Java Based Banking Fraud Detection System

ML-Based Anomaly Detection with Real-Time Transaction Simulation

PRESENTED BY

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Java Internship • Infosys SpringBoard

February 23, 2026

▶ Rule-Based Detection

▶ ML Anomaly Detection

Real-Time Simulation

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Introduction

In the digital banking era, **fraudulent transactions** pose significant threats to financial institutions and customers. Traditional rule-based systems struggle to detect **sophisticated fraud patterns** and **zero-day attacks**.
This project presents an **Intelligent Banking Fraud Detection System** that combines:

- **Rule-based detection** for known fraud patterns
- **Machine Learning models** for anomaly detection
- **Real-time transaction simulation** for testing
- **Interactive dashboards** for fraud monitoring
- **RESTful API gateway** for system integration

The system provides **real-time alerts**, **comprehensive reporting**, and **scalable deployment** for modern banking infrastructure.

Problem Statement

Financial institutions face increasing challenges in fraud detection:

- **Rising Fraud Complexity:** Fraudsters employ sophisticated techniques that evade traditional detection systems.
- **High False Positive Rates:** Rule-based systems generate excessive alerts, causing alert fatigue.
- **Delayed Detection:** Manual review processes result in delayed fraud identification.
- **Limited Adaptability:** Static rules cannot adapt to evolving fraud patterns.
- **Scalability Issues:** Legacy systems struggle with high transaction volumes.

Solution: A hybrid system combining **rule-based detection** with **ML-based anomaly detection**, integrated with **real-time simulation** and **comprehensive dashboards**.

Motivation

- **Financial Impact:** Global banking fraud losses exceeded $32 billion in 2024, emphasizing urgent need for advanced detection.
- **Customer Trust:** Effective fraud prevention is crucial for maintaining customer confidence in digital banking.
- **Regulatory Compliance:** Financial institutions must comply with PCI-DSS, GDPR, and local banking regulations.
- **AI Integration:** Machine learning enables detection of complex patterns invisible to traditional systems.
- **Real-time Response:** Immediate fraud detection prevents unauthorized transactions before completion.
- **Scalability Requirement:** Modern systems must handle millions of transactions daily while maintaining accuracy.

Objectives

Primary Objectives:

1. Develop a **hybrid fraud detection system** combining rule-based and ML approaches.
2. Create a **transaction simulation engine** for fraud scenario testing.
3. Implement **real-time anomaly detection** using machine learning models.
4. Design **interactive dashboards** for fraud trend visualization.
5. Build a **RESTful API gateway** for seamless system integration.

Technology Stack

Backend Development:

- **Programming Language:** Java (Spring Boot Framework)
- **Database:** MySQL
- **ORM:** Hibernate

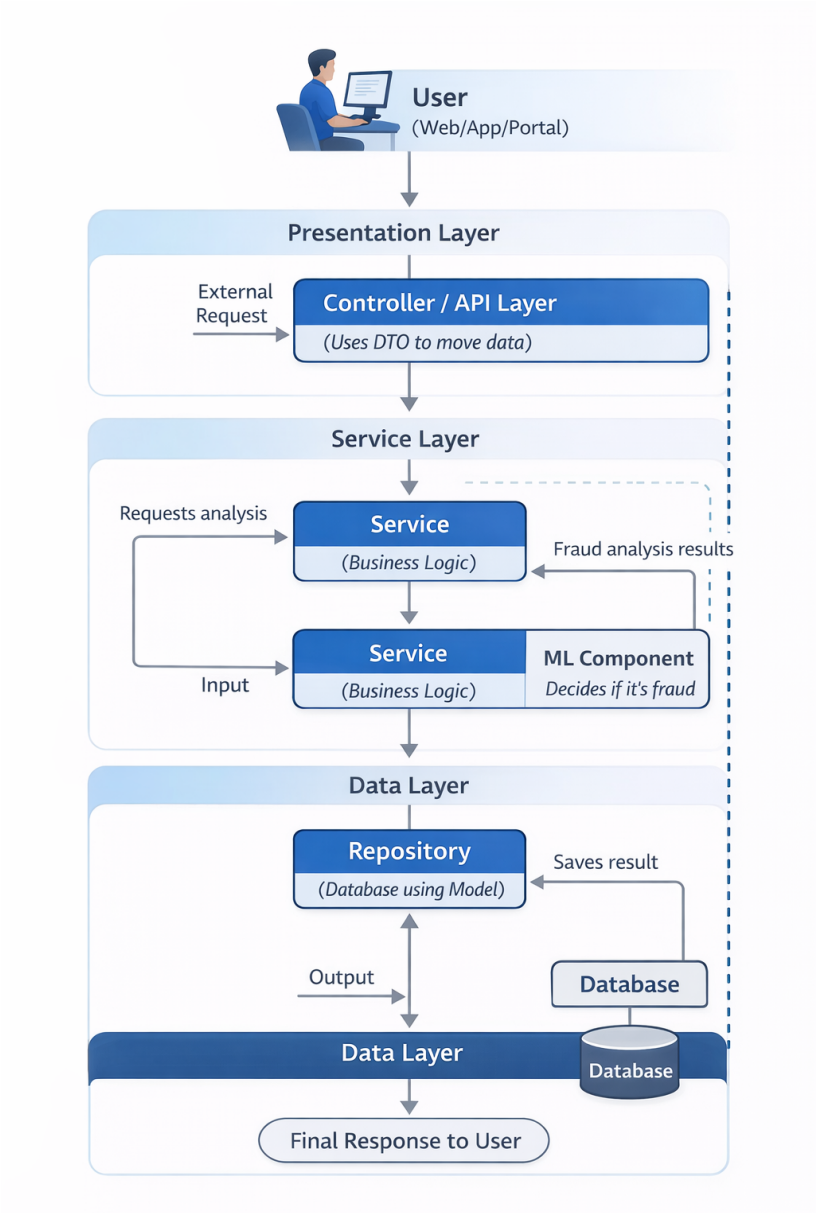
Frontend & Visualization:

- **Template Engine:** Thymeleaf

Build & Deployment:

- **Build Tool:** Maven

System Architecture



Module Explanation

1. **Data Modeling Module**
   - Transaction schema design with user profiles and fraud labels
   - Feature engineering pipeline (transaction patterns, velocity checks)
2. **Simulation Engine Module**
   - Generates synthetic transactions (normal and fraudulent)
   - Configurable fraud scenarios (card-not-present, account takeover)
3. **Rule-Based Detection Module**
   - Predefined rule sets (velocity, amount thresholds, geographic anomalies)
   - Real-time rule evaluation with configurable severity levels
4. **ML-Based Detection Module**
   - Trained models for anomaly scoring
   - Ensemble approach combining multiple algorithms

Module Explanation (Continued)

5. **Dashboard Module**
   - Real-time fraud alerts and transaction monitoring
   - Trend analysis and pattern visualization
   - Configurable alert thresholds and notifications
6. **API Gateway Module**
   - RESTful endpoints for transaction submission
   - Webhook support for fraud alerts
   - Authentication and rate limiting
7. **Reporting Module**
   - Automated daily/weekly fraud reports
   - Compliance audit trail generation
   - Performance metrics and KPI tracking
8. **Database Management Module**
   - Efficient indexing for fast query performance

Simulation Module

The **Transaction Simulation Engine** enables comprehensive testing of fraud detection capabilities before production deployment.

Key Features:

- **Normal Transaction Generation:** Creates realistic transaction patterns based on user behavior models
- **Fraud Scenario Simulation:** Generates various fraud types:
  - Card testing (multiple small transactions)
  - Account takeover (sudden pattern change)
  - Geographic anomalies (impossible travel)
  - High-value fraud (unusual amount patterns)
- **Configurable Parameters:** Transaction volume, fraud ratio, time windows
- **Real-time Injection:** Simulated transactions flow through detection pipeline
- **Performance Testing:** Validates system scalability under load

Execution Flow

Transaction Processing Pipeline

1. **Transaction Ingestion**
   - API receives transaction data (amount, merchant, location, time)
   - Initial validation and schema verification
2. **Feature Extraction**
   - Calculate transaction velocity (transactions per hour)
   - Compute statistical features (deviation from user average)
   - Geographic and temporal features
3. **Rule-Based Evaluation**
   - Apply predefined rules sequentially
   - Generate alert if rules triggered
   - Assign risk score based on rule severity
4. **ML-Based Scoring**
   - Pass features to trained ML models
   - Anomaly score calculation
   - Ensemble prediction aggregation

Execution Flow (Continued)

5. **Decision Making**
   - Combine rule-based and ML scores
   - Apply decision threshold (configurable)
   - Classify as: FRAUD/NORMAL
6. **Dashboard Update**
   - Real-time metrics update (fraud rate, alert count)
   - Visualization refresh
   - Store in database for historical analysis

Project Milestones

Milestone 1: Weeks 1–2 — Setup & Data Modeling

- **Objective:** Establish project environment and transaction models
- **Tasks:** Configure APIs, design fraud simulation datasets, define rule sets
- **Evaluation (Week 2):** Data models created; APIs configured; fraud scenarios defined

Milestone 2: Weeks 3–4 — Simulation Engine & Detection Core

- **Objective:** Build transaction generator and rule-based anomaly detector
- **Tasks:** Develop fraud scenarios, test detection accuracy with rules
- **Evaluation (Week 4):** Simulation and detection engine functional with rule-based alerts

Project Milestones (Continued)

Milestone 3: Weeks 5–6 — Dashboards & API Gateway

- **Objective:** Visualize fraud trends and enable API integration
- **Tasks:** Implement dashboards, connect APIs, test reporting functions
- **Evaluation (Week 6):** Dashboards and APIs operational; reports accurate

Milestone 4: Weeks 7–8 — ML Plug-in & Deployment

- **Objective:** Integrate ML-based detection and finalize system
- **Tasks:** Plug in ML models, run accuracy benchmarks, deploy fraud simulator
- **Evaluation (Week 8):** ML plug-in integrated; system deployed; anomaly detection effective

Algorithms

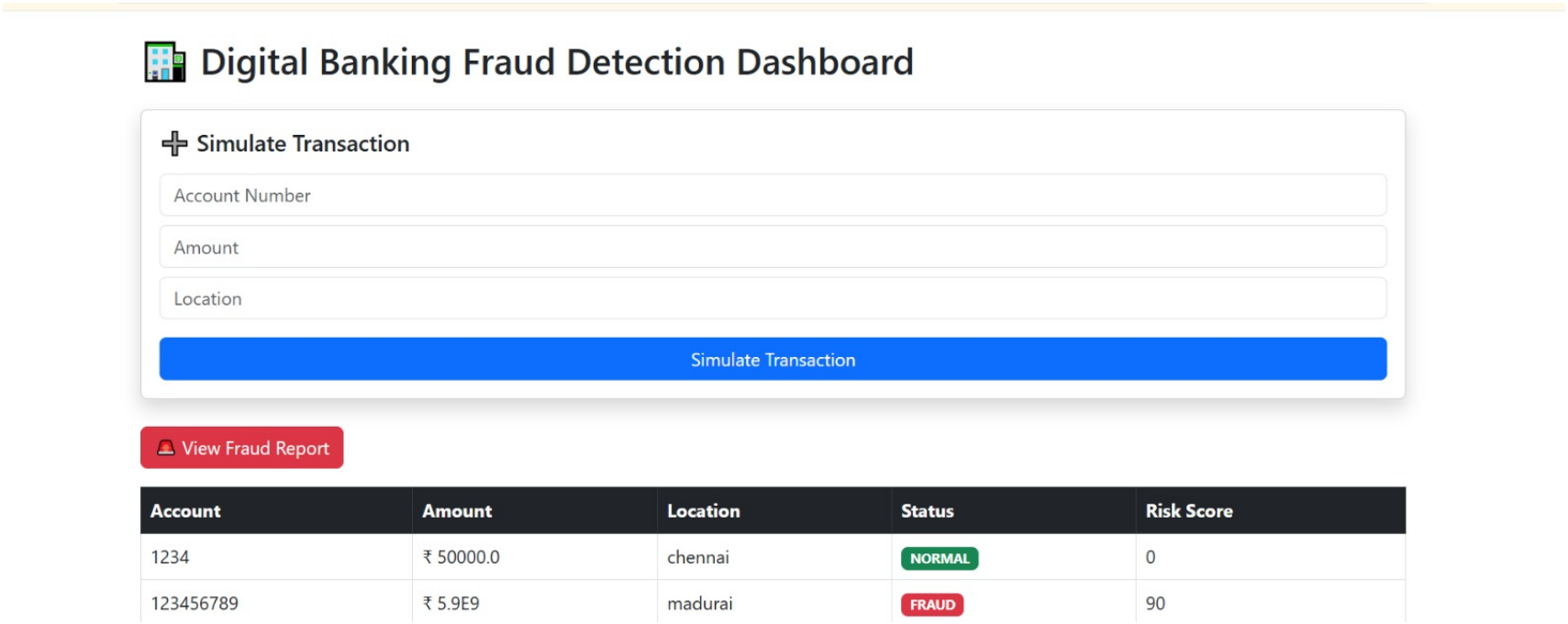
1. Rule-Based Detection Algorithm

1. Input transaction T with features ($amount$, $location$, $time$, $merchant$)
2. For each rule R in rule set:
   - Evaluate condition: if $R(T) = \text{TRUE}$, increment risk score
3. If total risk score $>$ threshold θ_r, flag as suspicious
4. Generate alert with triggered rules and severity
5. Output: decision ($APPROVED|REVIEW|DECLINED$) and risk score

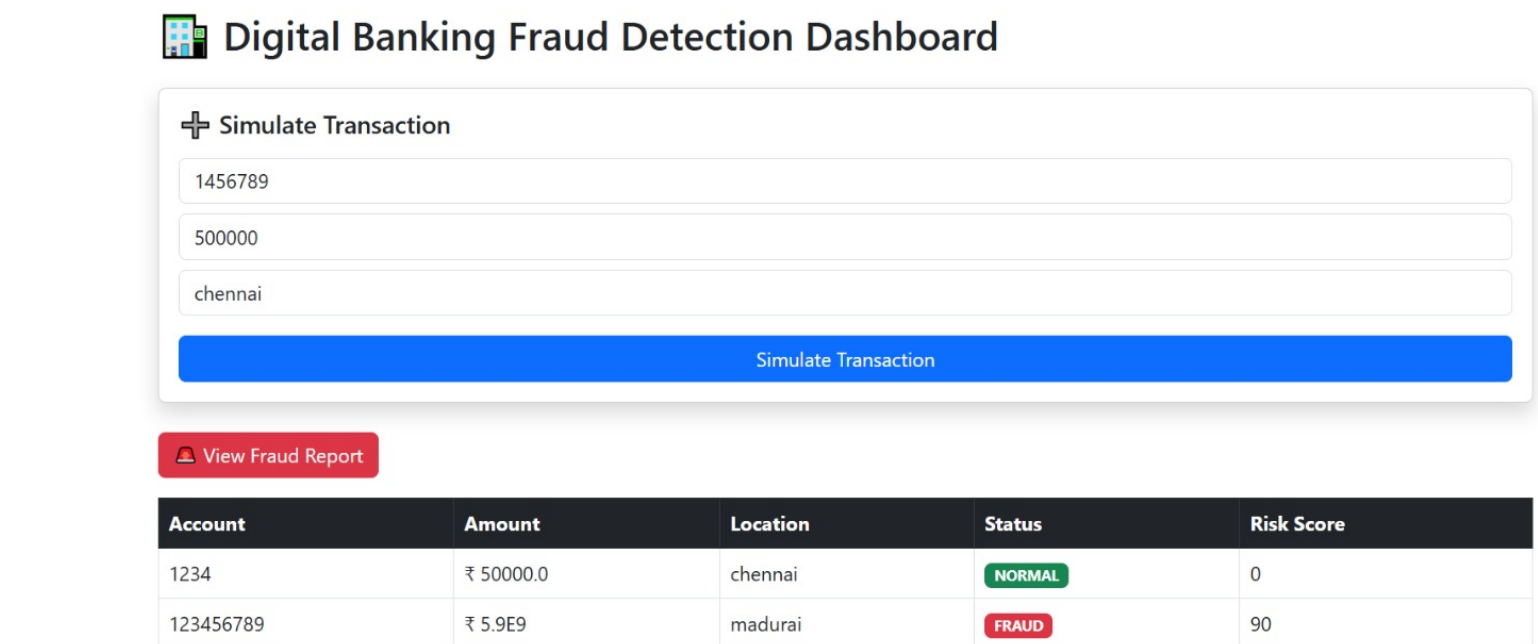
Example Rules:

- Transaction amount $>$ \$5000 (high-value rule)
- Velocity $>$ 5 transactions in 10 minutes (rapid fire)
- Geographic distance $>$ 500km from last transaction within 1 hour (impossible travel)

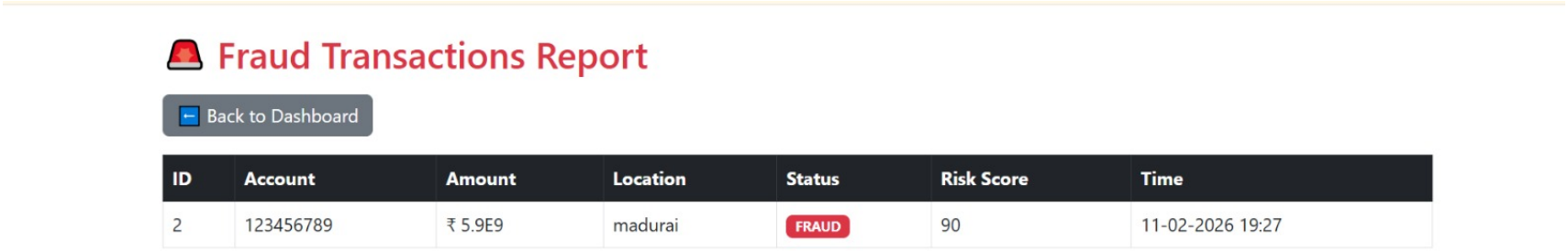
Implementation Screenshot 1



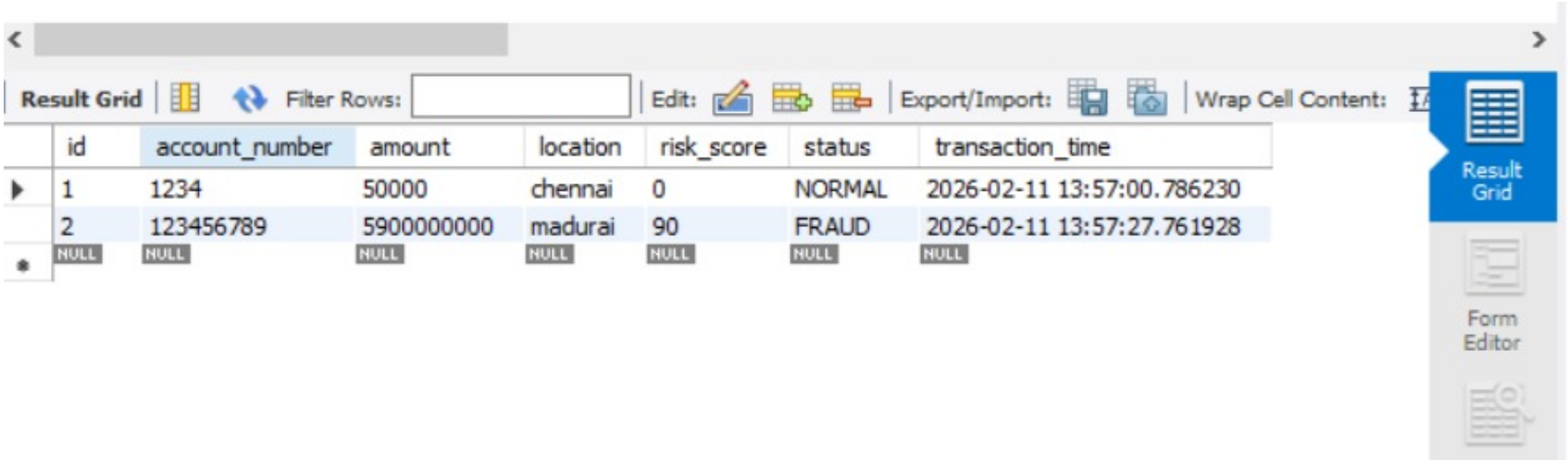
Implementation Screenshot 2



Implementation Screenshot 3



Implementation Screenshot 4



Advanced Discussion

1. **Model Interpretability**
   - SHAP values reveal feature importance for individual predictions
   - Helps fraud analysts understand why transactions were flagged
   - Enables rule refinement based on ML insights

2. **Handling Imbalanced Data**
   - Fraud typically $< 1\%$ of transactions (severe class imbalance)
   - Applied SMOTE for synthetic minority oversampling
   - Class weights adjusted in loss function
   - Ensemble methods reduce bias toward majority class

3. **Real-time Streaming Architecture**
   - Apache Kafka ensures message durability and ordering
   - Micro-batching for efficient ML inference
   - Stateful processing for velocity calculations

Advanced Discussion (Continued)

4. **Feature Engineering Techniques**
   - **Temporal Features:** Time since last transaction, day of week, hour of day
   - **Aggregate Features:** Rolling averages, standard deviations over time windows
   - **Categorical Encoding:** One-hot encoding for merchant categories
   - **Geographic Features:** Distance from home location, country risk scores

5. **Model Deployment Strategy**
   - A/B testing for new model versions
   - Shadow mode deployment (parallel evaluation without affecting decisions)
   - Gradual rollout with monitoring
   - Automated rollback on performance degradation

6. **Challenges & Solutions**
   - **Challenge:** Concept drift (fraud patterns evolve)
   - **Solution:** Scheduled model retraining (weekly) with recent data

Challenges and Limitations

Technical Challenges:

- **Data Quality:** Incomplete or noisy transaction data affects model accuracy
- **Concept Drift:** Fraud patterns evolve, requiring continuous model updates
- **Real-time Constraints:** Balancing detection accuracy with low latency
- **Scalability:** Handling peak transaction loads during high-traffic periods

Operational Limitations:

- **False Positives:** Legitimate transactions flagged cause customer friction
- **Model Bias:** Risk of discriminatory patterns in training data
- **Adversarial Attacks:** Sophisticated fraudsters may learn to evade detection
- **Regulatory Compliance:** Must explain automated decisions (GDPR, fair lending)

Mitigation Strategies: Regular audits, human-in-the-loop review, explainable AI, continuous monitoring

Conclusion

The **Intelligent Banking Fraud Detection System** successfully demonstrates a **hybrid approach** combining rule-based and ML-based detection methods.

Key Achievements:

- Created comprehensive **simulation environment** for scenario testing
- Developed **interactive dashboards** for fraud trend analysis
- Built **scalable API gateway** for system integration

Impact: The system enhances fraud prevention capabilities, reduces financial losses, and improves customer trust through rapid detection and response.

Limitations: Performance depends on data quality, requires ongoing model maintenance, and faces challenges with evolving fraud tactics.

Future Work

The system can be further enhanced through:

- **Deep Learning Integration:** Implement LSTM/GRU networks for sequential pattern detection across transaction histories.
- **Graph-Based Analysis:** Use graph neural networks to detect fraud rings and network-based patterns.
- **Federated Learning:** Enable collaborative model training across institutions without sharing sensitive data.
- **Explainable AI:** Expand LIME/SHAP integration for better decision transparency and regulatory compliance.
- **Mobile Application:** Develop mobile app for real-time fraud alerts and customer verification.
- **Blockchain Integration:** Explore distributed ledger for immutable fraud event logging.
- **Advanced Simulation:** Add adversarial attack simulation to test system robustness.
- **Multi-language Support:** Extend dashboard and reporting to multiple languages.

Project Deliverables

As per Infosys SpringBoard internship requirements, the following two deliverables are submitted at project completion:

Deliverable 1: GitHub Repository

- Contains complete project source code (Backend + Frontend + supporting files)
- Includes **MIT License** file in the root of the repository
- Repository is publicly accessible for review and evaluation

Deliverable 2: Agile Documentation

- Documents project execution in **dated format** for each milestone week
- Records tasks completed, outputs produced, and evaluation criteria met per sprint
- Included **inside the GitHub repository** as `AGILE_DOCS.md`
- Covers all 4 milestones (Weeks 1–2, 3–4, 5–6, 7–8)

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