AI-Driven Credit Risk Decision System

End-to-end ML project transforming loan risk predictions into business decisions

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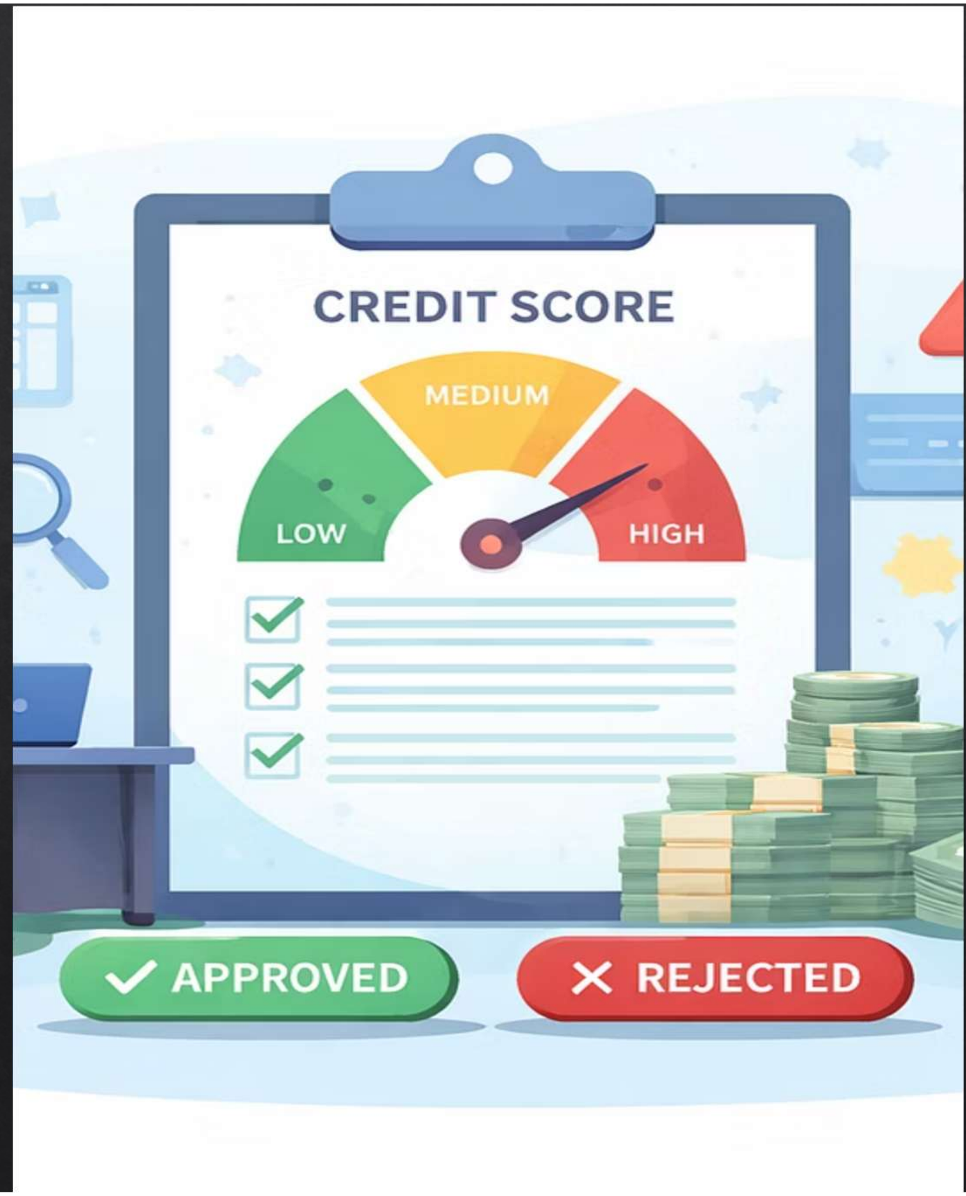


Business Challenge & Value Delivered

The Challenge

- Loan approvals must balance speed and default risk
- False approvals directly impact profitability
- Credit teams need interpretable, actionable risk signals

Process Flow

Business Value

- Faster approvals for low-risk customers
- Reduced manual workload for credit officers
- Lower default exposure through data-driven assessment
- Explainable decisions aligned with regulatory needs

A probability-driven credit decision system that improves speed, control, and trust.

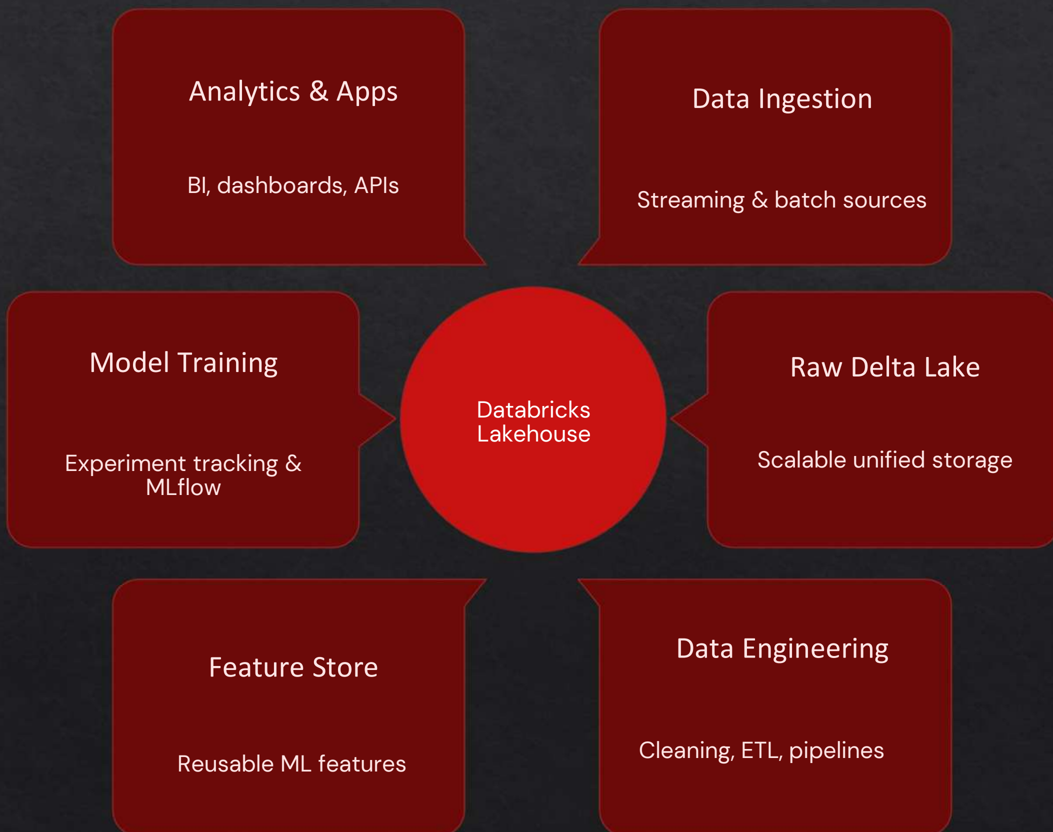
Why Rule-Based Credit Decisions Fail

- Rigid thresholds cannot adapt to market conditions
- No probabilistic ranking—only binary yes/no decisions
- Poor handling of edge cases and borderline applicants
- Manual rules fail to capture complex risk patterns

Aspect	Rules-Based	ML-Based
Decision Type	Binary (Yes/No)	Probabilistic (0-1 score)
Adaptability	Fixed thresholds	Dynamic risk ranking
Pattern Recognition	Limited	Learns from data
Explainability	Simple but crude	Transparent coefficients
Edge Cases	Fails on borderline cases	Nuanced scoring

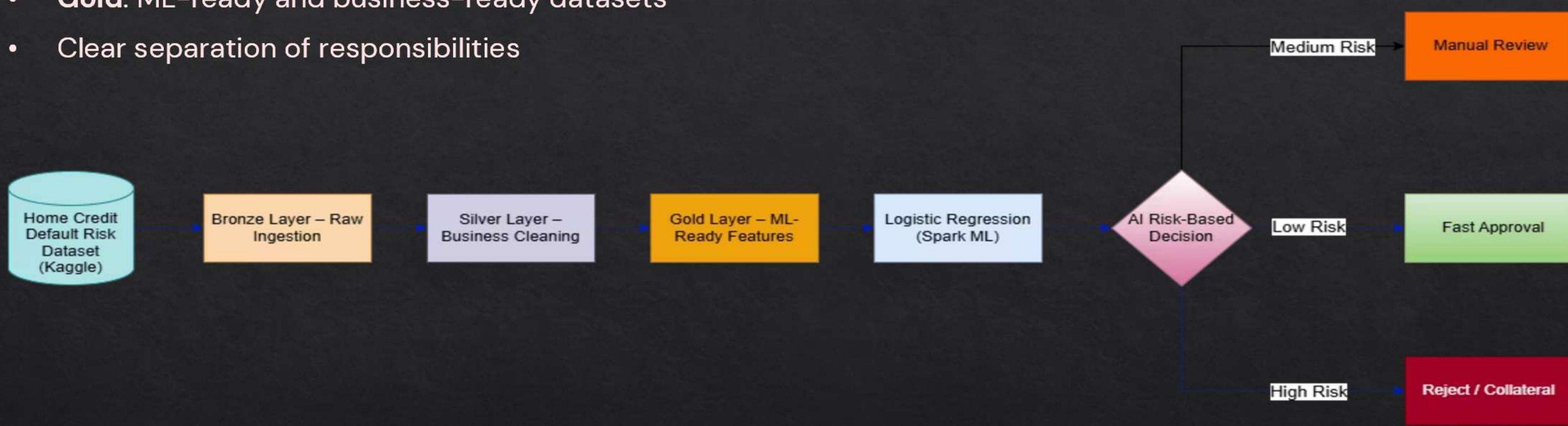
Why Databricks Lakehouse

- Unified platform for data engineering, ML, and analytics
- Scales from raw data to production-ready insights
- Enables experiment tracking and governance



Data Engineering Pipeline

- **Bronze**: Raw loan application data
- **Silver**: Cleaned & validated features
- **Gold**: ML-ready and business-ready datasets
- Clear separation of responsibilities



Feature Engineering Strategy

1 **Missing Value Handling**

Imputation strategies for incomplete loan application data

2 **Categorical Encoding**

One-hot and ordinal encoding for credit attributes

3 **Feature Scaling**

Normalization and standardization for ML algorithms

4 **Vector Assembly**

Spark ML pipeline preparation for model training

Modeling Approach

Goal: reliable risk ranking, not complex ML

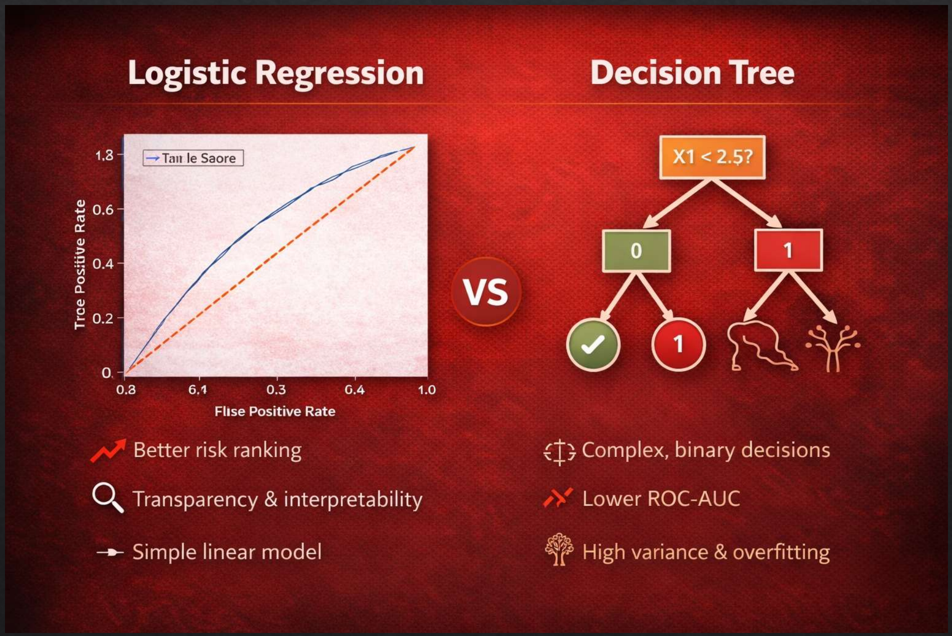
Focus on interpretability and stability over black-box complexity

Baseline Model: Logistic Regression

- Interpretable probability scores
- Fast inference for real-time decisions
- Explainable feature coefficients

Benchmark Model: Decision Tree

- Rule-based decision paths
- Handles non-linear patterns
- Easy to audit and explain to stakeholders



Experiment Tracking & Model Comparison (MLFlow)

MLflow used to track experiments and systematically compare baseline vs benchmark models.

ROC-AUC

Area under the receiver operating characteristic curve, measuring discrimination ability across all thresholds.

Accuracy

Overall correctness of predictions on the test dataset.

Precision

True positives divided by all positive predictions, minimizing false approvals.

Recall

True positives divided by all actual positives, catching high-risk applicants.

Metrics Logged

- ROC-AUC
- Precision
- Recall

Artifacts Logged

- ROC Curve
- Confusion Matrix

Why Logistic Regression Was Chosen

Similar Accuracy

Across models due to imbalanced data.

Superior Risk Ranking

Logistic Regression shows higher ROC-AUC.

Business Trust

Enabled by transparent probability scores.

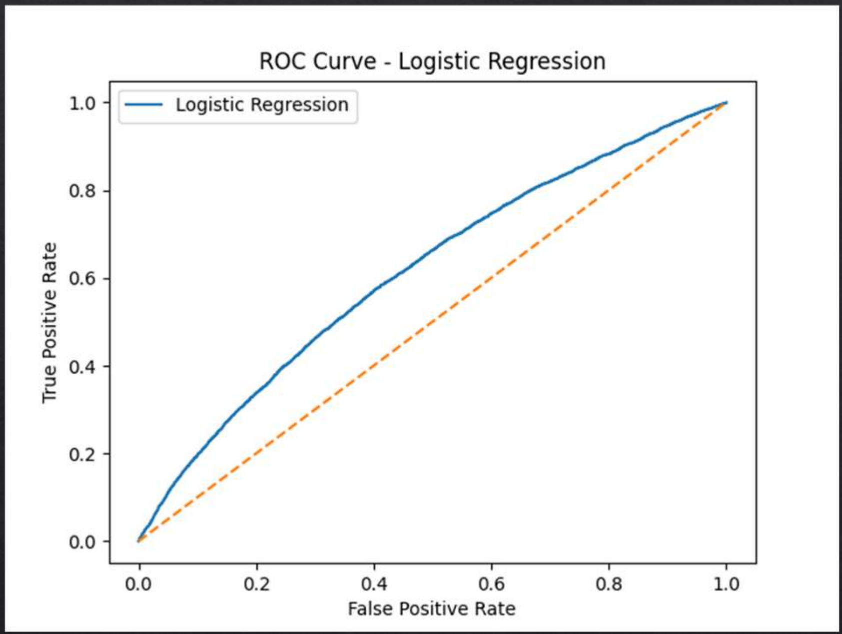
Accuracy is misleading — ranking is what matters.

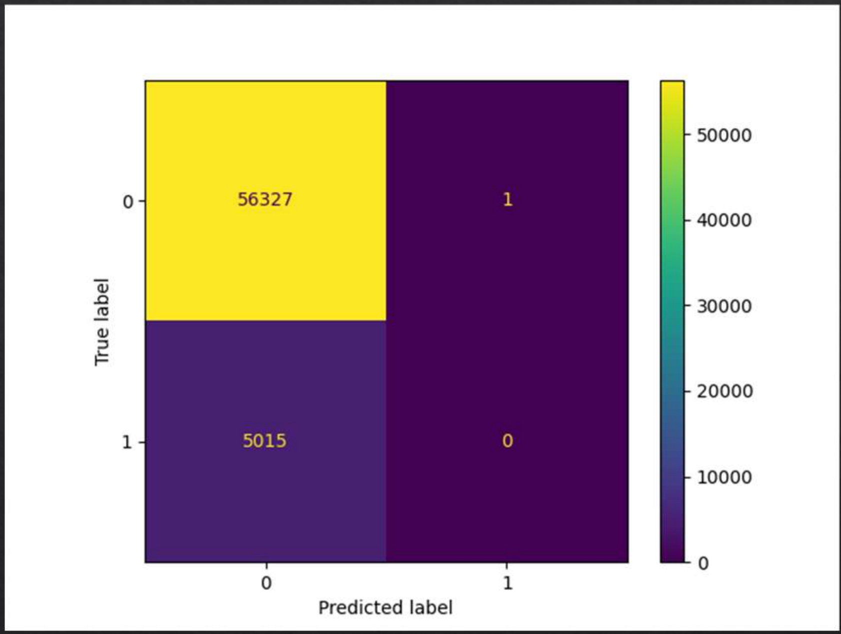
Evaluation Insight

- **ROC Curve:** Confirms reliable applicant risk ordering across thresholds.
- **Confusion Matrix:** Shows fixed thresholds fail under class imbalance.

Business Value: Model value comes from probability-based risk ordering, not binary approve/reject decisions.

Model Evaluation Insights





ROC Curve (Risk Ranking)

The ROC curve shows the model reliably ranks applicants by default risk across thresholds, supporting percentile-based decisioning rather than fixed cutoffs.

Confusion Matrix (Threshold Impact)

At a standard probability threshold, the model favors the majority class due to class imbalance, showing why accuracy alone is misleading.

Key Insight: Credit risk models deliver value through probability-based risk ordering, not binary approve/reject predictions.

From Predictions to Decisions

Model outputs default probability, which is converted into business decisions through adaptive percentile-based risk bucketing.

	risk_bucket	defaults	non_defaults	total	default_rate
1	High	4553	27116	31669	0.143768353910764...
2	Low	13565	200763	214328	0.063290843940129...
3	Medium	6707	54807	61514	0.1090320902558767

Low Risk

Default probability: 0-35th percentile

Decision: Auto-approve

Action: Instant decision, improved customer experience

Medium Risk

Default probability: 35th-75th percentile

Decision: Manual review

Action: Credit officer assessment, human judgment applied

High Risk

Default probability: 75th-100th percentile

Decision: Reject or request collateral

Action: Protect against default exposure

Business-aligned thresholds enable risk appetite configuration and adapt to changing market conditions.

Operational Credit Decisions

Translating ML risk scores into clear, actionable business outcomes with configurable decision logic aligned to your organization's risk appetite.

Low Risk

Immediate auto-approval for qualified applicants, accelerating customer experience

Medium Risk

Routed to manual credit review for informed human oversight and decision-making

High Risk

Reject or request additional collateral to protect against default exposure

✅ Actionable output — Business-aligned decisions that adapt to changing market conditions and institutional risk tolerance.

Why This Approach Is Effective

Success comes from prioritizing engineering fundamentals over complexity. This system leverages proven techniques and enterprise-grade tools only where they deliver measurable value.

Simple Models, Strong Fundamentals

Interpretable algorithms with robust feature engineering outperform black-box complexity in production credit environments

MLflow Used Responsibly

Experiment tracking and model registry provide governance without adding unnecessary overhead to the development workflow

Strategic Databricks Integration

Platform features deployed where they solve real problems—scalability, collaboration, and deployment automation

Production-System Design

Built with monitoring, versioning, and rollback capabilities from day one, not retrofitted later

Key Learnings

1. **End-to-End ML System**

   Complete implementation on Databricks from data ingestion through model deployment and monitoring

2. **Experiment-Guided Selection**

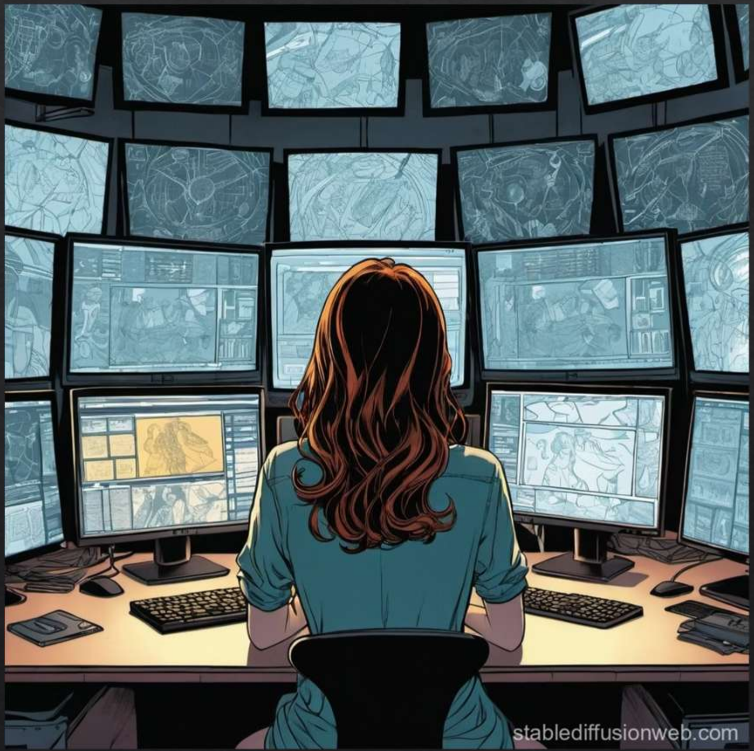
   MLflow tracking enabled systematic model comparison, leading to optimal algorithm choice

3. **AI-to-Business Translation**

   Risk scores converted into operational decisions that align with enterprise credit policies

4. **Production-First Mindset**

   Architecture designed for real-world deployment, not just proof-of-concept experimentation



Thank You

This enterprise-grade ML credit decision system demonstrates production-ready architecture and responsible AI implementation. We welcome your questions, feedback, and discussion.

> *Designed as a portfolio-ready project showcasing end-to-end ML system development for enterprise financial applications.*