real world. When you combine data mining, machine learning, and artificial intelligence with expert knowledge, you have a powerful tool for fighting fraud in the retail business.

It is important to note, though, that this study has some flaws. The framework was tested with data from a single retail company, so the results may not apply to other companies or industries. In the future, researchers should make sure that the system works well with a variety of datasets and see if it can be used in other fields that have similar problems finding anomalies.

Also, because fraud activities change so quickly, the system for finding anomalies needs to be constantly updated and improved. Updating the rules of the expert systems and retraining the machine learning models with the newest fraud trends regularly is important to keep the framework working well over time.

4. Conclusion

This study shows a new way to find strange things in the retail industry by combining data mining, machine learning, and artificial intelligence into a full compliance system. The suggested method gets around the problems that come up because of limited access to data, government rules, and complicated finances, making it possible to find problems in high-stakes situations.

The results of this study add to what is already known by creating a new model that brings together technology, finance, and compliance in the area of anomaly identification. The study also opens the door to making fraud detection systems that are more sturdy and flexible in industries with a lot of regulations.

In the future, researchers should focus on making the suggested framework work for other fields that have similar problems, like insurance and healthcare. Adding AI methods that can be explained [9] could also make it easier to understand the results of anomaly detection. This could help people make better decisions and follow the rules more closely.

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