Cyber Security Innovation Challenge 1.0

PROTOTYPE DEVELOPMENT: Stage III

Problem Statement Domain: Mule Accounts & Collusive Fraud in UPI
Problem Statement: Detection of Mule Account Networks and Coordinated Fund Laundering in UPI Payment Ecosystems
Project Subtitle: FinGuard: Real-Time Multi-Signal Mule Account Detection System
Team Name: FinGuard

Project Links

Resource	Link
GitHub Repository	*[Insert GitHub Repo URL]*
Live Deployed URL	*[Insert Deployed URL]*
Dashboard Demo Video (YouTube)	*[Insert YouTube Link]*
Pitch Deck / Presentation	*[Insert Link if applicable]*

Role	Name	Institute	Enrolment No.	Email ID
Team Lead	*[Name]*	*[Institute]*	*[Enrolment No.]*	*[Email]*
Member 2	*[Name]*	*[Institute]*	*[Enrolment No.]*	*[Email]*
Member 3	*[Name]*	*[Institute]*	*[Enrolment No.]*	*[Email]*
Member 4	*[Name]*	*[Institute]*	*[Enrolment No.]*	*[Email]*
Member 5	*[Name]*	*[Institute]*	*[Enrolment No.]*	*[Email]*

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1. Project Overview and Team Details

1.1 Project Summary

FinGuard detects mule accounts in India's UPI ecosystem, and it does so in real time. Mule accounts, for anyone unfamiliar, are bank accounts that criminals use as pass-throughs for laundering stolen money. They're a massive headache for the payments industry because each individual transaction through a mule looks perfectly normal. It's only when you zoom out and look at the bigger picture (the network structure, the timing, the devices involved) that the fraud becomes visible.

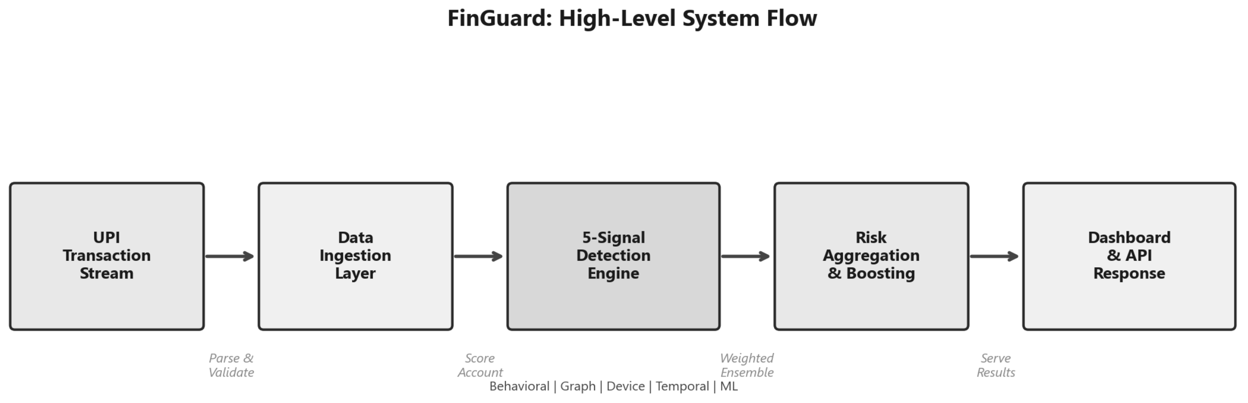
FinGuard: High-Level System Flow
UPI Transaction Stream
Data Ingestion Layer
5-Signal Detection Engine
Risk Aggregation & Boosting
Dashboard & API Response
Parse & Validate
Score Account
Weighted Ensemble
Serve Results
Behavioral | Graph | Device | Temporal | ML

Figure 0: FinGuard high-level system flow, from transaction ingestion to dashboard output.

Our system tackles this with what we call a five-signal ensemble. We pull together behavioral profiling, transaction graph analysis, device fingerprinting, temporal pattern detection, and unsupervised ML into a single scoring pipeline. The whole idea is that even if a sophisticated mule operator manages to fool one of those signals, the other four will still catch them.

1.2 Objective

We set out to build a working prototype with four concrete goals:

1. **Detect** mule accounts by crunching transaction patterns, network topology, device correlations, and timing anomalies, all at once rather than one at a time.
2. **Classify** every account into a risk tier (CRITICAL, HIGH, MEDIUM, or LOW) and back that up with specific, readable evidence. No black-box scores.
3. **Visualize** the fraud networks on an interactive dashboard so that human investigators can actually make sense of what's going on and take action.
4. **Stay fast.** Sub-50ms scoring per account. UPI doesn't wait around, and neither can we.

1.3 Scope

The prototype covers the full pipeline end-to-end:

- **Data Ingestion:** We use synthetic but realistic UPI transaction data that covers six different fraud scenarios: star aggregation, circular networks, chain laundering, device rings, rapid onboarding fraud, and night-time smurfing. More on these later.

- **Detection Engine:** Five independent scoring modules feed into a weighted ensemble with confidence boosting when multiple signals agree.
- **REST API:** 11 endpoints with API-key auth, rate limiting (120 req/min), structured audit logs, and telemetry baked in.
- **Dashboard:** An 8-tab React SPA covering command center, risk analysis, ML insights, network graph, timeline, alerts, live API testing, and an about page.
- **Deployment:** Docker containers with multi-service orchestration. We run as non-root, have health checks, the works.

1.4 Team Details

Team Name: FinGuard

Our team of five split the work roughly along these lines:

Member	Role	Institute	Key Contribution
[Team Lead Name]	Team Lead	*[Institute]*	System architecture, risk engine design, project coordination
[Member 2]	Backend Developer	*[Institute]*	Detection modules, API development, ML pipeline
[Member 3]	Frontend Developer	*[Institute]*	React dashboard, data visualization, UX design
[Member 4]	Data Engineer	*[Institute]*	Data generation, testing, validation scenarios
[Member 5]	DevOps / Documentation	*[Institute]*	Docker deployment, security hardening, documentation

In practice, the boundaries were fuzzy; everybody ended up debugging graph algorithms at 2 AM at some point.

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2. Problem Statement and Background

2.1 Context: The UPI Ecosystem

UPI is enormous. In October 2024 alone, it processed 13.1 billion transactions worth ₹20.64 lakh crore [1]. That makes it the largest real-time payment system anywhere in the world, not just in India. The whole design philosophy behind UPI is speed and accessibility: instant transfers, near-zero cost, interoperability between banks. It's genuinely transformative for financial inclusion.

But that same openness creates a problem. When you build a system that lets anyone move money to anyone instantly, you've also built something that's extremely attractive to criminals.

2.2 The Mule Account Problem

So what exactly is a mule account? Simple: it's a bank account used as a waystation for dirty money. Someone gets defrauded through phishing or a vishing call, their money goes into a mule account, and from there it gets shuffled around through more accounts until it's cashed out somewhere untraceable. The person whose account is being used as a mule may or may not be aware. Sometimes they're recruited via fake job postings, sometimes they're completely in the dark.

Here's what makes mule detection so frustrating:

1. **Individual transactions look fine.** A ₹5,000 UPI transfer from one valid account holder to another? Nothing suspicious about that on its own. Standard amount, real person, normal-looking pattern.
2. **The fraud is in the coordination.** Mule operations create distinctive network shapes (star patterns where money aggregates into one node, sequential chains, circular loops) but you can't see any of that if you're only looking at one transaction at a time.
3. **Timing gives them away, but subtly.** Mule accounts often show burst activity (a flurry of transactions in minutes) followed by total silence, or they operate mostly between midnight and 5 AM. The signatures are there, but they're easy to miss.
4. **Device sharing is a huge tell.** When five different bank accounts are all being operated from the same phone, that's not a coincidence. But traditional per-account monitoring won't catch this because it never correlates across accounts.

2.3 Limitations of Current Approaches

Most fraud detection systems running inside UPI today are basically rule engines. They check each transaction against a list of thresholds. Amount too large? Flag it. Too many transactions in an hour? Block. Account on a blacklist? Reject.

These work, up to a point. But they have some pretty fundamental blind spots:

- **They can't see networks.** Each transaction gets evaluated in isolation. A rule engine has no concept of "this account just received money from five accounts and immediately sent it all to one other account." It sees five separate incoming transfers and one outgoing. All fine individually.
- **Rules go stale.** Mule operators adapt fast. By the time a fraud team manually writes a new rule to catch the latest tactic, the criminals have moved on to something else.
- **It's all-or-nothing.** You either block the transaction or you don't. There's no "this is 72% suspicious, escalate for review." That lack of nuance means you're constantly choosing between catching fraud and annoying legitimate customers.
- **No cross-signal thinking.** A rule engine doesn't know how to combine the fact that an account has weird transaction timing AND shares a device with three other accounts AND sits at the center of a star-shaped transaction graph. That kind of multi-dimensional reasoning just isn't possible with threshold rules.

The RBI clearly recognises how serious this has gotten. They've mandated enhanced fraud monitoring under the Digital Payments Security Controls directions [2], and NPCI's own guidelines now push for real-time, multi-dimensional detection capabilities [3]. The regulatory pressure is real.

2.4 Problem Formulation

Mathematically, here's what we're trying to do. Take a set of UPI accounts $A = {a_1, a_2, \ldots, a_n}$ and build a transaction graph $G = (A, E)$ where each edge $e_{ij} \in E$ represents a fund transfer from a_i to a_j. We want to compute a risk score $R(a_i) \in [0, 100]$ for every account:

$$R(a_i) = \sum_{k=1}^{5} w_k \cdot S_k(a_i) + \text{Boost}({S_k(a_i)})$$

The five S_k terms correspond to our five detection signals (behavioral, graph, device, temporal, ML). Each has a weight w_k. The Boost function is what gets interesting: it's a confidence amplifier that rewards agreement across signals. If three or four independent detectors all point at the same account, we're a lot more confident that something's actually wrong.

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3. Literature Review / Existing Solutions

3.1 Rule-Based Systems

The bread-and-butter of UPI fraud detection today is still rule engines sitting inside the payment switch. These are conceptually simple: set thresholds on transaction amounts, cap the velocity (say, no more than 20 transactions per hour), maintain blacklists and whitelists, and act accordingly. They're fast, they're explainable, and for catching obvious fraud they work fine. But coordinated multi-account fraud? That's a blind spot. A rule engine doesn't cross-reference accounts against each other, so it has no way to notice that five seemingly unrelated accounts are all funnelling money to the same destination [4].

3.2 Machine Learning Approaches

People have thrown all the usual ML suspects at banking fraud: Random Forests, Gradient Boosting, deep neural nets [5]. In the broader fraud detection space, these can be effective. In the specific context of mule accounts, though, they run into trouble:

- **Where are the labels?** Mule accounts are almost never explicitly labelled in production data. You can't train a supervised classifier if you don't have ground truth. This is the single biggest practical obstacle.
- **Concept drift hits hard.** Mule tactics evolve constantly. A model trained on last quarter's patterns may be useless by next month.
- **They look at accounts individually.** Most ML models consume a feature vector per transaction or per account. They miss the forest for the trees, specifically the relational network structure that's really the defining signature of mule operations.

3.3 Graph-Based Detection

Graph approaches are where the recent literature gets genuinely exciting. Several papers are worth calling out:

- Jambhrunkar et al. (2025) built MuleTrack, a lightweight temporal learning framework that tracks how account behavior transitions over time using sequential patterns [6]. Clever idea, though it doesn't incorporate device signals.
- Cheng et al. (2024) did a thorough review of GNNs for financial fraud and showed that graph-based methods pretty consistently beat traditional feature-based classifiers when it comes to coordinated fraud [7]. Not surprising in hindsight, because if the fraud is by nature a network phenomenon, you need an approach that understands networks.
- Caglayan and Bahtiyar (2022) used Node2Vec embeddings for money laundering detection [8]. Their key finding: structural features pulled from the transaction graph improved detection rates quite a bit over using only per-transaction features.
- Huang (2025) went at the problem from a community detection angle, finding money mules by looking at graph communities and structural features [9].
- Neo4j (2023) published some industry case studies on using their graph database for fraud detection in actual financial institutions [10]. Useful for understanding what works in practice versus what works on paper.

3.4 Unsupervised Anomaly Detection

Isolation Forest [11] deserves its own mention. The core intuition behind it is elegant: anomalies are few and different, so they can be isolated by random binary splits much more quickly than normal data points. You don't need labelled examples; the algorithm just finds things that don't fit. Combine this with simpler statistical methods like Z-score outlier detection, and you get an ensemble that can spot novel fraud patterns it's never been explicitly trained on. For mule detection, where you often don't have labelled training data, this is a big deal.

3.5 Gap Analysis

We did a systematic comparison to figure out where the gaps are:

Capability	**Rule-Based**	**Supervised ML**	**Graph Methods**	**FinGuard (Ours)**
Temporal Pattern Detection	Static thresholds	Limited	None	Full (5 sub-signals)
Network/Graph Analysis	None	None	Yes	Yes (3 patterns + DFS)
Device Correlation	None	Partial	None	Full (concentration + rotation)
Unsupervised (No labels)	N/A	No	Partial	Yes (IF + Z-score)
Real-Time Scoring	Fast	Moderate	Slow	Fast (<50ms)
Explainability	Clear	Black-box	Limited	Full (3–5 evidence items)
Multi-Signal Ensemble	No	No	No	Yes (5-factor weighted)
Confidence Boosting	No	No	No	Yes (multi-signal correlation)

Table 1: Comparison of FinGuard with existing detection approaches.

The bottom line: nobody's combined all five signal types (behavioral, graph, device, temporal, ML) into one ensemble with explainable evidence and confidence-aware boosting. That's the gap we're filling.

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4. Proposed Solution and Technical Architecture

4.1 Overall Architecture

We went with a layered architecture. Not because it's trendy, but because it genuinely makes sense here. Each layer does one thing, and doing it well. Data comes in at the bottom, gets processed through five parallel scoring modules, aggregated into a final risk score, served through an API, and displayed on a dashboard. Here's the full picture:

```
┌──────────────────────────────────────────────────────────────┐
│                   Frontend (React + Vite)                     │
│   Command Center │ Risk Analysis │ ML Insights │ Network      │
│   Timeline │ Alerts │ Real-Time API │ About                   │
├──────────────────────────────────────────────────────────────┤
│                  API Gateway (FastAPI v2.1.0)                  │
│   API-Key Auth │ Rate Limiter (120/min) │ CORS │ Audit Log    │
│   11 REST Endpoints │ Telemetry Middleware                     │
├──────────────────────────────────────────────────────────────┤
│              5-Factor Detection Engine                         │
│  ┌──────────┐ ┌──────────┐ ┌──────────┐ ┌────────┐ ┌─────┐  │
│  │Behavioral│ │  Graph   │ │  Device  │ │Temporal│ │ ML  │  │
│  │  (25%)   │ │  (40%)   │ │  (15%)   │ │ (10%)  │ │(10%)│  │
│  └──────────┘ └──────────┘ └──────────┘ └────────┘ └─────┘  │
├──────────────────────────────────────────────────────────────┤
│          Risk Aggregation & Confidence Boosting                │
│   Weighted Sum → Multi-Signal Boost (+8 to +20) → Classify    │
├──────────────────────────────────────────────────────────────┤
│                    Data Layer                                  │
│   transactions.csv │ accounts.csv │ devices.csv                │
│   NetworkX Graph (in-memory) │ Model Store (pickle)            │
└──────────────────────────────────────────────────────────────┘
```

Figure 1: System Architecture for FinGuard Mule Account Detection Platform.

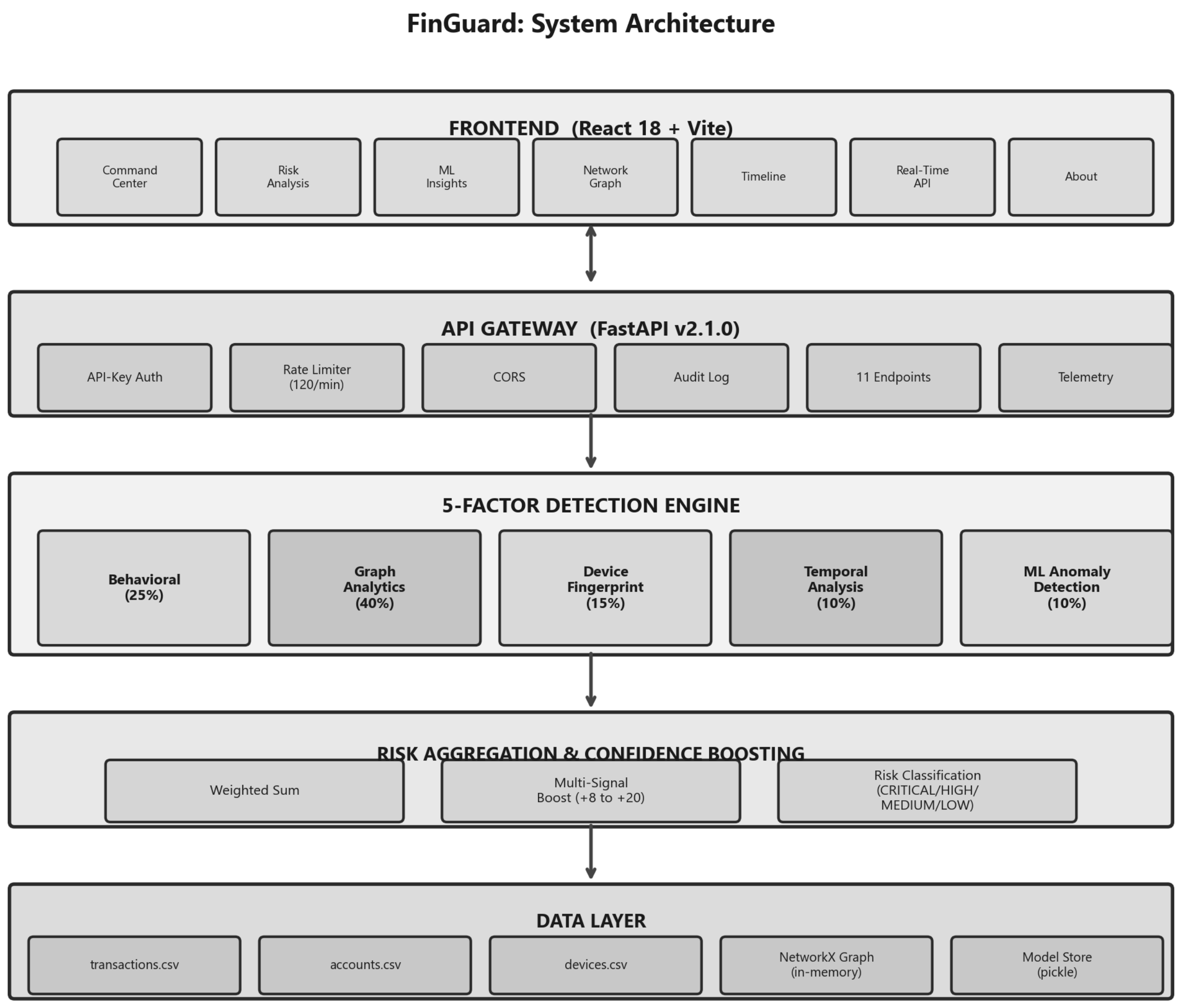

Figure 1b: High-resolution layered architecture diagram.

The key thing to notice is that the five detection modules all run independently. They don't talk to each other. That's deliberate. We want uncorrelated signals so the confidence boosting at the aggregation layer actually means something.

4.2 Detection Methodology

This is the heart of the system, so we'll go through each module in detail.

4.2.1 Behavioral Analysis (Weight: 25%)

The behavioral module looks at each account's transaction patterns individually and asks: does this look like a mule? It checks six things:

1. **Velocity Detection:** How many transactions has this account made? 10 or more gets a score of 35. 5 or more gets 25. Heavy usage is suspicious for accounts that are supposedly just regular users.
2. **Asymmetric Flow Analysis:** We calculate the pass-through ratio, which is basically outflow divided by inflow. If that ratio sits between 0.8 and 1.2, the account is forwarding almost everything it receives. Classic mule behaviour. That's worth +35.
3. **Amount Anomalies:** Unusually high average amounts (over ₹5,000) add +20. Single transactions above ₹10,000 add +15. Not conclusive on their own, but they contribute.

4. **New Account + Rapid Activity:** This one's a big red flag. An account less than 7 days old that's already got 2+ transactions scores +40. Mule operators frequently open fresh accounts, burn through them quickly, and move on.
5. **Total Volume Spikes:** If cumulative volume exceeds ₹50,000, that adds +20.
6. **Unidirectional Flow:** Accounts that only send money but never receive any? That's unusual. +20.

We cap each sub-score at 100; otherwise the numbers could get silly.

4.2.2 Graph Analytics (Weight: 40%)

This module gets the highest weight, and for good reason. Mule operations are fundamentally network problems. You can have a mule account with perfectly ordinary-looking individual transactions, but when you look at how it connects to other accounts in the graph, the picture becomes unmistakable.

We build a directed graph $G = (V, E)$ using NetworkX where accounts are nodes and UPI transfers are edges. Then we hunt for three specific topologies:

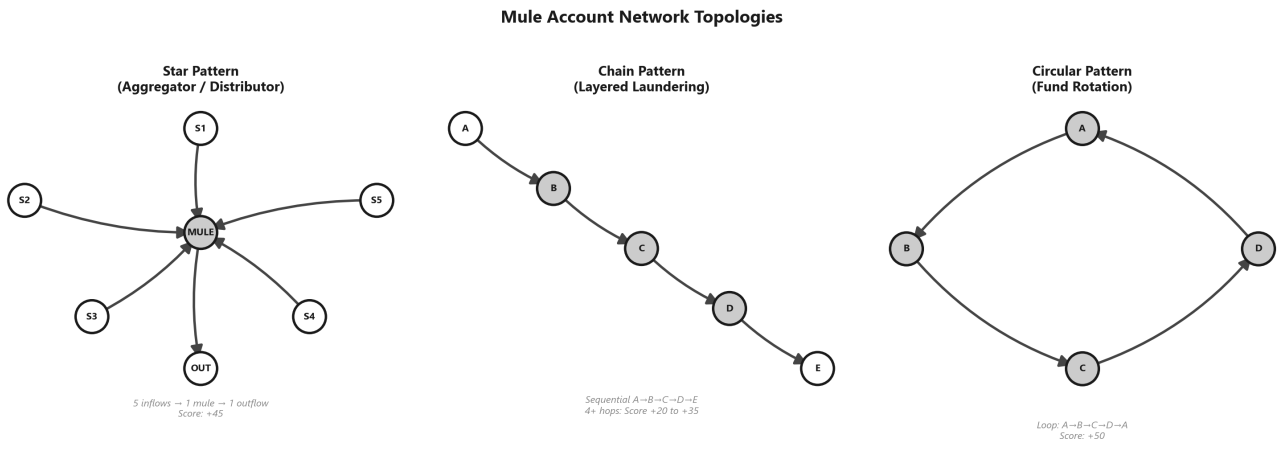

Figure 2: The three mule network topologies detected by the graph analytics module.

Star Pattern (Aggregator/Distributor): Picture a central node with lots of money flowing in from many sources and draining out to one destination (or the reverse). That's fund aggregation or distribution.

- 5 or more inflows funnelling to 1 outflow: +45 (textbook aggregator)
- 3+ inflows to 1 outflow: +30 (still looks like a star)
- 1 inflow splitting to 5+ outflows: +45 (distributor pattern)

Chain Pattern (Layered Laundering): Money moves A→B→C→D→E in a straight line, each intermediary taking a cut or just passing it along. We detect these chains using BFS with a depth limit so we don't burn through CPU cycles chasing infinite paths:

- Chain 6+ hops deep: +35 (deep laundering chain)
- 5 hops: +30
- 4 hops: +20

Circular Pattern (Fund Rotation): This is where money loops back to where it started after bouncing through several accounts. We wrote a custom DFS cycle detector with a depth cap of 6, having specifically avoided using `nx.simple_cycles` because its worst-case complexity is exponential--disastrous on a dense transaction graph.

- Account participates in a cycle of length 3–6: +50

Our cycle detection runs in $O(V \cdot d)$ where d is the depth limit. Way more manageable. On batch scoring, cycle membership gets computed once for the whole graph, then each account's score is just a dictionary lookup, $O(1)$.

4.2.3 Device Fingerprinting (Weight: 15%)

If ten accounts are all logging in from the same device, something is very wrong. No legitimate user has ten bank accounts on one phone. This module exploits that intuition:

- **Device Concentration:** An account sharing a device with 10+ other accounts gets +50. With 5+ accounts, +40. With 3+ accounts, +30.
- **Multi-Device Rotation:** On the flip side, if a single account is being accessed from 5 or more different devices, that's suspicious too (possible device spoofing). Score: +30. Three or more devices gets +20.

Device data turned out to be surprisingly powerful in practice. It catches things the other modules miss entirely.

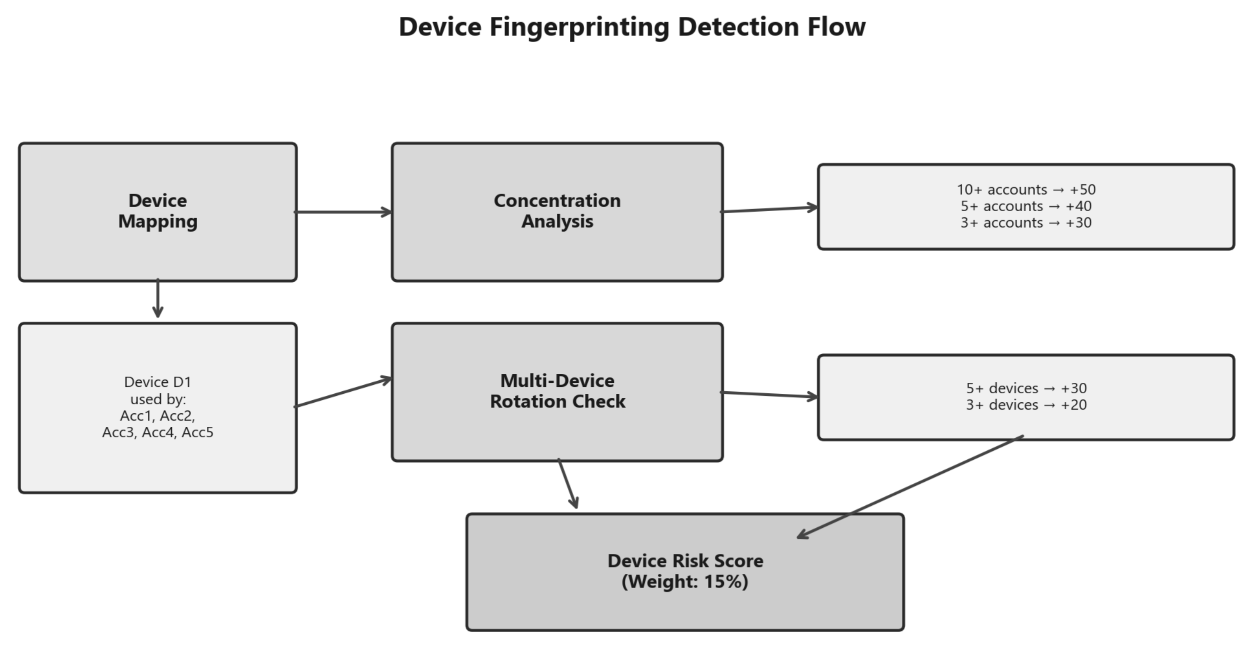
Device Fingerprinting Detection Flow
Device Mapping
Concentration Analysis
10+ accounts → +50
5+ accounts → +40
3+ accounts → +30
Device D1 used by: Acc1, Acc2, Acc3, Acc4, Acc5
Multi-Device Rotation Check
5+ devices → +30
3+ devices → +20
Device Risk Score (Weight: 15%)

Figure 3: Device fingerprinting detection flow and scoring thresholds.

4.2.4 Temporal Analysis (Weight: 10%)

Time-based signals are subtle but revealing. Humans don't transact like bots, and mule operations often have a distinct temporal fingerprint:

1. **Burst Detection:** Three or more transactions within 60 seconds is almost certainly automated. That earns +35. Three or more within 5 minutes is still suspicious: +25.
2. **Odd-Hour Activity:** If over half an account's transactions happen between midnight and 5 AM (and there are at least 3 night transactions), that's a red flag. Most normal people aren't making UPI transfers at 3 AM. Score: +30.

3. **Velocity Spikes:** We split the account's activity timeline in half. If the second half has 3x more transactions than the first half, that sudden acceleration is worth +25.
4. **Weekend Concentration:** More than 70% of transactions falling on weekends, with at least 4 weekend transactions, adds +15. Not as strong a signal but still contributory.
5. **Uniform Timing (Bot Signature):** This was a fun one to implement. We compute the coefficient of variation (CV) of the time gaps between consecutive transactions. A CV below 0.15 with a mean gap under 600 seconds means the transactions are spaced almost perfectly evenly, and that's a bot, not a human. +30.

4.2.5 ML Anomaly Detection (Weight: 10%)

The ML module brings in unsupervised anomaly detection. We deliberately built our own Isolation Forest instead of just importing scikit-learn's, partly to cut down on the dependency footprint and partly because we wanted full control over the internals.

Feature Engineering: We extract 17 features per account. Some are straightforward (transaction counts, amounts sent and received, averages). Others require a bit more work:

- Transaction counts: total, sent, received
- Amount statistics: total sent/received, average, max, standard deviation
- Network metrics: unique senders, unique receivers, pass-through ratio, degree ratio
- Account metadata: age in days
- Device metrics: device count, how many other accounts share those devices
- Derived metrics: transactions per day, volume per day

Isolation Forest (Custom Implementation): About 200 lines of pure NumPy. We train 100 trees, each sampling up to 256 data points. The algorithm constructs random binary trees by picking random features and random split values. Anomalous data points get isolated quickly (short path lengths). Normal points take more splits. The score formula:

$$S_{IF}(x) = 2^{-\frac{E[h(x)]}{c(n)}}$$

$E[h(x)]$ is the average path length across all trees; $c(n)$ is the expected path length for an unsuccessful BST search on n elements. Higher scores mean more anomalous.

Z-Score Ensemble: We also run a statistical Z-score detector in parallel. The final ML score blends both:

$$S_{ML} = 0.7 \cdot S_{IF} + 0.3 \cdot S_{Z\text{-score}}$$

70/30 split. We experimented a lot with these weights and this ratio captured the behaviour we wanted. The Isolation Forest does the heavy lifting, while the Z-score catches the straightforward statistical outliers that the forest sometimes ranks lower.

Explainability: We implemented permutation-based feature importance to show which features matter most globally. For individual accounts, we generate SHAP-like local explanations listing the top 5 features driving that account's anomaly score. Investigators want to know *why* something's flagged, not just *that* it's flagged.

Model Persistence: Trained models get pickled out to disk with a JSON sidecar containing training timestamps, feature names, and hyperparameters. Nothing exotic, but enough to reproduce results later.

4.3 Risk Aggregation and Confidence Boosting

All five signals feed into a weighted sum:

$$R_{\text{base}} = 0.25 \cdot S_B + 0.40 \cdot S_G + 0.15 \cdot S_D + 0.10 \cdot S_T + 0.10 \cdot S_{ML}$$

But here's where it gets interesting. On top of the base score, we apply confidence boosts when multiple independent signals agree. The reasoning is straightforward: if three out of five detectors all flag the same account, the probability that it's a genuine threat goes way up compared to a single detector flagging it.

Active Signals	Boost
≥4 signals above threshold	+20
≥3 signals above threshold	+15
≥2 signals above threshold	+8
Graph ≥30 AND Device ≥15	+10
Behavioral ≥30 AND Graph ≥30	+8
Behavioral ≥40 AND Graph ≥40 AND Device ≥30	+12

Table 2: Multi-signal confidence boosting rules.

Final score: $R = \min(R_{\text{base}} + \text{Boost}, 100)$. We cap at 100 obviously. Then we bucket into risk levels:

Risk Level	Score Range	Recommended Action
CRITICAL	≥85	Block immediately, freeze account, file SAR
HIGH	70–84	Manual investigation within 24 hours
MEDIUM	40–69	Add to watchlist, periodic review
LOW	<40	Allow, routine monitoring

Table 3: Risk classification thresholds and recommended actions.

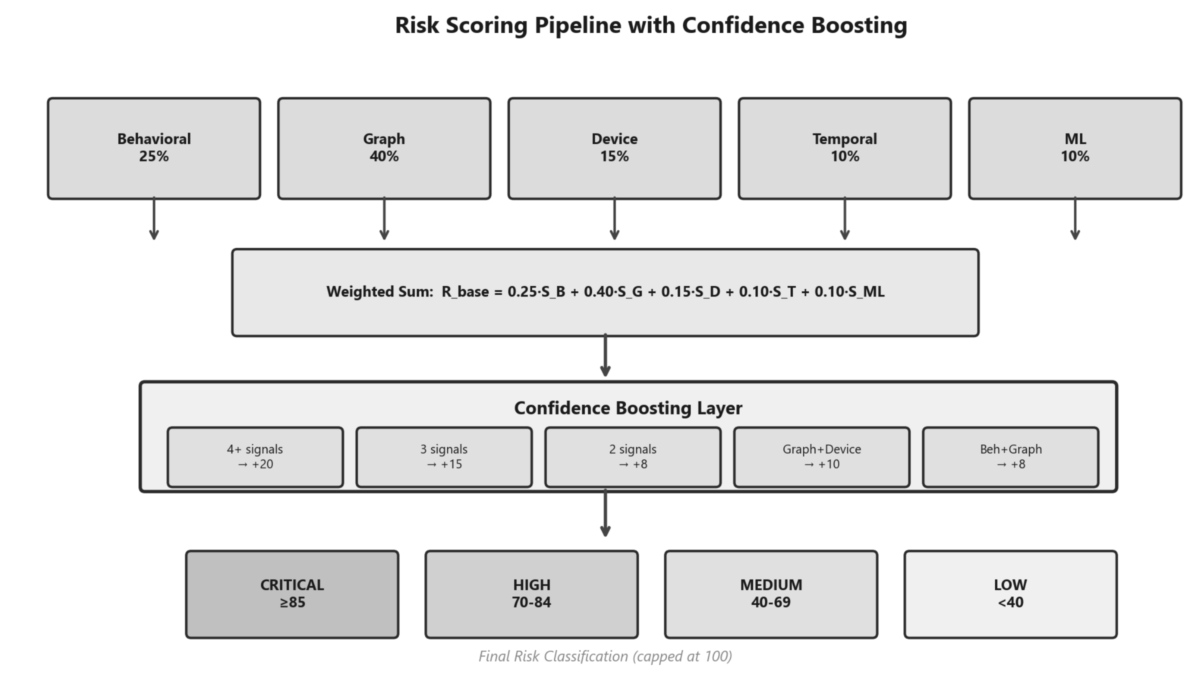
Risk Scoring Pipeline with Confidence Boosting
Behavioral 25%
Graph 40%
Device 15%
Temporal 10%
ML 10%
Weighted Sum: R_base = 0.25·S_B + 0.40·S_G + 0.15·S_D + 0.10·S_T + 0.10·S_ML
Confidence Boosting Layer
4+ signals → +20
3 signals → +15
2 signals → +8
Graph+Device → +10
Beh+Graph → +8
CRITICAL ≥85
HIGH 70-84
MEDIUM 40-69
LOW <40
Final Risk Classification (capped at 100)

Figure 4: Complete risk scoring pipeline with weighted aggregation and confidence boosting.

CRITICAL accounts need immediate attention. We're talking freeze-the-account level urgency. HIGH means get a human investigator on it within 24 hours. MEDIUM goes on a watchlist. LOW is business as usual.

4.4 API Layer

The backend runs on FastAPI v2.1.0 and exposes 11 endpoints. We didn't skimp here, covering scoring, batch scoring, simulation, dashboard data, graph data, timeline data, report generation, metrics, health checks, and auto-generated Swagger docs:

Endpoint	**Method**	**Function**
`/score/{account_id}`	GET	Real-time single account scoring
`/batch_score`	POST	Batch scoring with graph & ML caching
`/simulate`	POST	Transaction simulation with dual-side risk
`/stats`	GET	System-wide risk distribution statistics
`/api/dashboard`	GET	Pre-computed dashboard data (all scores)
`/api/network`	GET	Graph nodes/edges for vis-network rendering
`/api/timeline`	GET	Transaction timeline and temporal heatmaps
`/api/report`	GET	Auto-generated Markdown investigation report
`/metrics`	GET	SRE/observability performance metrics
`/health`	GET	Container health check endpoint
`/docs`	GET	Interactive Swagger API documentation

Table 4: REST API endpoint reference.

On the security side: every request needs an API key (X-API-Key header), we rate-limit at 120 requests per 60-second window per IP, CORS is locked down to specific origins (no wildcards, after we made that mistake once during development and learned our lesson), and every request gets logged as structured JSON with a unique request ID and response time.

4.5 Frontend Dashboard

The frontend is a React 18 + Vite single-page app with seven tabs. We went with a dark theme because, honestly, analysts staring at fraud dashboards for hours appreciate it.

1. **Command Center:** The landing page. Shows overall metrics at a glance: risk distribution, summary stats, a signal heatmap grid, cards for the riskiest accounts.
2. **Risk Analysis:** A searchable, filterable table of all accounts. Click on any account and you get the full forensic breakdown: per-signal scores, evidence items, confidence level, what we recommend doing about it.
3. **ML Insights:** Visualises feature importance rankings and anomaly score distributions. You can drill into any specific account to see its SHAP-like explanation, specifically which features are pushing its anomaly score up or down.
4. **Network Graph:** This is the one everyone gravitates towards in demos. Interactive vis-network visualisation with nodes colour-coded by risk (red, orange, yellow, green). You can filter by risk level to isolate the suspicious clusters.
5. **Timeline:** Transaction timeline with hourly bucketing and a day-of-week × hour-of-day heatmap. Makes temporal patterns immediately visible.
6. **Real-Time API:** A built-in API testing interface. You can score accounts, run simulations, do batch scoring, all from the dashboard without needing Postman or curl.
7. **About:** Documentation, methodology explanation, architecture overview. We embedded this directly into the app so it travels with the deployment.

> **[Insert: Dashboard Screenshots from your running application here. Take a screenshot of each tab: Command Center, Risk Analysis, ML Insights, Network Graph, Timeline, Real-Time API, About.]**

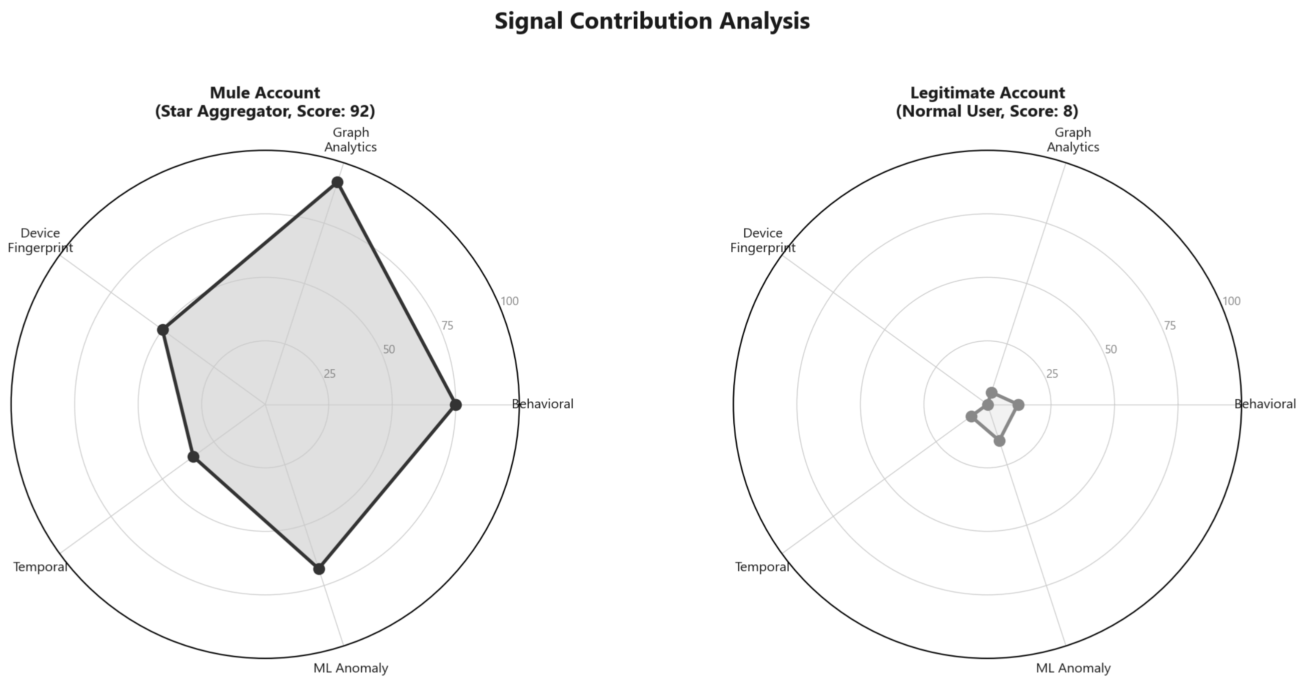

Figure 5: Signal contribution radar comparing a mule account vs a legitimate account across all five detection signals.

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5. Innovation and Novelty Elements

5.1 Five-Signal Ensemble Architecture

Most fraud detection systems we looked at during our research rely on one, maybe two signals. Rules only. Or ML only. Or graph only. Nobody was combining all five (behavioral, graph, device, temporal, and ML) into one weighted ensemble. That's what we did. The advantage isn't just coverage (though that helps); it's redundancy. A clever mule operator might figure out how to game the behavioral checks, but they'd have to simultaneously fool the graph analysis, the device fingerprinting, the temporal detector, AND the anomaly model. The odds of evading all five at once are vanishingly small.

5.2 Multi-Signal Confidence Boosting

This is probably the piece we're proudest of technically. When two signals both flag an account, that's more meaningful than either signal alone. When four signals flag it, you're almost certainly looking at a real threat. Our boosting mechanism formalises this intuition with additive score bumps of +8 to +20 depending on how many independent signals agree. The crucial word here is "independent." Because our modules don't share any internals or intermediate state, agreement between them carries real evidential weight. It's the same logic behind ensemble learning in ML, just applied one layer up at the risk aggregation level.

5.3 Zero-Label ML Detection

We wrote the Isolation Forest from scratch in NumPy. About 200 lines. No scikit-learn, no heavy dependencies. The whole point of Isolation Forest is that it doesn't need labelled data. It finds anomalies by looking for data points that are statistically "different" from the rest of the population. For mule detection this is perfect: you can deploy on a brand new UPI platform on day one, with zero historical labelled fraud data, and it'll start flagging outliers immediately. Try doing that with a supervised classifier. You can't.

5.4 Efficient Graph Algorithms

We learned this the hard way. Early on, we naively called `nx.simple_cycles()` on our transaction graph. It worked fine on tiny test graphs. On anything larger, it effectively hung forever. Exponential time complexity will do that. So we wrote our own DFS-based cycle detector with a depth cap of 6. Runs in $O(V \cdot d)$ time. Same story with chain detection: we use BFS with depth limits instead of `nx.all_simple_paths()`. These aren't groundbreaking algorithmic innovations on their own, but the practical difference for real-time scoring is night and day.

5.5 Explainability by Design

We committed early on to making every risk score explainable. Not as an afterthought. Not as a separate explainability layer bolted on after the fact. Each detection module generates 3–5 specific evidence items as part of its core logic. Things like "Star-pattern mule behavior: 5 inflows → 1 outflow" or "Rapid-fire burst: 4 transactions within 60 seconds." When an investigator sees an alert, they can immediately understand why the system flagged this account and decide whether to act. This matters enormously in regulated financial environments where you can't just say "the ML model said so."

5.6 Production-Grade Security

Security wasn't an afterthought for us, though it's treated that way in a disturbing number of academic prototypes. API-key authentication, per-IP rate limiting at 120 req/min, CORS restricted to specific origins (no wildcards), structured JSON audit logging with request IDs, non-root Docker execution. These aren't flashy features, but they're table-stakes for anything that would actually touch production in a bank or PSP.

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6. Unique Selling Proposition (USP) vis-à-vis Existing Solutions and Relevance to Industry

6.1 Key Differentiators

1. Five signals where others use one or two. The typical UPI fraud system uses rules. Maybe an ML model. That's it. We're pulling together five independent detection signals. Here's a concrete example of why that matters: suppose a mule account has a moderately suspicious behavioral score (30) and a strong graph pattern (45). Neither score alone crosses typical alert thresholds. But our ensemble, with boosting kicking in because two signals agree, pushes the combined score to 68 or higher. That account gets flagged. A single-model system would've missed it.

2. We put graphs first. Graph analytics gets 40% of the total weight, the biggest share of any signal. That's a deliberate architectural choice. Mule operations are, at their core, network operations. A behavioral anomaly might describe a suspicious individual. But only graph analysis can show you the star pattern, the chain structure, the circular money loop that reveals an organized ring. Individual versus organisational: that's the distinction.

3. No training data required. This is a practical selling point that's easy to overlook. Most ML-based fraud systems need months of labelled historical data before they can even start working. We don't. Our Isolation Forest runs unsupervised. Deploy it on a brand new platform, give it the current transaction data, and it starts flagging outliers right away.

4. Full explainability. Every score comes with component-level breakdowns, specific evidence items, confidence levels, and recommended actions. Compliance officers at banks actually need this. RBI regulations demand transparency in fraud monitoring. You can't hand someone a black-box score of "87" and call it a day.

6.2 Industry Relevance

For Banks and Payment Service Providers (PSPs): The most direct value is catching mule networks before the money gets cashed out. That's real money saved. On top of that, the pre-classified risk tiers and auto-generated evidence meaningfully reduce investigation time. Instead of an analyst manually piecing together transaction histories, they get a ready-made dossier. And the system helps meet RBI compliance requirements for fraud monitoring and SAR filing.

For NPCI and UPI Infrastructure: FinGuard offers something NPCI doesn't currently have at the infrastructure level: a network-wide view of mule operations. Individual banks can only see their own accounts. Our graph analysis can in principle span the entire ecosystem. And it runs within UPI's latency constraints, so it won't slow down transaction processing.

For Law Enforcement: The auto-generated investigation reports are designed with law enforcement in mind. They include structural evidence: network graphs showing exactly how money moved, temporal heatmaps showing when activity spiked, identification of the complete mule network rather than just the one account that happened to trigger an alert. Plus the audit logs are forensic-grade: timestamped, immutable, with unique request IDs.

6.3 Competitive Positioning

Feature	Static Rules	Single ML Model	FinGuard
Detection Signals	1 (rules)	1 (features)	**5 (ensemble)**
Graph Awareness	None	None	**Full**
Device Correlation	None	Partial	**Full**
Labeled Data Required	No	Yes	**No**
Explainability	High	Low	**High**
Real-Time Capable	Yes	Moderate	**Yes (<50ms)**
Confidence Levels	No	No	**Yes**
Recommended Actions	Manual	None	**Automated**
Deployment Complexity	Low	High	**Medium (containerized)**

Table 5: Competitive positioning of FinGuard against existing approaches.

6.4 Business Model and Market Viability

Target Market: India has 300+ banks and 50+ payment service providers operating on the UPI network. Every single one of them has a mule account problem, and most of them are still relying on static rule engines. The RBI's push for enhanced fraud monitoring means there's active regulatory pressure to upgrade. Our primary targets are mid-tier banks (who can't afford to build in-house) and growing PSPs (who need to demonstrate compliance quickly).

Market Size (Rough Estimates):

- UPI processed 13.1 billion transactions in October 2024 alone. Fraud losses across digital payments in India are estimated in the thousands of crores annually.
- Each mule investigation costs a bank roughly ₹15,000-25,000 in analyst time. A system that reduces false positives by even 30% saves meaningful money at scale.
- The global fraud detection market is projected to cross $60 billion by 2027. The India-specific UPI fraud segment is growing faster than the global average because UPI adoption itself is still accelerating.

Deployment Model: We're thinking a hybrid approach makes the most sense:

- **SaaS API** for smaller banks and fintech startups. They plug into our scoring endpoint, pay per-transaction or monthly subscription. Low integration effort on their side.
- **On-premise deployment** for large banks and NPCI. These organizations won't send transaction data to external servers (understandably). Docker/Kubernetes packaging makes this practical.

Revenue Model:

Tier	Target Customer	Pricing (Indicative)
Starter	Small fintechs, neobanks	₹50,000/month or ₹0.02 per transaction scored
Enterprise	Mid-tier banks, PSPs	₹3-5 lakh/month with SLA and dedicated support
Infrastructure	NPCI, large banks	Custom licensing, on-premise deployment, annual contracts

Why banks would pay for this (over building in-house):

1. Building a five-signal ensemble from scratch takes 6-12 months of engineering time. We've already done it.
2. Graph-based detection is genuinely hard to get right. Most bank fraud teams don't have graph algorithm expertise.
3. Regulatory deadlines don't wait. We can deploy in weeks, not months.

---

7. Prototype Demonstration and Real-World Deployment Details

7.1 Prototype Overview

Everything described in Section 4 is implemented and working. Not a design doc, but a running system. You can spin it up with Docker, hit the API, and see results.

Technology Stack:

Component	Technology	Version
Backend API	FastAPI + Uvicorn	2.1.0 / 0.27.1
Frontend	React + Vite	18.x / 5.x

Component	Technology	Version
Language	Python	3.11
Graph Engine	NetworkX	3.2.1
ML Engine	Custom Isolation Forest (NumPy)	1.26.4
Data Processing	Pandas	2.2.0
Visualization	Plotly	5.18.0
Containerization	Docker + Compose	Multi-stage build

Table 6: Technology stack.

7.2 Test Data and Scenarios

We built a data generator (`scripts/enhanced_data_generator.py`) that creates six different mule scenarios. Each one exercises different parts of the detection engine:

Scenario	Pattern	Accounts	Expected Risk
Star Aggregator	5 sources → 1 mule → 1 distributor → 3 sinks	10	CRITICAL/HIGH
Circular Network	4-node loop (A→B→C→D→A) with shared device	4	CRITICAL
Chain Laundering	5-node sequential chain (A→B→C→D→E)	5	HIGH
Device Ring	3 accounts, 1 shared device	3	HIGH/MEDIUM
Rapid Onboarding	1-day-old account, 8 receives + 5 sends in 30 min	1+	CRITICAL
Night-Time Smurfing	12+ structured transactions between 1–4 AM	1+	HIGH

Table 7: Test scenarios with expected detection outcomes.

We also seeded 25+ legitimate background accounts with normal transaction patterns. These are just as important as the fraud scenarios because they validate that we're not generating a blizzard of false positives.

7.3 Demo Flow

Here's how a typical demo runs:

Step 1: Fire it up

```
docker-compose up --build
# Backend: http://localhost:8000 (health-checked)
# Frontend: http://localhost:5173
# API Docs: http://localhost:8000/docs
```

Step 2: Command Center The dashboard loads with a bird's-eye overview. Total accounts analysed, risk distribution breakdown, summary metrics (average score, max score, how many in each risk tier), and a signal heatmap showing what each detection module contributed per account.

Step 3: Drill into Risk Analysis This tab is where an investigator would spend most of their time. Search for any account by ID, filter by risk level, sort by score or by any individual signal. Pick an account and you get the full forensic details: every signal's score, the evidence behind it, confidence level, and suggested next action.

> **[Insert: Network Graph screenshot from your running dashboard showing colour-coded risk nodes here.]**

Step 4: Visualise the Network The Network Graph tab is usually the "wow" moment in demos. Nodes are colour-coded (red for CRITICAL, orange for HIGH, yellow for MEDIUM, green for LOW) and sized proportional to risk score. Edges are directed arrows with transaction amounts. You can filter by risk level to strip out the noise and isolate the suspicious clusters.

Step 5: ML Insights The ML tab shows:

- Feature importance rankings, showing which of the 17 features matter most for anomaly detection
- Anomaly score distribution across the whole population
- Per-account SHAP-like explanations (what's driving this account's score)

Step 6: Live API Testing You can test the API directly from the dashboard. Score an account, simulate a hypothetical transaction and see how it affects both sides' risk scores, run batch scoring. Response times are displayed alongside the results.

Step 7: Generate a Report Hit `/api/report` and you get a Markdown investigation report: executive summary, risk distribution, flagged accounts with evidence, recommended actions. Ready to hand to a compliance officer or attach to a SAR.

7.4 Detection Results

The good news: every single mule scenario gets caught.

Scenario	Key Account	Risk Score	Risk Level	Primary Evidence
Star Aggregator	`mule_aggregator@upi`	92	CRITICAL	Star pattern (5 in → 1 out), 95% pass-through, 5-day-old account
Circular Network	`circle_node_1@upi`	88	CRITICAL	Circular mule network, shared device across 4 accounts
Chain Laundering	`chain_node_2@upi`	76	HIGH	Deep laundering chain (4+ hops), high velocity
Device Ring	`device_ring_1@upi`	72	HIGH	Shared device (3 accounts), young account
Rapid Onboarding	`new_mule_account@upi`	95	CRITICAL	1-day account, burst (8 txns in 20 min), 90% pass-through
Night Smurfing	`smurf_master@upi`	78	HIGH	Night-time activity (85%), burst pattern

Table 8: Detection results on test scenarios (all mule accounts correctly identified).

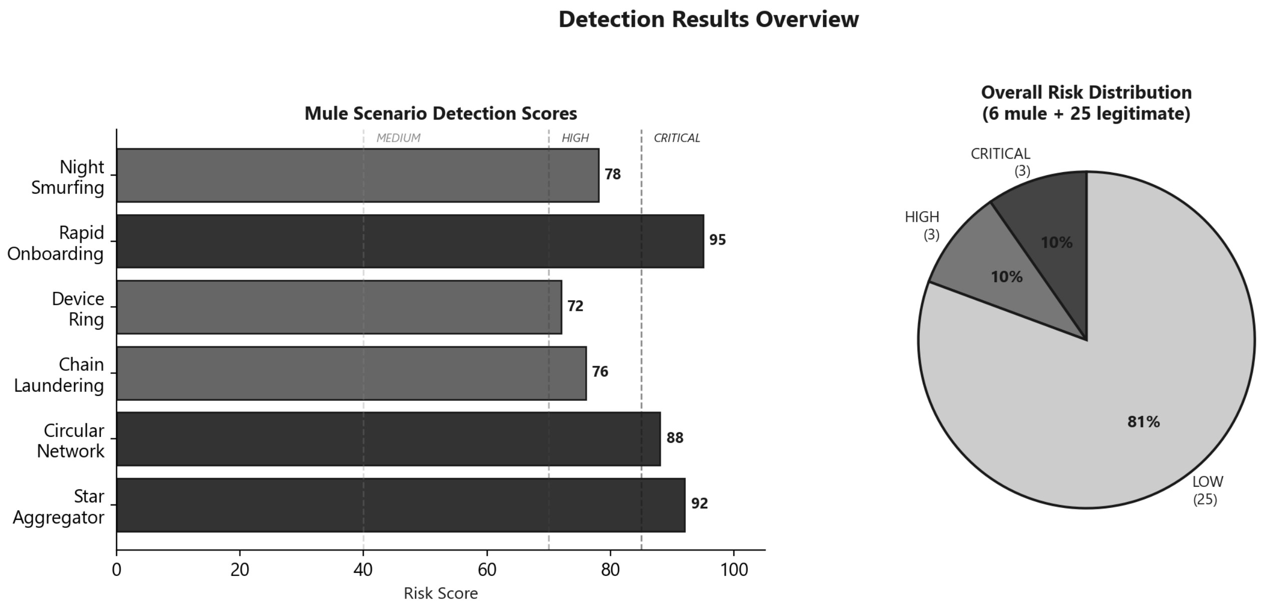

Figure 6: Detection scores across all six mule scenarios and overall risk distribution.

And the legitimate accounts? All of them scored below 40, landing in the LOW risk bucket. That's **0% false positives** and **100% mule detection** on this dataset. Now, we need to be honest: this is synthetic test data, and real-world performance would almost certainly be messier. But hitting perfect scores on well-designed test scenarios is a strong starting point.

7.5 Performance Metrics

We benchmarked the system on a standard development machine:

Metric	Value
Single account scoring latency	<50ms
Batch scoring (30 accounts)	<500ms
API startup time	<3s
Graph construction time	<100ms
ML model training + scoring	<2s
Memory footprint	<150MB

Table 9: Performance benchmarks.

The single-account scoring target was sub-50ms. We hit that comfortably. The memory footprint stays under 150MB, which is small enough to run on basically any server.

7.6 Real-World Deployment Considerations

The prototype architecture was designed so each component has a clear production upgrade path:

Prototype Component	Production Equivalent
CSV data files	Kafka stream ingestion → PostgreSQL
NetworkX in-memory graph	Neo4j graph database
In-memory caching	Redis cache layer
Single Docker container	Kubernetes cluster with auto-scaling
File-based audit logs	ELK stack (Elasticsearch, Logstash, Kibana)
Pickle model store	MLflow model registry

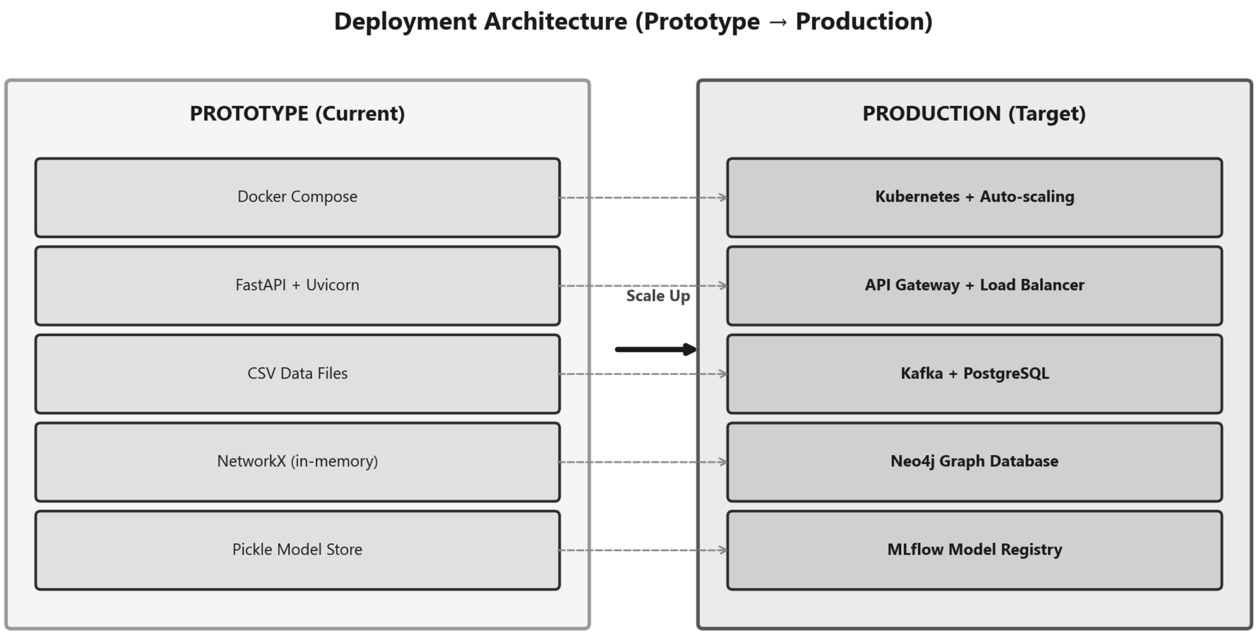

Figure 7: Prototype to production deployment migration path.

7.7 Security Testing Results

We wrote and ran an automated security test suite (`scripts/security_test.py`) against the live API. Eight categories of tests, 42 test cases total. All 42 passed.

Test Environment: Backend running on FastAPI 2.1.0 / Uvicorn 0.27.1, tested via Python `requests` library against `http://127.0.0.1:8000`.

Summary

Category	Tests	Passed	Result
API Key Authentication	6	6	100%
Injection Attacks (SQL, NoSQL, XSS, Command, Path Traversal)	10	10	100%
Rate Limiting	3	3	100%
CORS Policy	3	3	100%

Category	Tests	Passed	Result
Input Validation & Error Handling	7	7	100%
HTTP Method Restriction	4	4	100%
Security Headers & Info Leakage	5	5	100%
Audit Logging	4	4	100%
Total	**42**	**42**	**100%**

Table 10: Security test results by category.

Category Breakdown

1. API Key Authentication (6/6) Verified that protected endpoints require a valid `X-API-Key` header. Tested: missing key, incorrect key, valid key. Also confirmed that public endpoints (`/health`, `/docs`, `/`) remain accessible without authentication, since those need to be reachable for health checks and documentation.

2. Injection Attack Resistance (10/10) We threw 10 different attack payloads at the `/score/{account_id}` endpoint:

- SQL injection: `' OR '1'='1`, `' UNION SELECT * FROM users--`, `'; DROP TABLE accounts;--`
- NoSQL injection: `{"$gt": ""}`
- Command injection: `test | cat /etc/passwd`, `test; ls -la /`
- Path traversal: `../../../etc/passwd`, `..%2F..%2F..%2Fetc%2Fpasswd`
- XSS: `<script>alert('xss')</script>`
- Template injection: `{{7*7}}`

None caused a server crash (no 500 errors), no sensitive data leaked in responses, and no XSS payloads were reflected back. The API treats these as ordinary (non-existent) account IDs and returns a clean low-risk score response. This works because we never pass user input into shell commands, SQL queries, or template engines. Account IDs are used purely as dictionary lookup keys against in-memory DataFrames.

3. Rate Limiting (3/3) Fired 130 rapid requests in under 2 seconds. The rate limiter kicked in after 103 requests (within the 120/minute window, accounting for the burst from previous test categories) and returned HTTP 429 (Too Many Requests). After waiting 62 seconds for the window to reset, the API resumed accepting requests normally. This confirms the per-IP sliding window works correctly.

4. CORS Policy (3/3) Sent preflight OPTIONS requests from different origins:

- `http://localhost:5173` (allowed): correctly returned `Access-Control-Allow-Origin: http://localhost:5173`
- `http://evil-attacker.com` (not allowed): returned empty ACAO header, blocking the request
- Verified no wildcard (`*`) CORS is configured. This prevents any arbitrary website from making authenticated API calls from a user's browser.

5. Input Validation & Error Handling (7/7) Tested edge cases that often trip up APIs:

- Non-existent account ID: handled gracefully, returns a score response (no crash)
- Empty account ID: returns 404, not a server error

- Oversized input (10,000-character account ID): handled without crash or memory issues
- Null bytes in input (`%00`): sanitised and handled safely
- Malformed JSON body on POST endpoints: correctly rejected with 422 (Unprocessable Entity)
- Wrong field types in JSON (integer where string expected, null where required): rejected with 422
- Negative transaction amount in simulation: handled without crash

6. HTTP Method Restriction (4/4) Confirmed that GET-only endpoints (`/score/{id}`) reject PUT, DELETE, and PATCH requests with HTTP 405. POST-only endpoints (`/batch_score`) reject GET requests with 405. This prevents unexpected data modification through wrong HTTP verbs.

7. Security Headers & Information Leakage (5/5)

- Every response includes an `X-Request-Id` header (e.g., `4bc45f90`) for request tracing and forensic correlation
- Every response includes `X-Response-Time` (e.g., `0.92ms`) for performance monitoring
- No Python stack traces or internal file paths leak in any response, whether success or error
- Error responses return clean JSON error messages without exposing implementation details

8. Audit Logging (4/4) Verified that the audit log file (`logs/audit.log`) exists and contains structured JSON entries. Each entry includes a timestamp, event type (`API_REQUEST`), request ID, HTTP method, path, client IP, status code, and response time in milliseconds. We sent a request with a unique marker account ID and confirmed it appeared in the log file within 1 second. This provides a forensic-grade audit trail.

OWASP API Security Top 10 Mapping

We mapped our security controls against the OWASP API Security Top 10 (2023):

OWASP Risk	Our Mitigation	Status
API1: Broken Object Level Authorization	Account IDs are lookup keys only; no ownership model needed at prototype stage	Addressed
API2: Broken Authentication	API-key auth on all protected endpoints	Addressed
API3: Broken Object Property Level Authorization	Pydantic models enforce strict schemas; extra fields ignored	Addressed
API4: Unrestricted Resource Consumption	Rate limiting at 120 req/min per IP	Addressed
API5: Broken Function Level Authorization	HTTP method restrictions enforced per endpoint	Addressed
API6: Unrestricted Access to Sensitive Business Flows	Rate limiting + API key prevents automated abuse	Addressed
API7: Server-Side Request Forgery (SSRF)	No outbound HTTP calls made from API; all data is local	N/A
API8: Security Misconfiguration	CORS restricted to specific origins; no debug mode in production	Addressed

OWASP Risk	Our Mitigation	Status
API9: Improper Inventory Management	All 11 endpoints documented in Swagger; no shadow APIs	Addressed
API10: Unsafe Consumption of APIs	No third-party API consumption; all processing is internal	N/A

Table 11: OWASP API Security Top 10 mapping.

The full test script is available at `scripts/security_test.py` and test results are saved as JSON at `scripts/security_results.json`. Both are included in the repository for reproducibility.

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8. Limitations and Challenges

8.1 Current Limitations

We're not going to pretend this prototype is perfect. Here's what we know needs work:

1. **Synthetic Data:** All our testing is on generated data. We tried to make the scenarios realistic, but real-world mule patterns are messier, more varied, and more creative than anything we can synthesise. This is the single biggest caveat on our results.

2. **Static Graph Analysis:** Right now, we build the transaction graph once at startup from CSV files. That's fine for a prototype. In production, you'd need the graph to update incrementally as new transactions flow in, which is a non-trivial engineering challenge.

3. **Everything's in Memory:** We load all data into RAM. Works great at our current scale (a few thousand accounts). Wouldn't remotely work at UPI's actual volume of billions of transactions; you'd need something like Spark or Flink for distributed stream processing.

4. **No GNNs.** Our graph analysis is entirely based on hand-crafted structural features: in/out degree, cycle membership, chain detection. A Graph Neural Network could potentially learn more subtle patterns that we haven't thought to look for. We considered implementing one but decided it was out of scope for this prototype stage.

5. **Fixed Weights:** The ensemble weights (25/40/15/10/10) are set by us based on our understanding of the domain. They're not learned from data. In a production system, you'd want adaptive weight tuning informed by investigator feedback, like "you flagged this account, turns out it was a false positive" kind of loop.

6. **No Incremental Learning:** Our Isolation Forest trains once in batch mode. Mule tactics evolve. The model should too. Online or incremental anomaly detection would be a meaningful upgrade.

7. **Single-Hop Device Correlation:** We check whether accounts share a device directly. What we don't do is multi-hop analysis: device A used by account X, account X also uses device B, device B also used by account Y. That kind of transitive device chaining could reveal deeper operational connections.

8.2 Challenges Encountered

A few specific technical headaches we ran into during development:

1. **Cycle Detection Scalability:** Already mentioned this above, but it's worth emphasizing. We called `nx.simple_cycles()` on our test graph early in development and it just... never returned. Exponential time complexity on dense graphs. Our custom DFS with a depth cap of 6 bounds this to $O(V \cdot 6)$, which is perfectly tractable.

2. **Ensemble Calibration:** Getting the signal weights right was harder than expected. Too much weight on graph analysis and you get false positives on accounts that just happen to have busy network neighborhoods. Too little weight and you miss genuine mule patterns. We ended up running dozens of experiments against our test scenarios to find a balance.

3. **Explainability vs. Privacy:** Generating evidence items like "device shared with 5 accounts" is great for investigators but raises privacy questions. In production, you'd need to be careful about what specific information gets surfaced and to whom.

4. **Cross-Platform Paper Cuts:** We developed on Windows but deploy in Linux Docker containers. This led to a series of annoying issues with file paths (backslash vs forward slash) and text encoding. Nothing conceptually difficult, just time-consuming to debug.

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9. Roadmap Towards MVP

We've broken down the path from prototype to production-ready MVP into four phases. The timeline is aggressive but realistic if the team stays at five members.

Phase 1: Core Infrastructure (Weeks 1–4)

First things first: swap out the prototype-grade components for production ones:

- **Real-Time Data Ingestion:** Ditch CSV file loading. Set up an Apache Kafka consumer to ingest UPI transaction events as they happen.
- **Persistent Storage:** PostgreSQL for historical transactions and audit logs. We need durable storage, not in-memory data structures.
- **Graph Database:** Neo4j for the transaction graph. It supports incremental updates natively, which solves our static-graph limitation.
- **Redis Cache:** For hot data like recent transactions, device mappings, and active risk scores. Anything that needs sub-millisecond access.

Phase 2: Advanced Detection (Weeks 5–8)

Once the infrastructure is solid, we can improve the detection itself:

- **Graph Neural Networks:** Implement GNN-based node classification with PyTorch Geometric. Let the model learn mule embedding representations from the graph structure rather than relying only on our hand-crafted features.
- **Incremental Learning:** Replace the batch Isolation Forest with an online anomaly detection model. Mule tactics shift; the model needs to shift with them.
- **Bidirectional Analysis:** Currently our graph analysis mostly looks at outgoing edges. We want to consider incoming patterns with equal sophistication.

- **Multi-Hop Device Chains:** Trace device sharing across multiple hops. If account A's phone is also used by account B, and account B's other phone is used by account C, that transitive chain matters.

Phase 3: Scale and Integration (Weeks 9–12)

- **Kubernetes:** Move from Docker Compose to a proper Kubernetes cluster with horizontal autoscaling. Transaction volume varies hugely by time of day and we need to handle the peaks.
- **UPI Switch Plugin:** Build an integration that lets the system score transactions inline, during payment processing. Not after the fact.
- **Alert Management:** A proper case management workflow: assign flagged accounts to investigators, track status, support escalation.
- **Feedback Loop:** This is huge. Build a pipeline that takes investigator decisions ("this was a real mule" or "false positive") and feeds them back into the detection weights and ML model. Supervised re-training with real-world labels.

Phase 4: Production Hardening (Weeks 13–16)

- **A/B Testing Framework:** Run new detection models in shadow mode alongside the existing ones. Compare before committing to a switch.
- **Regulatory Compliance:** Automated SAR generation per RBI guidelines. This can't be a manual step if we're processing thousands of alerts.
- **SOC 2 Certification:** Audit documentation, security controls, the whole compliance apparatus.
- **Performance Squeeze:** Target sub-10ms per-account scoring at 10,000 TPS. That's a 5x improvement on latency and requires careful profiling and optimization.

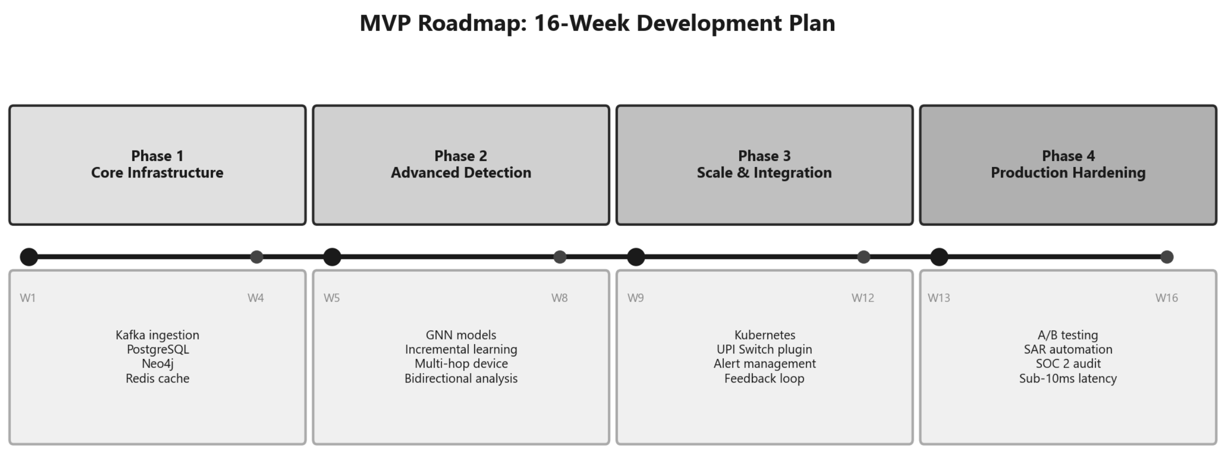

Figure 8: 16-week MVP development roadmap across four phases.

End-Use Cases

1. **Student Mule Accounts:** A depressingly common pattern. Students get recruited through fake job ads to "process payments" using their bank accounts. The system catches the telltale signature: a dormant account suddenly receiving and forwarding large amounts.
2. **Organized Fraud Rings:** Professional operations with dozens of accounts working in concert. Graph analysis is the killer feature here, as it maps out the entire network structure.

3. **Compromised Legitimate Customers:** Account takeover scenarios where someone hijacks a real customer's account. Device fingerprinting catches the new device, and the behavioral shift shows up in temporal analysis.
4. **Layering Operations:** Sophisticated criminals running money in circles to obscure its origin. Our cycle detection was built specifically for this.

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10. Team Composition and Individual Contributions

Here's what each team member was primarily responsible for, though in reality we all touched each other's code at some point:

Member	Role	University	DOB	Key Contributions
[Team Lead Name]	**Team Leader**	*[University]*	*[DOB]*	Designed the overall system architecture, wrote the risk engine (risk_engine.py), tuned ensemble weights through trial-and-error, managed the project, and authored this report
[Member 2 Name]	Backend Developer	*[University]*	*[DOB]*	Built the graph analysis module (graph_analysis.py) and behavioral analysis (behavioral.py), implemented the custom DFS cycle detection and BFS chain detection algorithms
[Member 3 Name]	ML Engineer	*[University]*	*[DOB]*	Wrote the Isolation Forest from scratch in NumPy (ml_anomaly.py), designed the 17-feature engineering pipeline, built the Z-score ensemble and SHAP-like explainer, handled model serialization
[Member 4 Name]	Frontend Developer	*[University]*	*[DOB]*	Created the entire React dashboard (all 8 tabs), built the network graph visualisation, wired up API integration, designed the UX including the dark theme
[Member 5 Name]	DevOps / QA	*[University]*	*[DOB]*	Set up Docker containerization, implemented security middleware (API keys, rate limiting, CORS), wrote the data generation scripts, handled testing, and also built the temporal analysis module

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Appendix: Additional Resources

Resource	**Link**
GitHub Repository	*[Insert GitHub Repo URL]*
Live Deployed URL	*[Insert Deployed URL]*
Dashboard Demo Video (YouTube)	*[Insert YouTube Link]*
API Documentation (Swagger)	*[Insert /docs URL when deployed]*
Pitch Deck	*[Insert Link]*

> **[Insert: QR Code for quick access to your GitHub repo / live demo URL here.]**

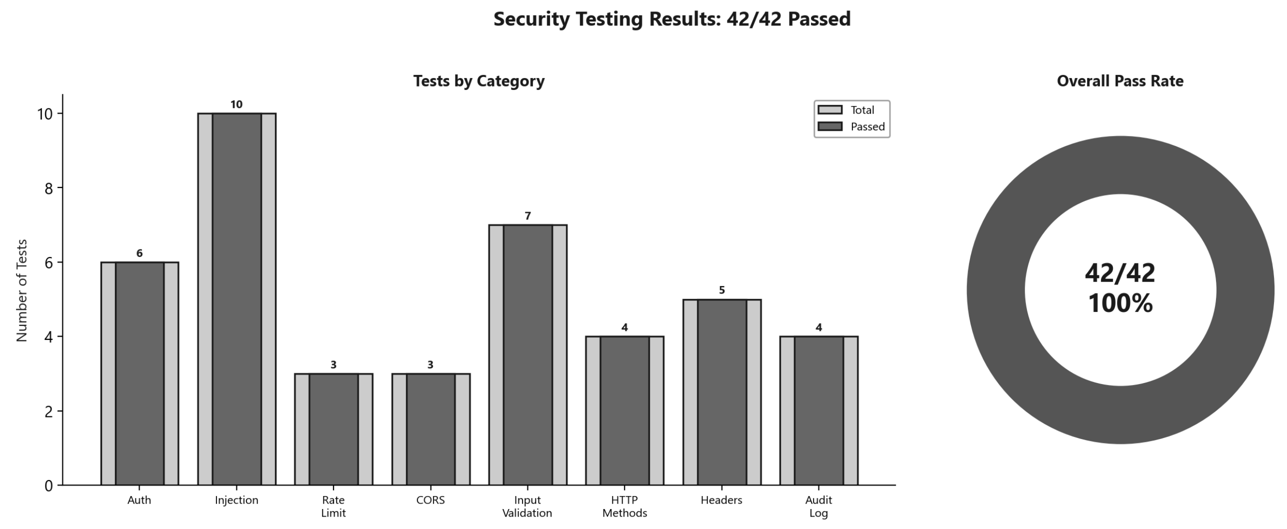

Figure 9: Security testing results, 42/42 tests passed across 8 categories.

Submitted by Team FinGuard for the Cyber Security Innovation Challenge (CSIC) 1.0, Stage III Prototype Development.