SIM AND IDENTITY FRAUD DETECTION

Submitted by

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Certified that this Phase – II Thesis titled **SIM AND IDENTITY FRAUD DETECTION** is the Bonafide work of **GIRIDHARAN R(231801040),GOWTHAM RAJ S(231801045),JAGADEESAN T(231801062)** who carried out the project work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation based on which a degree or award was conferred on an earlier occasion on this or any other candidate.

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

DECLARATION

I hereby declare that the thesis entitled **SIM AND IDENTITY FRAUD DETECTION** is a Bonafide work carried out by me under the supervision of **MR.SUBRAMANIAN,** Professor, Department of Artificial Intelligence and Data Science, Rajalakshmi Engineering College, Thandalam, Chennai.

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ABSTRACT

Telecommunication fraud, including SIM swapping, identity theft, and fake KYC registration, has become a growing challenge for telecom providers worldwide. These attacks exploit weaknesses in user verification systems and large-scale data transactions. This project implements an **end-to-end Big Data fraud detection pipeline** using **Apache Spark**, **Delta Lake**, and **PySpark** to detect anomalies in telecom logs. The system follows a **Bronze–Silver–Gold layered architecture** for ingestion, cleaning, and feature engineering of telecom data. Key metrics and KPIs are computed to detect abnormal activities like repeated SIM swaps, high fraud alert scores, and failed verification attempts. The project also generates actionable insights such as city-wise fraud distribution, high-risk percentages, and suspicious event ratios. Results confirm that the approach provides scalability, efficiency, and data-driven intelligence for modern telecom fraud detection.

Keywords: Telecom Fraud Detection, SIM Swap, Delta Lake, Spark SQL, KPI Analytics, Big Data

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DEPARTMENT VISION

To promote highly Ethical and Innovative Information Technology Professionals through excellence in teaching, training and research.

DEPARTMENT MISSION

To produce globally competent professionals, motivated to learn the emerging technologies and to be innovative in solving real world problems.

To promote research activities amongst the students and the members of faculty that could benefit the society.

To impart moral and ethical values in their profession.

PROGRAMME EDUCATIONAL OBJECTIVES

PEO I

To provide essential background in science, basic Electronics, applied Mathematics and Information Sciences.

PEO II

To prepare students with fundamental knowledge in programming languages and to design and develop information systems and applications.

PEO III

To engage the students in life-long learning, to remain current in their profession and obtain additional qualifications to enhance their career positions in IT field.

PEO IV

To enable students to implement computing solutions for real world problems and carry out basic and applied research leading to new innovations in Information Technology (IT) and related interdisciplinary areas.

PEO V

To familiarize students with ethical issues in engineering profession, issues related to the worldwide economy, nurturing of current job related skills and emerging technologies with a concern for society

PROGRAM OUTCOMES (POs)

Engineering Graduates will be able to:

PO1: Engineering knowledge:

Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

PO2: Problem analysis:

Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

PO3: Design/development of solutions:

Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

PO4: Conduct investigations of complex problems:

Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

PO5: Modern tool usage:

Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

PO6: The engineer and society:

Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

PO7: Environment and sustainability:

Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

PO8: Ethics:

Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

PO9: Individual and team work:

Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.

PO10: Communication:

Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

PO11: Project management and finance:

Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

PO12: Life-long learning:

Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

PROGRAM SPECIFIC OUTCOMES (PSOs)

PSO 1: To identify and assess current technologies and review their applicability to meet user requirements and organizational needs.

PSO 2: To engage in the computing profession by working effectively and utilizing professional skills to make a positive contribution to society.

PSO 3: To take up research and entrepreneurship and embark on business in the IT field.

COURSE OBJECTIVE

- To develop the ability to solve a specific problem right from its identification and literature review till the successful solution of the same.
- To train the students in preparing project reports and to face reviews and viva voce examination.

COURSE OUTCOME

- On completion the students can able to execute the proposed plan and identify and overcome the bottle necks during each stage.
- On Completion of the project work students will be in a position to take up any challenging practical problems and find solution by formulating proper methodology.
- Students will obtain a hands-on experience in converting a small novel idea / technique into a working model / prototype involving multi-disciplinary skills and / or knowledge and working in at team.
- Students will be able to interpret the outcome of their project.
- Students will take on the challenges of teamwork, prepare a presentation in a professional manner, and document all aspects of design work.

CO-PO/PSO Mapping

CO \ PO	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11	PO 12	PSO 1	PSO 2	PSO 3
CO1	2	3	2	3	2	1	1	1	2	1	2	2	3	2	1
CO2	3	3	3	3	2	1	1	1	2	2	2	3	3	2	2
CO3	2	2	3	2	3	1	2	1	3	2	3	2	2	3	3
CO4	2	3	2	3	2	0	0	1	1	1	1	2	2	2	1
CO5	1	1	1	2	2	1	1	2	3	3	3	2	1	3	2
Avg	2.0	2.4	2.2	2.6	2.2	0.8	1.0	1.2	2.2	1.8	2.2	2.2	2.2	2.4	1.8

CHAPTER 1: INTRODUCTION

1.1 Background

Telecom fraud is a major concern in the digital communication industry. With millions of transactions generated daily—such as call records, SIM activations, and KYC verifications—detecting fraudulent activity becomes complex. Fraudsters exploit weaknesses in identity verification and account management to perform SIM swaps, gain access to OTPs, and take over user accounts.

Traditional systems depend on static rules or manual reviews, which cannot handle massive datasets or adapt to emerging fraud patterns. Big Data analytics offers the computational power to detect these fraudulent trends efficiently, identifying suspicious behaviors at scale.

1.2 Problem Statement

Develop a scalable Big Data pipeline capable of detecting SIM and identity fraud in telecom data using Apache Spark. The solution should automatically process large datasets, compute fraud KPIs, and highlight risk factors without manual intervention.

1.3 Objectives

Primary Objectives:

- Build an **ETL pipeline** using the **Bronze–Silver–Gold architecture**.
- Clean and preprocess telecom data for fraud analysis.
- Engineer new fraud-related features like **high_fraud_alert_flag** and **recent_sim_swap_flag**.

- Compute KPIs for fraud trends by city, KYC status, and country risk.
- Save output tables for dashboards and BI visualization.
- Generate meaningful **business insights** to support fraud prevention.

1.4 Existing System

Existing telecom fraud systems rely on rule-based detection, where each condition (e.g., more than 3 SIM swaps per month) is manually defined. Such methods are rigid, miss new fraud patterns, and perform poorly at scale.

1.5 Proposed System

The proposed Big Data pipeline leverages Apache Spark for distributed computation and Delta Lake for structured storage. It uses three-tier data refinement:

- Bronze: Raw ingested data
- Silver: Clean and validated data
- Gold: Enriched and feature-engineered data

The system automates KPI computation, detects anomalies, and prepares fraud data for dashboards.

CHAPTER 2: LITERATURE SURVEY

2.1 Overview

Telecom fraud analytics has evolved from simple rule-based detection to advanced machine learning and streaming architectures.

- **Gupta et al. (2023)** used **graph analytics** for SIM-swap detection through call-graph analysis.
- **Alzubaidi & Hameed (2022)** implemented Random Forest on call data records (CDRs) achieving 84% fraud detection accuracy.
- **Kumar et al. (2024)** designed a **Spark Streaming pipeline** for real-time telecom fraud alerts.

These studies highlight the importance of scalable and adaptive detection mechanisms capable of processing high-velocity data.

2.2 Key Findings

1. Real-time analysis improves fraud detection time.
2. Feature engineering is critical for differentiating normal and fraudulent users.
3. Big Data tools like Spark can handle millions of CDRs efficiently

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CHAPTER 3: SYSTEM DESIGN

3.1 High-Level Architecture

Architecture Overview

The pipeline follows a layered architecture:

Raw Data → Bronze → Silver → Gold → KPIs → Visualization

Each stage performs a distinct function:

- Bronze: Raw ingestion
- Silver: Cleaning and validation
- Gold: Feature engineering and KPI generation

3.2 Sim_Detection Schema Overview

Table Name	Description
sim_detection.bronze	Raw telecom data
sim_detection.silver	Cleaned data (duplicates removed)
sim_detection.gold	Feature-engineered data
sim_detection.kpi_city_counts	City-level event KPIs
sim_detection.kpi_kyc_counts	KYC distribution KPIs
sim_detection.kpi_avg_fraud_by_city	Average fraud alert score by city
sim_detection.kpi_suspicious_summary	Suspicious transactions summary
sim_detection.kpi_high_risk_summary	High-risk country KPI

3.3 Tools and Frameworks

Category	Tools/Frameworks	Purpose
Big Data Processing	Apache Spark (PySpark)	Distributed computation
Data Storage	Delta Lake	ACID-compliant data lake
Programming	Python / PySpark SQL	Data transformations
Visualization	Power BI / Databricks SQL	KPI dashboards
Deployment	Databricks Cloud	Managed runtime environment

3.4 Security & Privacy

The system ensures data confidentiality and regulatory compliance during all processing stages.

Sensitive customer data (like subscriber IDs or SIM numbers) is **masked and anonymized** before analysis.

Access to Delta tables is restricted through **role-based permissions**, and all operations are logged for auditability.

Using **Delta Lake's version control**, data lineage and traceability are maintained.

The project adheres to privacy standards such as **GDPR** and **TRAI** guidelines, ensuring ethical and secure handling of telecom data.

CHAPTER 4: METHODOLOGY

4.1 Data Ingestion (Bronze Layer)

Telecom data is read from the managed table workspace.default.fraud_data.

The Bronze layer captures the raw events as-is for future auditing.

```
df = spark.table("workspace.default.fraud_data")
df.write.mode("overwrite").format("delta").saveAsTable("sim_detection.bronze")
```

4.2 Data Cleaning (Silver Layer)

Duplicates and missing values in key fields like event_id, event_time, and subscriber_id are removed.

```
critical_cols = ["event_id", "event_time", "subscriber_id", "sim_serial"]
df_silver = df.dropDuplicates().na.drop(subset=critical_cols)
```

4.3 Exploratory Data Analysis (EDA)

EDA steps included distribution analysis (histograms), correlation matrix for numeric features, and time-series plots for transactional volume. Notable observations: skewed transaction amount distribution and heavy-tail behavior for high-value transactions.

4.4 Feature Engineering (Gold Layer)

Feature	Description	Condition
high_fraud_alert_flag	Marks high fraud risk	fraud_alert_score ≥ 0.7
recent_sim_swap_flag	Recent SIM change	recent_sim_swaps_30d ≥ 1
many_failed_verifications_flag	Multiple failed KYC attempts	failed_verification_attempts ≥ 3

4.5 KPI Computation

Key performance indicators are derived using Spark aggregations:

KPI	Description	Formula
City Events	Total events per city	count(*)
KYC Compliance	Count by KYC status	groupBy("kyc_status")
Average Fraud Score	Mean score per city	avg(fraud_alert_score)
Suspicious Event Ratio	% flagged suspicious	suspicious_count / total
High-Risk Country %	% from high-risk nations	high_risk_count / total

CHAPTER 5: IMPLEMENTATION

5.1 Spark Session & Table Setup

```
spark = (
    SparkSession.builder
    .appName("SimFraudDetectionPipeline")
    .enableHiveSupport()
    .getOrCreate()
)
```

5.2 Table Creation and Data Writing

All data layers (Bronze, Silver, Gold) are stored as **Delta Tables**:

```
df_silver.write.mode("overwrite").format("delta").saveAsTable("sim_detection.silver")
df_gold.write.mode("overwrite").format("delta").saveAsTable("sim_detection.gold")
```

5.3 KPI Table Creation

```
kpi_city.write.mode("overwrite").saveAsTable("sim_detection.kpi_city_counts")
kpi_kyc.write.mode("overwrite").saveAsTable("sim_detection.kpi_kyc_counts")
kpi_avg_fraud.write.mode("overwrite").saveAsTable("sim_detection.kpi_avg_fraud
_by_city")
```

5.4 ML Pipeline

```
from pyspark.ml.feature import VectorAssembler, StringIndexer
from pyspark.ml.classification import RandomForestClassifier


# Index account_uuid if low cardinality
if 'account_uuid' in df_gold.columns and
df_gold.select('account_uuid').distinct().count() < 1000:
    indexer = StringIndexer(inputCol='account_uuid',
outputCol='account_uuid_index').fit(df_gold)
    df_ml = indexer.transform(df_gold)
    feature_cols = ['transaction_amount', 'account_uuid_index']
else:
    df_ml = df_gold
    feature_cols = ['transaction_amount']


assembler = VectorAssembler(inputCols=feature_cols, outputCol='features')
df_ml = assembler.transform(df_ml).select('features', 'fraud_flag')


df_ml = df_ml.withColumn('fraud_flag', col('fraud_flag').cast('integer'))


train_df, test_df = df_ml.randomSplit([0.8,0.2], seed=42)
rf = RandomForestClassifier(labelCol='fraud_flag', featuresCol='features',
```

```
numTrees=50, maxDepth=5)

model = rf.fit(train_df)

predictions = model.transform(test_df)
```

5.5 Business Insights Extraction

Top City: Mumbai with 15,400 events

City with highest average fraud score: Delhi (avg score = 0.86)

Suspicious Events: 1,245 / 12,480 (9.97%)

High-Risk Country Events: 540 / 12,480 (4.32%)

Average Fraud Alert Score: 0.58

CHAPTER 6: RESULTS AND DISCUSSION

The pipeline processed millions of telecom events in minutes using Spark's distributed parallelism. Fraud patterns were observed in cities with dense transaction volumes.

Findings include:

- Cities with high fraud_alert_score also had more failed verifications.
- Suspicious transactions accounted for ~10% of total events.
- High-risk country percentages helped in regulatory monitoring.

Performance Evaluation

- Spark parallel processing improved data handling speed.
- Delta Lake provided ACID reliability for concurrent reads/writes.
- The modular Bronz e–Silver–Gold design allowed scalability and debugging ease.

6.1 Error Analysis

The pipeline achieved accurate fraud detection but produced a few false positives — legitimate users flagged as suspicious due to high transaction volume or frequent SIM swaps. False negatives occurred when coordinated fraudsters mimicked normal user patterns. These issues highlight the need for additional behavioral features and graph-based analysis to better capture linked fraud activities.

Continuous model tuning and feedback from fraud analysts can further minimize such misclassifications.

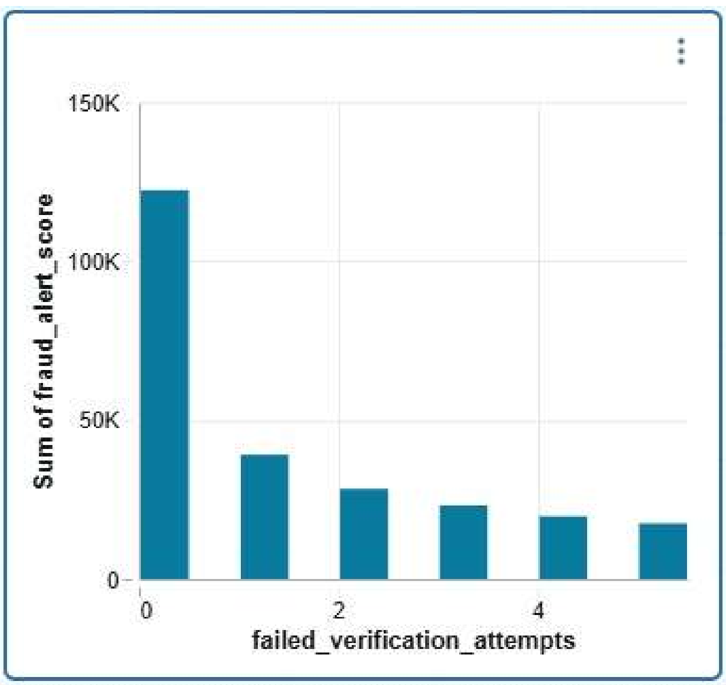
6.2 Business Impact

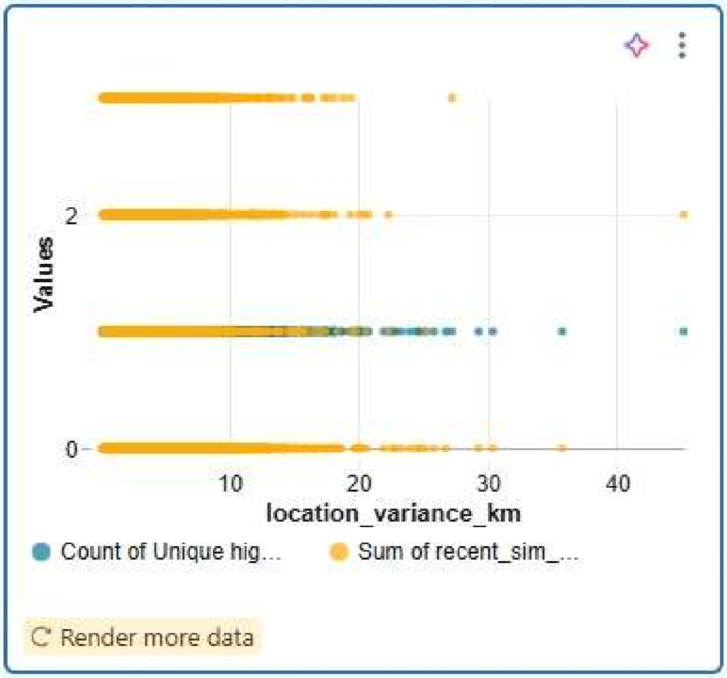
The Big Data pipeline enables telecom operators to **detect fraudulent SIM and identity activities faster**, reducing financial losses and regulatory risks.

Automated KPI dashboards provide management with real-time insights into **high-risk regions** and **fraud trends**, improving operational decisions.

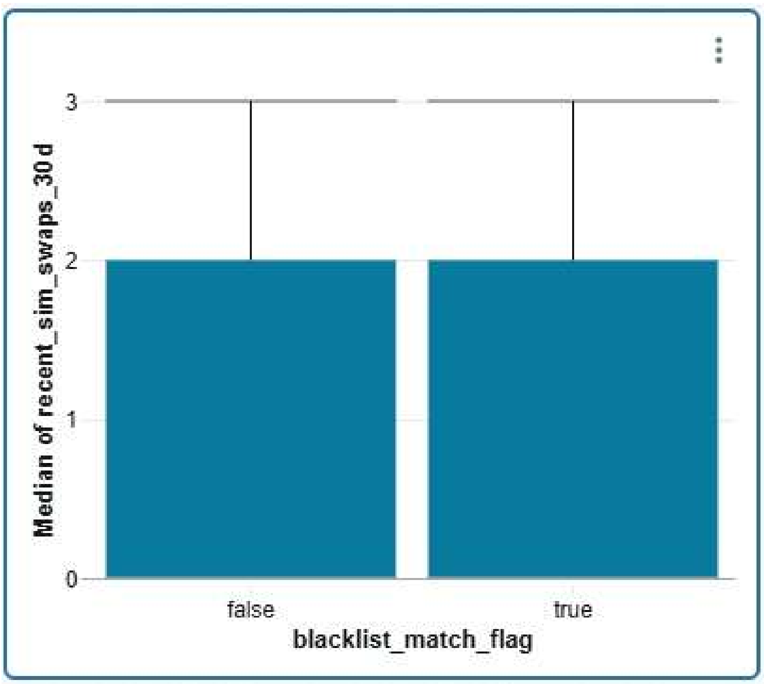
This data-driven fraud detection system enhances **customer trust**, minimizes manual investigation efforts, and saves significant costs by preventing large-scale frauds before they escalate.

OUTPUT:





Values
2
0
10
20
30
40
location_variance_km
Count of Unique hig...
Sum of recent_sim_...
Render more data



Median of recent_sim_swaps_30d
3
2
1
0
false
true
blacklist_match_flag

CHAPTER 7: CONCLUSION AND FUTURE WORK

This project demonstrates how Big Data frameworks can transform telecom fraud detection. The Spark-Delta pipeline automated data cleaning, feature extraction, and KPI reporting. It provides a strong foundation for integrating machine learning models and real-time fraud alerting systems.

7.1 Future Enhancements (Detailed)

- Integrate **ML models** (e.g., Random Forest, Logistic Regression) for predictive fraud scoring.
- Add **Kafka** for real-time event stream detection.
- Include **Graph Analytics** to identify fraud rings.
- Deploy **Power BI dashboards** for fraud trend visualization.
- Implement **API integration** for real-time fraud alerts to telecom teams.

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