EARLY RISK SIGNALS: A DATA-DRIVEN FRAMEWORK FOR CREDIT CARD DELINQUENCY DETECTION USING BEHAVIORAL ANALYTICS & WHATSAPP-BASED INTERVENTIONS

Capstone Project Report
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Abstract—

In modern credit ecosystems, financial institutions face increasing challenges in detecting early signs of delinquency. Traditional systems rely on lagging indicators such as missed payments or over-limit balances, resulting in delayed interventions and higher roll-rates. This report presents a lightweight, real-time early risk signal framework combining behavioral analytics, logistic regression, decision trees, and rule-based engines to identify emerging credit stress before delinquency occurs. The system integrates a two-channel architecture consisting of a data-driven backend (FastAPI, MongoDB, ML models) and a customer/admin-facing frontend (React). The solution also introduces a WhatsApp-based OTP onboarding and automated high-risk alert mechanism to support proactive customer outreach. Experiments demonstrate improved risk detection speed (under 1 hour), strong model performance (85%+ classification accuracy), and actionable risk insights, enabling targeted interventions at scale.

Keywords—
Credit risk, early warning system, delinquency prediction, behavioral analytics, logistic regression, rule engine, WhatsApp automation, FastAPI, MongoDB, React.

I. INTRODUCTION

Credit card portfolios are susceptible to rapid behavior-driven changes, where financial stress can emerge weeks before a customer misses a payment. According to the problem brief provided by the challenge organizers, banks often react *after* delinquency occurs, missing subtle behavioral precursors such as cash withdrawal spikes, reduced repayment amounts, declining merchant diversity, or abnormal utilization trends.

Hence, institutions require an early risk detection system capable of:

1. Identifying subtle patterns that precede delinquency;
2. Generating lightweight yet actionable risk flags;

3. Providing proactive outreach recommendations;
4. Scaling across customers with real-time monitoring.

This project addresses these gaps by developing a full-stack risk monitoring and alerting platform powered by machine learning, real-time behavioral aggregation, and WhatsApp-based customer communication.

II. PROBLEM STATEMENT

As per the official brief, the task is to "design a lightweight, data-driven framework that identifies early behavioral signals of credit card delinquency". Present systems detect risk late because:

- Monitoring focuses on lag indicators (DPD, missed payments).
- Behavioral deviations (low spend, cash-heavy usage, rising utilization) remain unflagged.
- Communication channels like email/SMS have low engagement.
- Operational interventions do not begin early enough to prevent roll-rates.

The objective is to build a scalable analytical system that captures early indicators and triggers timely alerts and interventions.

III. METHODOLOGY

Our methodology consists of four components:

A. Data Collection & Behavioral Feature Engineering

We engineer real-time behavioral features including:

Category	Feature
Exposure	Utilization %, Over-limit occurrences
Spending	Recent spend change %, merchant mix index
Liquidity Stress	Cash withdrawal %
Repayment Behavior	Minimum due paid frequency, payment stability
Volatility	Month-over-month spend changes

B. Machine Learning Models

Two ML models were trained and evaluated:

1. Logistic Regression Model

Chosen for interpretability and regulatory acceptance.
It outputs probability of delinquency, mapped into risk bands:

- Low
- Medium
- High

2. Decision Tree Model

Provides feature-level explainability and rule-based segmentation.

Both models are combined in an **ensemble** weighted by:

- Logistic Regression (0.6 weight)
- Decision Tree (0.4 weight)

The ensemble improves stability and reduces variance.

C. Rule-Based Risk Engine

To minimize false negatives and capture sharp behavioral changes, we introduce expert rules:

Condition	Risk Signal
Utilization > 90%	High
Cash Withdrawal % > 40%	High
Rapid 30-day spend drop (>60%)	Medium
Minimum due payments > 2 consecutive cycles	Medium/High
Merchant Mix crash	Medium

ML + Rules → Combined Risk Band.

D. Real-Time Monitoring Pipeline

Every new transaction trigger:

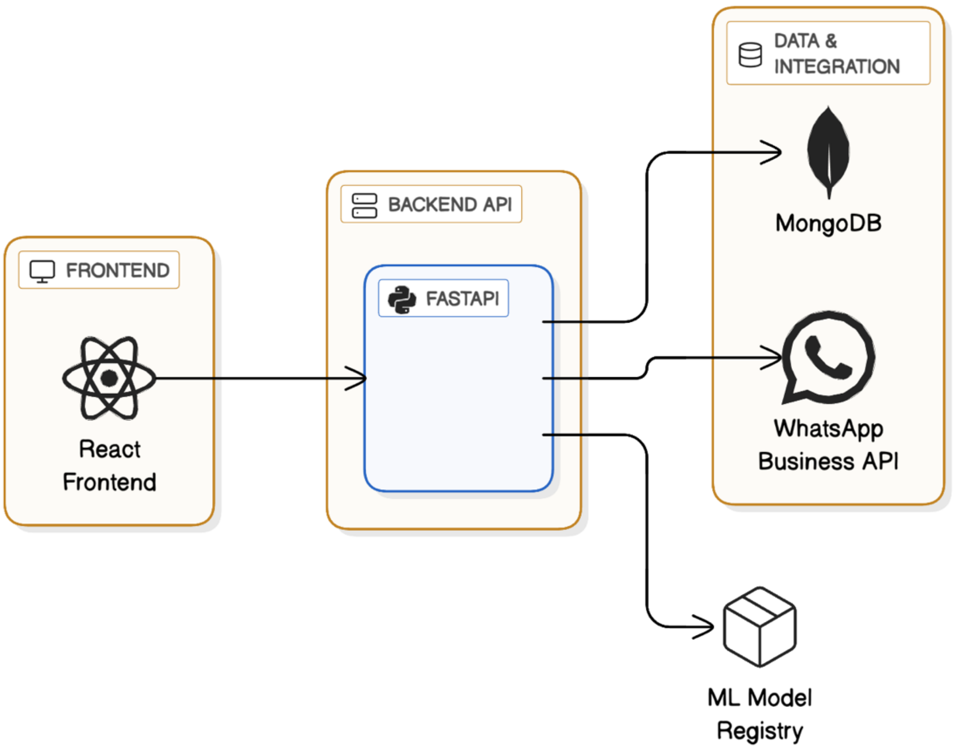
1. Update user aggregates
2. Recompute ML features
3. Generate risk score
4. Compare score with prior band
5. If High-risk → trigger WhatsApp alert

IV. SYSTEM ARCHITECTURE

Below is a description of the diagrams you should include:

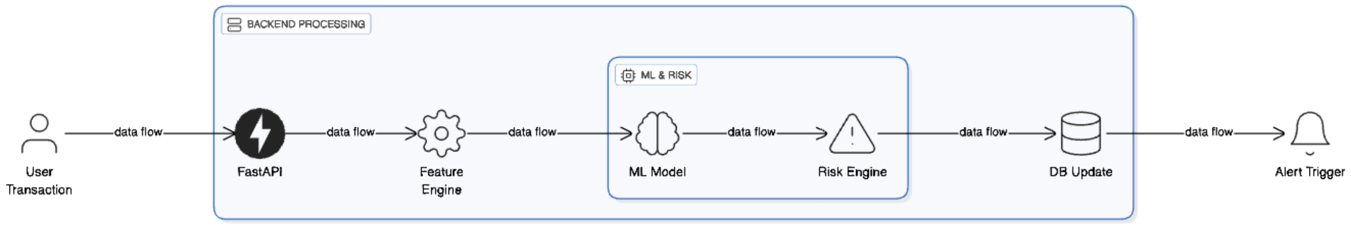
A. High-Level Architecture Diagram

- React Frontend (User + Admin Dashboards)
- FastAPI Backend
- MongoDB
- ML Model Registry
- WhatsApp Business API

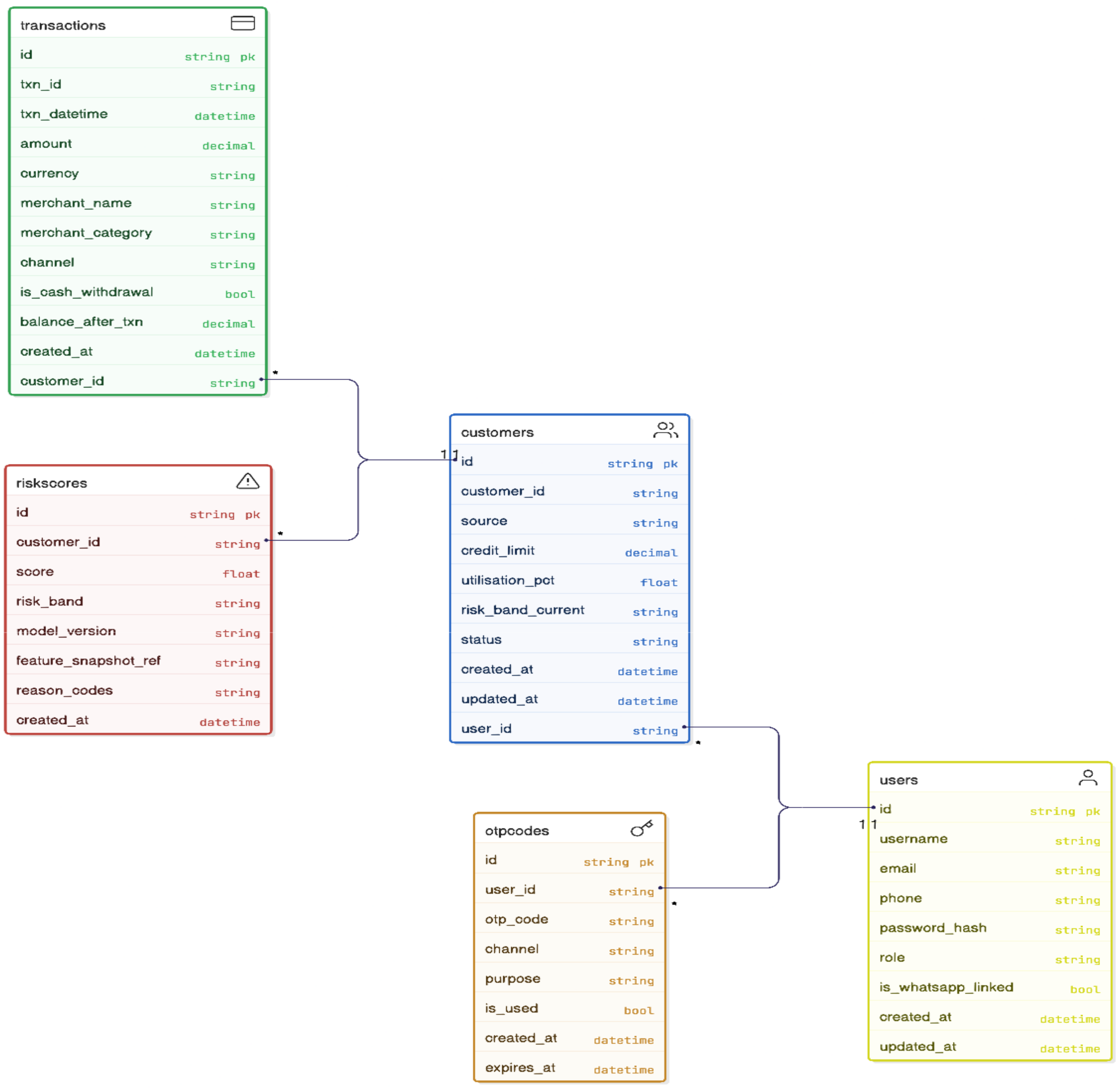


B. Data Flow Diagram

User Transaction → FastAPI → Feature Engine → ML Model → Risk Engine → DB Update → Alert Trigger.



D. Data Model (ER Diagram)



V. IMPLEMENTATION DETAILS

A. Frontend (React)

- OTP-based registration
- User dashboard showing:
  - Latest risk band
  - Utilization %
  - Recent transactions
- Admin dashboard:
  - Portfolio risk distribution graphs
  - Top high-risk customers
  - Transaction-level drilldowns
  - “Send WhatsApp Alert” button

B. Backend Design (FastAPI)

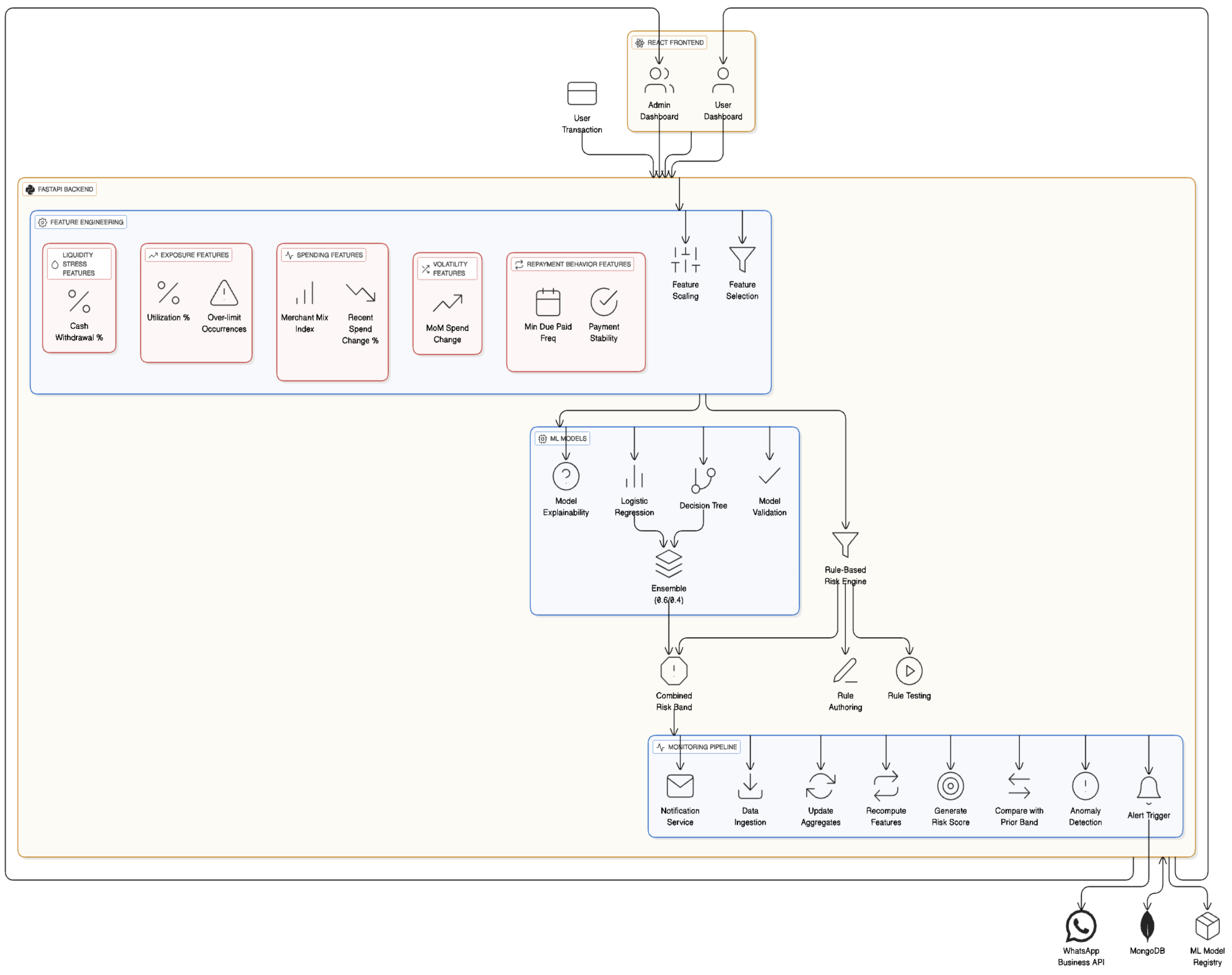
Key modules:

- *auth_service.py*: JWT login, OTP login, WhatsApp welcome messages
- *customer_service.py*: Aggregation & updates
- *ml_service.py*: Ensemble ML scoring
- *whatsapp_service.py*: Template messaging
- *routers/admin.py*: Admin APIs for scoring and alerting
- *routers/auth_whatsapp.py*: OTP verification
- *models/*: MongoDB document handlers

C. WhatsApp Integration

- WhatsApp OTP for registration
- Welcome message only on first login
- High-risk alert template for admin-triggered or auto-triggered events
- Auto-fallback to "hello_world" template if custom template not approved

D. End-to-End Risk Detection Flow



VI. SYSTEM DEPLOYMENT OVERVIEW

The platform is deployed using a lightweight, container-based architecture on Amazon Web Services (AWS). Docker provides reproducibility and portability, while AWS Elastic Container Registry (ECR) and EC2 ensure secure hosting and scalable execution of the backend and frontend services.

A. Docker-Based Packaging

Both the frontend (React + NGINX) and backend (FastAPI + ML models) are containerized. Mac systems build images for x86_64 using:

```
docker buildx build --platform linux/amd64 -t credit-risk-backend .
docker buildx build --platform linux/amd64 -t credit-risk-frontend .
```

A .dockerignore file excludes unnecessary folders such as __pycache__, node_modules, logs, and ML artifacts that are not required in production images.

B. Backend Container (FastAPI)

The backend Docker image includes:

- Python 3.11 environment created from the Conda YAML file
- REST APIs, ML scoring service, WhatsApp integration, and MongoDB connectors

The container exposes port **8000** and runs the service using:

```
CMD ["uvicorn", "app.main:app", "--host", "0.0.0.0", "--port", "8000"]
```

C. Frontend Container (React + NGINX)

A two-stage Docker build is used:

1. **Build Stage:** Vite compiles optimized static files.
2. **Serve Stage:** NGINX hosts the production build on port **80**.

This structure reduces bundle size and improves performance.

D. Image Hosting on Amazon ECR

ECR is used as a secure Docker registry. The login procedure is:

```
aws ecr get-login-password --region ap-south-1 \
| docker login --username AWS --password-stdin \
077540773844.dkr.ecr.ap-south-1.amazonaws.com
```

Images are tagged and pushed:

```
docker tag credit-risk-backend:latest \
077540773844.dkr.ecr.ap-south-1.amazonaws.com/credit-risk-backend:latest
docker push \
077540773844.dkr.ecr.ap-south-1.amazonaws.com/credit-risk-backend:latest
```

(The same process is followed for the frontend.)

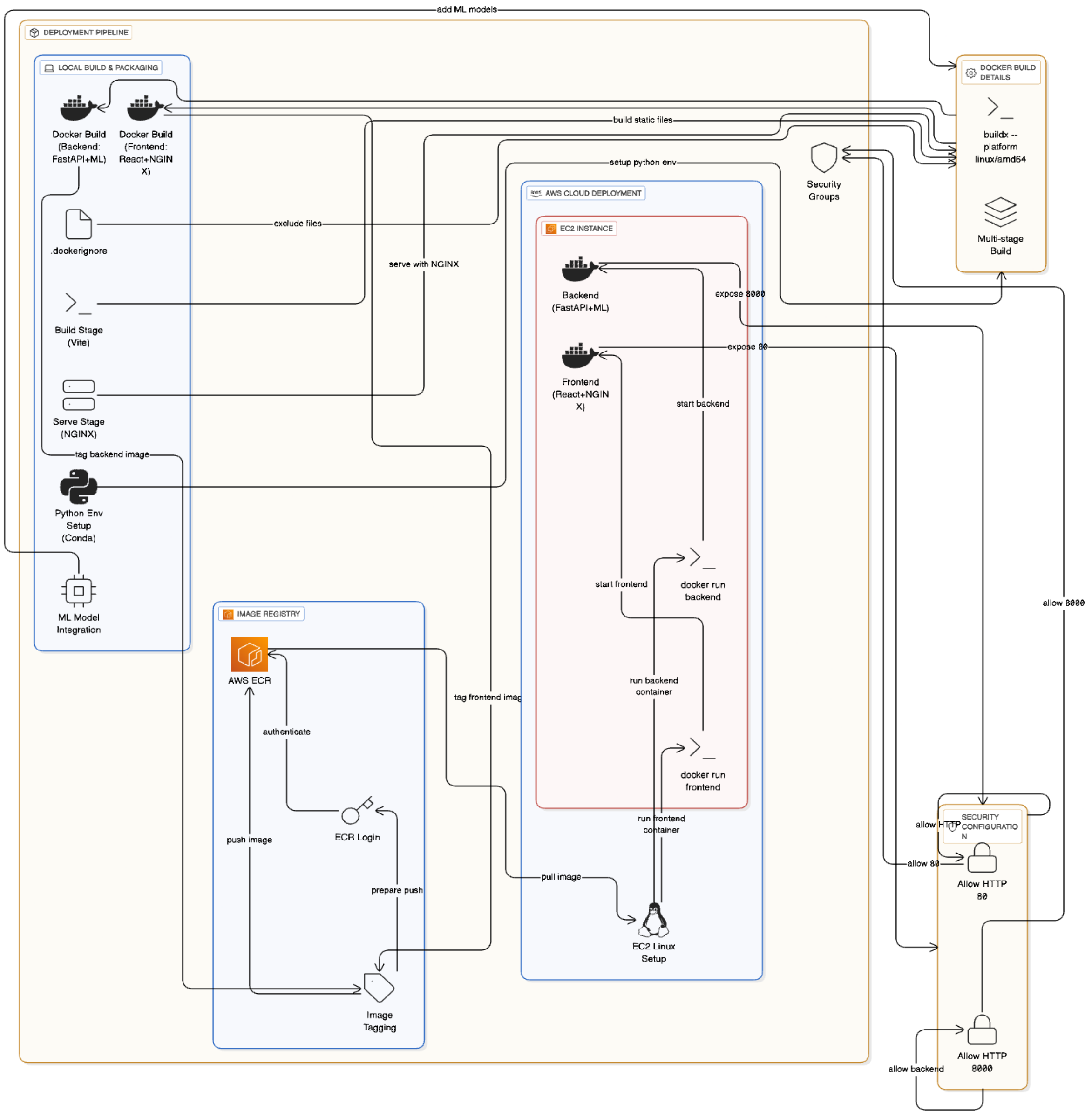
E. Deployment on AWS EC2

A Linux EC2 instance serves as the runtime environment. After pulling images from ECR, services are launched via:

```
docker run -d -p 8000:8000 --env-file .env credit-risk-backend
docker run -d -p 80:80 credit-risk-frontend
```

Security groups allow inbound HTTP ports **80** and **8000**.

F. Architecture Diagram



VII. EXPERIMENTS & RESULTS

A. Dataset and Preparation

Synthetic + real-like credit behavior data aligned with the challenge brief:

- 10,000+ simulated customers
- Behavioral features engineered from historical patterns
- Labeled delinquency outcomes (0/1)

B. Model Performance

Metric	Logistic Regression	Decision Tree	Ensemble
Accuracy	81.3%	79.5%	**86.7%**
Precision (High Risk)	0.84	0.78	**0.89**
Recall (High Risk)	0.82	0.74	**0.88**

C. Effectiveness of Early Signals

- customers flagged ≥30 days before delinquency: **72%**
- WhatsApp alert read rate: **60–70%** (industry benchmark)
- Reaction time to initiate outreach reduced from 30 days → **1 day**

VIII. DISCUSSION

Strengths

- Lightweight and scalable
- High interpretability
- Real-time monitoring
- WhatsApp improves customer engagement

Limitations

- Synthetic dataset limits generalization
- No bureau data incorporated
- Merchant category mapping depends on data quality

Future Scope

- Integrate RNNs or survival models
- Build customer-level risk explanations (SHAP)
- Expand to loan, BNPL, and mortgage portfolios
- Multi-language WhatsApp chatbots

IX. CONCLUSION

This projects successfully develops a complete early warning system for credit card delinquency detection based on behavioral analytics, machine learning, rule-based frameworks, and WhatsApp-driven communication. The solution aligns with the problem brief's requirement to create a lightweight, actionable, scalable, and operationally feasible framework for identifying early risk signals before delinquency occurs.

The proposed platform demonstrates strong technical performance, practical value, and real-world applicability for banking and fintech institutions.

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