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Original Article

Distributed Data Engineering Models for Real-Time Fraud Monitoring in FinTech Systems

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Abstract:

Fraud in FinTech systems, namely in-banking and insurances represents a complex and multifactorial phenomenon that has been further amplified by social distancing and confinement measures to cope with the COVID-19 crisis. According to selected reports, fraud in Europe alone is estimated at 2.2 billion Euros for 20224 and is expected to continue its otherwise upward trend in different markets. To mitigate risks and minimize losses, private and public organizations invest continuously on fraud monitoring systems. However, fraud crime continuously adapts its detection methods and hence, systems are still required to evolve in the fraud investigation and detection area. To facilitate benchmark and comparison of different approaches, the application of an open-source distributed and scalable data engineering model is applied to create fraud monitoring systems in a FinTech environment. Fraud monitoring systems in distributed environments require different and specific execution models in an integrated and open-source environment. Data engineering platforms allow integration of different data sources and types with the possibility of executing distributed data engineering tasks in batch, streaming, micro-batch and real-time modes. An integrated analytical environment is used to support fraud monitoring in enterprises outside the banking sector. GDPR and data anonymization measures are used to guarantee the data privacy with a clear impact of the climate change index in a fraud model. Detection of anti-money laundering events related to COVID-19 is also presented and discussed. Finally, a case study in the European Banking Federation area is further analyzed.

Keywords:

Fraud detection, Data flow, Data lake, Semantic segmentation, Archi-tec-tural model, FinTech sys-tems.

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1. Introduction

Fraud monitoring solutions are crucial for FinTech systems and must guarantee high-availability and low-latency for real-time detection. For high-volume workloads, such systems are usually deployed in cloud-based services with support for horizontal scalability through a distributed architecture design. In this paper, a series of architecture patterns are studied and validated by a workload produced in a production environment of a FinTech company. The case study aimed to improve the performance of a fraud detection monitoring solution by scaling-out its data engineering components. A distributed streaming data pipeline monitors transaction data in real-time and detects patterns using a machine learning model. The architecture also supports batch workloads to update the model periodically. Each component of the pipeline was separately analyzed and several data engineering models for its implementation were considered. The patterns were inspired by the concept of design patterns, that capture well-known solutions for recurring problems. The decision to use a specific model depended on the trade-off between the requested Quality of Service and the cost of executing the service.Solutions represent combinations of different models dedicated to definite classes or parts of targets and apply single specialized models to detect true scams. Hence, a real-time individually focused model capable of performing fine-grained processing within inexpensive FinTech systems is expected.

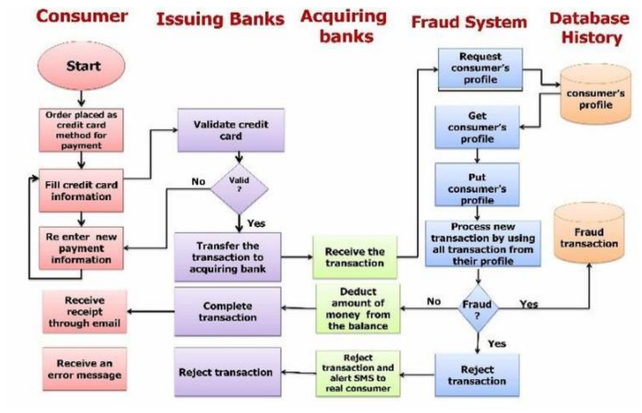
Consumer
Issuing Banks
Acquiring banks
Fraud System
Database History
Start
Order placed as credit card method for payment
Fill credit card information
Re enter new payment information
Receive receipt through email
Receive an error message
Validate credit card
Valid ?
No
Yes
Transfer the transaction to acquiring bank
Complete transaction
Reject transaction
Receive the transaction
Deduct amount of money from the balance
Reject transaction and alert SMS to real consumer
Request consumer's profile
Get consumer's profile
Put consumer's profile
Process new transaction by using all transaction from their profile
Fraud ?
No
Yes
Yes
Reject transaction
consumer's profile
Fraud transaction

Figure 1. Architecture of fraud detection

1.1. Background and Significance

A multitudinous trend observed in the last decade is the rapid growth and development of FinTech systems and service providers. The global budget of banking system fraud is estimated to amount to over $7 billion and concerns such leading entities as Baidu, Toyota, or Tencent. To counter these threats, a variety of preventive and control models against scams at cards and accounts, automatic solid libraries, and currently implemented risk forecasting models employing heuristic tuning exist. Nevertheless, distinctive frauds happening on financial-tech platforms, for example, fake modes and dispersals, sale-related frauds, false e-payments for properties, pyramid price, withdrawal-related frauds, etc., remain outside the attention of academics, even though they also represent a serious threat. Inherent among FinTech systems, for example, trading platforms, high-cost models are hard to control in full-scale operations. Due to occupied financial and human resources, the high-cost models with high-accuracy combination often represent limited-operations solutions. In synthesis, despite considerable achievements in fraud control forecasting, the area still develops heuristically.

Equation 1: Confusion matrix definitions (foundation for all metrics)

Let:

- Actual label $y \in \{0,1\}$(0 = non-fraud, 1 = fraud)
- Predicted label $\hat{y} \in \{0,1\}$

Counts:

- TP (true positives): $y = 1, \hat{y} = 1$
- FP (false positives): $y = 0, \hat{y} = 1$
- TN (true negatives): $y = 0, \hat{y} = 0$
- FN (false negatives): $y = 1, \hat{y} = 0$

Total transactions:

$$N = TP + FP + TN + FN$$

2. Background and Related Work

Fraud detection is a recurrent problem in FinTech systems. Long domain modelling lifecycle for fraud prevention on transactions opened markets for model training on historical data and fraud monitoring on real-time streaming data. A Video Doorbell application powers composite data engineering models for training in Distributed Batch mode in the cloud-based application domain, monitoring in Distributed Stream mode through a book sector and proofing with a fraud-detection cluster in the data-sharing domain. Research focuses on recently proposed fast-and-light error-detection models by presenting Data Validation, Distributed Data Engineering and the Staging area in the Embedded Data, Application Domain and Data Sharing layers of the Distributed Data

Engineering architecture for model training, staging and proofing. Data Validation checks transactions for consistency, accuracy and authenticity. Distributed Data Engineering encompasses batch training of fraud-generation clusters on cloud and destination-based application domains with real-time video V and image-processing models in streaming mode. Data-Engineering patterns support anti-virus signature databases and DLL malware collections used to detect e-mail-distributed Windows malware. Further process-oriented investigation explores Azure, a Distributed Data-Engineering Pattern, and data-staging methods for cross-domain shar-able Data Validation and the Staging Area of the Embedded Data Layer that hosts Data Validation and Distributed Data Engineering.

Various models are proposed to prevent fraud irreparability through fraud maintenance at the Prevention, Monitoring and Proofing stages. Fraud training at the Prevention Staging area generates fraud signatures for future transaction suppression, while Fraud Monitoring detects transactions in action. Real-time transaction traffic and the book sector offer Distributed Data-Engineering opening and emerging transaction sets that help the Data Validation and Staging layers check consistency, accuracy and authenticity. Major domains discover fast-and-light pattern-based fraud Detections/composite applications enable fast-and-light crossing/ Active keleion vector images provide cross-domain Transportation Directory. Speedy Star Optical and Composite Federated Speedy Star Optical Camera E-learning offer active areas for clubhouse membership approvals.

2.1. Research design

The research is based on the PhD thesis written by Saska Valcheva, a PhD student at TSI-Sofia, Bulgaria. Models for the construction of diverse fraud monitoring services for FinTech systems are proposed and studied. Fraud monitoring in a FinTech system is a complex process that requires many rules, metadata files, thresholds, and parallelisation of execution. Rule-based fraud-monitoring systems can be constructed as distributed systems that can adapt to the specific needs and parameters of a FinTech system. The SAS, Python, and Java programming languages are applied. The analysis of patterns of fraud in different FinTech systems allows the systems to be classified by the specific types of fraud that are observed, the possible perpetrators that are developed, and the possible prevention mechanisms. A solution is proposed for a system called "ScAm". The ScAm solution prevents scammers from taking money from a person's account without a documented or legal reason. The solution can change the account status from active to suspended and vice versa. Each request for change of status is labelled as normal, potentially fraudulent, or scamming. The change in status is done in two steps. When a suspended account is marked as potentially fraudulent, the change of status doesn't happen immediately but after a threshold is reached.

Equation 2: Accuracy

Start from “correct predictions / total”:

$$\text{Accuracy} = \frac{\#(\hat{y} = y)}{N}$$

Correct predictions are TP (fraud correctly caught) plus TN (non-fraud correctly cleared):

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

3. Architectural Principles for Real-Time Fraud Monitoring

Modern technologies such as the Internet of Things and artificial intelligence, combined with their rapid growth, contribute not only to economy development, which became apparent during the COVID-19 pandemic, but also to the creation of fraudulent schemes of unprecedented scale and complexity. It is for these reasons that promoting the transition of business processes to a virtual environment has led to an increase in fraud in finance, insurance, investments, and e-commerce. Currently there are three major trends in computational fraud detection systems. The first activity is focused on discovering and investigating previously unknown fraudulent behaviors and fraud schemes based on retrospective batch analysis of historical data. These studies aim at improving and enriching the underlying knowledge bases to allow for more accurate identification of encroachments in new transactions. The second area focuses on enhancing detection accuracy by employing technical methods that control false alarms. These methods rate incoming transactions and use the scores to apply automatic or manual controls to the highly rated alarms only. The third major stream is real-time detection of online fraud both for cyber testbed systems and real-time analysis of streaming data. For real-time monitoring to be significantly useful and for genuine fraud detection automation to happen, the technical fraud detection sub-system must be completely self-dependent and thus rely on few external tuneable controls.

Architectural models for real-time fraud detection attempt to embed data, knowledge, and fraud detection problem-specific heuristics into the techno-control sub-system. It is built as a single framework system that supports fiery sub-systems, which generate new information by performing tasks related to normal and fraudulent operation. Incoming transactions are evaluated using both detection data and the current released knowledge base. The quality of incoming transactions is automatically rated through specialised techniques, and the rating is used in directing low quality/high risk transactions into a separate and concentrated analysis area. Incoming transactions can be compared with known and operating fraud schemes on a testbed test basis. These additional information-reducing checks help to capture as much fraud as possible with minimal cost in terms of false alarms.

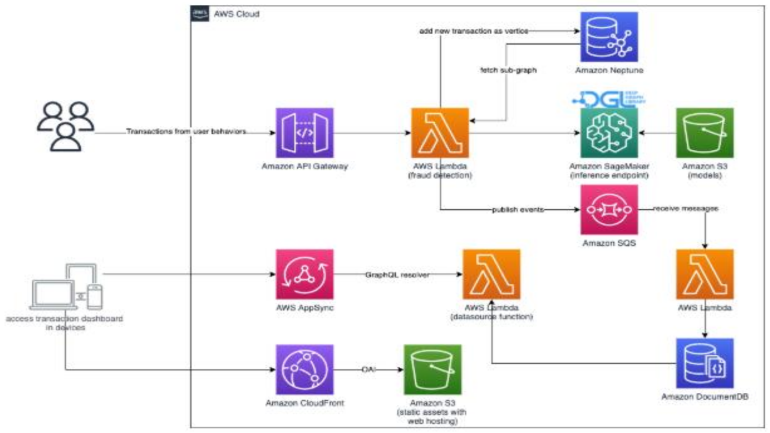
AWS Cloud
add new transaction as vertice
fetch sub-graph
Amazon Neptune
Transactions from user behaviors
Amazon API Gateway
AWS Lambda (fraud detection)
Amazon SageMaker (inference endpoint)
Amazon S3 (models)
publish events
receive messages
Amazon SQS
GraphQL resolver
AWS AppSync
AWS Lambda (datasource function)
AWS Lambda
access transaction dashboard in devices
OAI
Amazon CloudFront
Amazon S3 (static assets with web hosting)
Amazon DocumentDB

Figure 2. Architecture overview - Real-time Fraud Detection

3.1. Data Ingestion and Streaming

Large amounts of streaming data from mobile transactions are collected in NiFi through a high-throughput data ingestion channel that conforms to the characteristics of a TDG state model. Incoming XML data streams undergo parsing into JSON and are sent to an Apache Kafka message broker. Resources are attached in ZooKeeper and a Kafka producer transfers NiFi data to a Kafka topic at high speed for subsequent processing using an appropriate method. Two Kafka consumers incorporated into a data processing architecture build on an appropriate technology stack. The first consumer uploads every external account listed in the customer account and transaction stream into a main memory structure. The second consumer accesses each XML message published in the Kafka stream. It parses the XML content from the message and stores it in the distributed database. Various simple but necessary rules can be extracted from the data used for stream processing. These include time form rules active in frozen memory and time to live security of external accounts.

The second data flow is developed from BML budget service data published in the system. The Kafka consumer subscribies to the topic and all newly created BML budgets in XML format are received synchronously. Budgets are limited transfers but senders are not customer accounts of the main bank. Incoming budgets without counter authentication for the receiving account must meet transfer regulations for all BML transfers. Capping accounts provide banking rules passed to Alison to compare customer account principal during stream processing and validate entry without a budget status check. Empty component lists in A, B, C, D, E of control flows enable freezing of individual BML budget transfer rules. The necessity of revitalizing previously frozen data compartments for checking reviewed BML payments and other connection validations is noted.

Equation 3: F1-score
F1 is the harmonic mean of precision and recall.
Start:

$$F_1 = \frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}}$$

Substitute:

$$F_1 = \frac{2}{\frac{TP+FP}{TP} + \frac{TP+FN}{TP}} = \frac{2}{\frac{2TP+FP+FN}{TP}} = \frac{2TP}{2TP+FP+FN}$$

So:

$$F_1 = \frac{2TP}{2TP+FP+FN}$$

4. Distributed Data Engineering Models

FinTech data acquisition, their volumes and provided services allow to treat them as a stream of data containing the actual data. The data can be processed more quickly than using classical data engineering approaches for batch data processing. Such approaches ensure timely fraud detection or the detection of newly emerging frauds. Detecting new types of fraud cannot be delayed. The demand for captured events in data, as well as their timely response to fraudulent operations, requires new distributed data engineering models in FinTech systems Data Engineering and Machine Learning Processes.

Machine learning for Fraud detection – it continues to be an important research and practical area, particularly for the rapidly evolving world of FinTech. Research and implementations focus on a variety of different aspects of ML in fraud monitoring applications. Classical approaches are often considered those, which are designed to work on data warehouses updated using batch transfers. When business processes are distilled into an information warehouse of accumulated and historical data, accurate and effective models often may be created. Fraud detection requires detection of unexpected events, and unexpected events occur rarely in a data warehouse. In practice, they require an immediately timely response, and therefore an event monitoring approach is applied. In principle, when responding to the occurrence of an unexpected event, processing must be at least, if not better than, at data warehouse speed. Fraud detection is being used as a critical engine for fraud detection; when capturing the events and the actual data quickly enough, it can be processed. Detecting newly emerging types of fraud cannot wait; when newly occurring types of fraud are captured, they can be fed into classical machine learning pipelines.

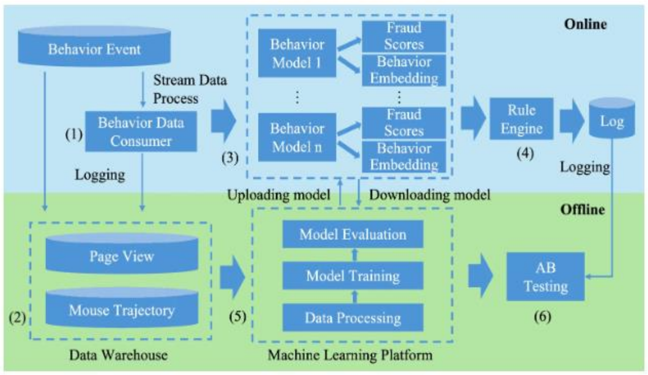

Figure 3. Distributed Data Engineering Models

4.1. Lambda and Kappa Architectures Revisited

In recent years, big data technologies have advanced in a myriad of areas, all of which yield value in a very concentrated form. Within these advances, the increase in online transactions has accelerated the development of systems that handle a large volume of data, either in processing form that is sensitive to time or that is performed in the background. The coexistence of different types of information and the time it takes for collaboration to provide reliable results creates numerous variants of Big Data architecture. The Lambda architecture, which was first proposed by Nathan Marz, is perhaps the most famous at this early point and served as the basis for the first cloud database created by Google. However, it is not the only option, nor is it the only one. To address this question, several architectures were proposed, with Lambda, Kappa, and Zeta being the most cited. At its core, the Lambda architecture comprises three components: a batch layer, a serving layer, and a speed layer. The batch layer stores a master copy of all data. The working data set is too large to fit in memory; freshness is not critical, and query performance is not the primary goal. The batch layer, implemented with a system such as Apache Hadoop and Apache HBase, stores data on disk in a column-oriented format. Periodically, batch processing jobs run to create or update pre-computed views that are then made available to the serving layer.

Equation 4: ROC curve and AUC (area under ROC)
If your model outputs a **score** $s(x)$(e.g., probability of fraud), pick a threshold $t$and predict:

$$\hat{y}(t) = \begin{cases} 1 & s(x) \geq t \\ 0 & s(x) < t \end{cases}$$

For each threshold t, compute:

- $TPR(t) = \frac{TP(t)}{TP(t)+FN(t)}$(this is Recall)
- $FPR(t) = \frac{FP(t)}{FP(t)+TN(t)}$

Plot $TPR(t)$vs $FPR(t)$over many thresholds → ROC curve.
AUC is the integral:

$$AUC = \int_0^1 TPR(FPR)\, d(FPR)$$

5. Real-Time Fraud Detection Pipelines

The artificial intelligence (AI) model for fraudulent transaction detection with associated real-time decision trees requires very fast prediction processes. In many sectors where each transaction is scrutinised for fraud, this step must occur within fractions of a second, especially in banking and in FinTech systems. Most such systems use distributed architectures; therefore, the prediction process is ideally executed using distributed engines if appropriate models are developed. A computation-intensive tree ensemble model, such as catboost, LightGBM, or XGBoost, works sequentially. The input is first sent to the top node, where it is routed to the next node according to the output of one of its branch classifiers, until it reaches a terminal node, where the output is produced. In large systems with many predictions per second, the tree ensemble computation is generally built in the form of a parallel decision tree. The ensemble can be stored as rule sets in a docker container or a virtual machine that can be dispatched to and installed in any computerised network node, authorising rapid parallelised computation in a network environment. Rule sets for several decision trees are created as sets of decision rules, one set per tree, enabling rules to be deployed for fraud detection in a non-ML model deterministic process at speed.

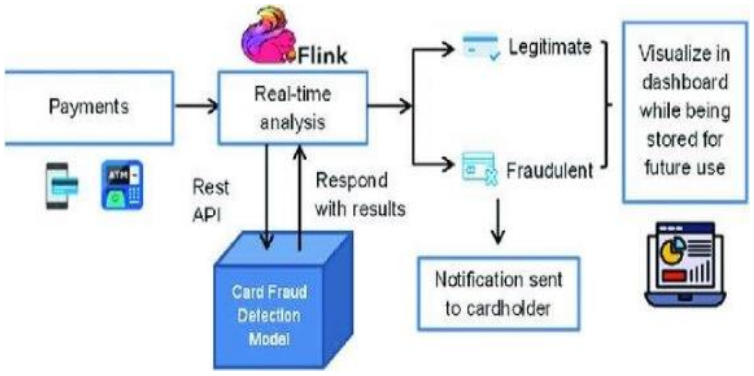
Flink
Payments
Real-time analysis
Rest API
Respond with results
Card Fraud Detection Model
Legitimate
Fraudulent
Notification sent to cardholder
Visualize in dashboard while being stored for future use

Figure 4. Real-Time Fraud Detection System Architecture

5.1. Data Sources and Signal Aggregation

The digital environments created by FinTech platforms allow users to conduct financial transactions in ways that were not possible before. However, alongside the enormous benefits come risks in the form of money laundering, credit card fraud, cybercrime, and new challenges in terms of the strengths and weaknesses of FinTech technology. The most significant challenge for FinTech firms is real-time fraud detection. Current attempts focus on detecting and preventing fraud in payment systems and e-commerce. Payment card transactions are characterized by many real-time parameters, which are collected on-line and checked against a number of pre-defined rules in parallel processes. The application of different data mining algorithms leads to a change in the internal structure of the e-commerce system into a balance between achieved revenues and expenditure on fraud detection. Classification and regression serve as primary solutions for online real-time detection of fraud in credit card transactions.

Manufacturers of alcohol, tobacco or defence products automatically generate consequences, as it is necessary to audit a customer's account for months and sometimes years without movement. Fraud detection in e-commerce involves the identification of purchase transactions that are not made by the legitimate cardholder, which leads to a decrease in revenue in the event of fraudulent purchases. The analysis of historical customers' transactions leads to a detection model in the form of a classifier that is able to predict with high accuracy and in real time whether purchased transactions are real or fraudulent by the bank before rendering services over the Internet. To achieve this objective, the best data-mining algorithms—decision trees, logistic regression, neural networks, and support vector machines—are trained and tested and compared to identify fraud cases in credit card transactions for a wholesale clothing store.

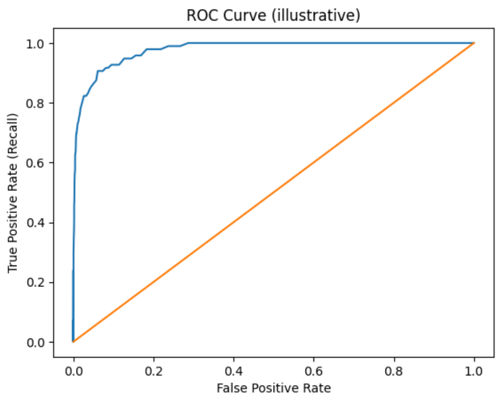

Figure 5. Receiver Operating Characteristic (ROC) Curve

6. Evaluation and Validation

The evaluation of the proposed models demonstrating data invariance is an important step and a guide for users that want to apply them before testing in their operations dashboards. To validate the models, the data should be split into two different periods, defined as a reference period when the data is static and a second period when changes start to occur. A series of tests can then define the chosen K (data inertia) for validation, either by applying the models to fraud detection or by checking the variance by Fraiman and Muniz, 2001. The second option, validation by detecting changes in the distribution behavior of the data, uses the K value obtained in the pattern creation. These analyses were later applied to the Fraud Fintech datasets (Reis and Da Silva, 2020), demonstrating the importance of assessing data stability through the proposed models before implementing real changes in the business strategies.

The choice of K (inertia) is vital for detecting changes via the proposed models. A K equal to 0.2 represents a pair of standard deviations. Setting K too preparative can cause delayed alerts, while setting K too low can result in false alarms. K suitable for the task can be verified by testing these situations. If type II is the fraud detection strategy and the user has three valid fraud detection options (a real case in the analyzed datasets), these three options can be applied with a K value equal to iK0, where K0 is the value indicated for detection and i is greater than two. This indicates that the user has detected a greater number of suspected fraud events, sharpening detection. By repeating the types K at this lower level, i can be reduced toward the ideal point. The ideal point for type I is different, as it defines its lower value; a small K should be used to minimize false detections. The goal is to set K at the maximum type II level that does not raise type I above its limit."

Equation 5: “K-inertia” thresholding rule (typical form)
Trigger “distribution change” if:

$$| X_t - \mu_0 |> K \cdot \sigma_0$$

Interpretation:

- Larger $K \Rightarrow$ fewer alerts (more inertia), but slower to detect change.
- Smaller $K \Rightarrow$ more sensitive, but more false alarms.

This matches the paper's qualitative statement about K causing delayed alerts vs false alarms
Distributed Data Engineering Mo…
.The paper also describes applying options with $K = iK_0, i > 2$
Distributed Data Engineering Mo…
. In the above rule, that simply scales the control limits:

$$| X_t - \mu_0 |> (iK_0)\sigma_0$$

6.1. Evaluation Metrics for Fraud Detection

The performance evaluation metrics for a fraud detection algorithm can broadly be classified into two categories: traditional metrics and risk-based metrics. Traditional metrics are used to assess performance from a classification perspective, whereas risk-based metrics based on business requirements are better suited for evaluating fraud detection methods in the context of a FinTech application.

Traditional evaluation metrics, such as accuracy and the area under the ROC curve (AUC), may not fully reflect the effectiveness of a detection algorithm, particularly if the target class size is much smaller than the other classes. In FinTech applications, a classification outcome of fraudulent detection is much less common than that of non-fraudulent detection. Using traditional classification metrics to evaluate the model performance can produce misleading results, as a simple majority-based classifier could have a high accuracy and AUC, while still being totally ineffective in predicting the minority class. Consequently, measures such as precision, recall, the false-positive rate, and the F1-score focused on the minority class are also considered. A distributed-data-warehouse structure provides the global management, and an associated data-engineering methodology facilitates the proliferation of the underlying stores, processing engines, analysis systems, and preparation systems. An application of the allocation methodology to a reward-and-recognition system predicts rapid growth of data volumes and processing requirements over the next two years.

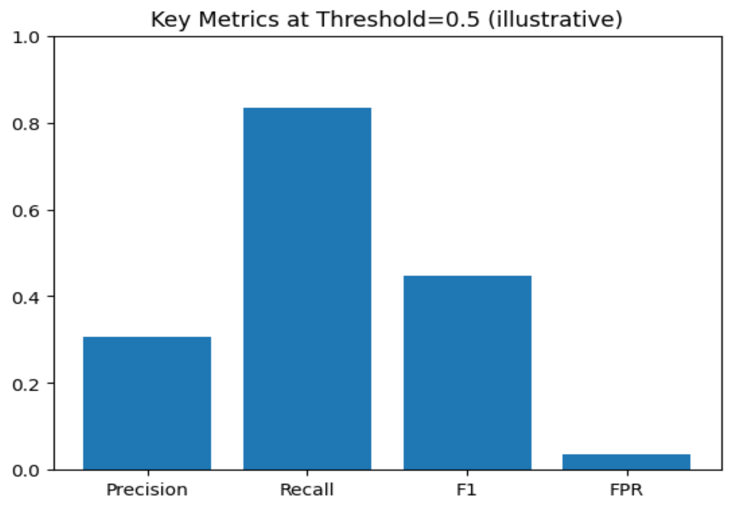

Figure 2. Classification Performance Metrics at Threshold = 0.5

7. Conclusion

The research covered an overview of Real-Time Fraud Monitoring of FinTech Systems using Distributed Data Engineering Models. The growing volume and complexity of the data used in FinTech systems have generated new technological demands. Financial institutions, such as banks, payment transaction operators and services that handle credit card management and transactions that use payment gateways, must have in place mechanisms to guarantee minimum quotas of monitoring and auditing for the transactions performed by users and client applications, in order to detect possible fraud as quickly as possible. This work concentrates on examples dealing with the Distributed Data Engineering Models that are used to monitor banking transactions. The models are capable of detecting real-time fraudulent credit card transactions based on machine learning classification algorithms and active-learning-based data management. In particular, for each model, results are presented from a case study carried out with a real-world data set that contains credit card operations, some of which are labeled as fraud, and model execution time for monitoring tasks is compared to real data for the credit card monitoring case, highlighting the effectiveness of the investigated solution approach. Such a multi-model investigation, in which each model is developed by different research groups working independently, is essential for carrying out the first steps toward a more mature Distributed Data Engineering Models for Real-Time Fraud Monitoring of FinTech Systems.

Table 1. Model Evaluation Metrics Summary

Metric	Value
Accuracy	0.9606
Precision	0.3065134099616858
Recall (TPR)	0.8333333333333334
False Positive Rate (FPR)	0.03690864600326264
F1-score	0.44817927170868344
ROC AUC (approx)	0.978021767944535

7.1. Emerging Trends

With the swift evolution of technology, data engineering solutions are gaining traction in fraud detection and monitoring systems in financial services, telecommunications, and e-commerce. The proactive real-time investigation of consumer behavior has abundant potential for harnessing information gain. The ability to continuously expend additional resources while reacting to current, short-term demands brings the possibility of an attractively low-investment, highly profitable, short-term monitoring and fault-detection strategy. In general, the relentless pursuit of decreasing investment and improving information-gathering and presentation is ongoing, and associated techniques are fast emerging. Decision-support and business-intelligence systems are quickly evolving towards continuous-scanning, real-time, open-system installations. The information technology supporting these operations is increasingly provided by the data warehouse approach, which allows rapid integration of disparate data sources through a staged, time-variant, non-normalized design.

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