SafePayAI - Semi-Technical Pitch

"Every 8 seconds, someone in India falls victim to a UPI fraud. As digital payments skyrocket to billions of transactions daily, fraudsters are evolving faster than traditional rule-based detection systems can keep up. SafePayAI changes that game."

The Problem

Traditional fraud detection relies on **static rules** — if amount > ₹50,000, flag it. But fraudsters adapt instantly.

Core challenges:

- **Class imbalance:** Legitimate transactions outnumber fraudulent ones 1000:1
- **Evolving patterns:** Fraud techniques change weekly
- **False positives:** Blocking legitimate users damages trust
- **Real-time demands:** Decisions must happen in milliseconds

Our Solution

SafePayAI uses a **two-stage AI architecture**:

1️⃣ GAN-Powered Data Augmentation

We use **Generative Adversarial Networks** to solve the class imbalance problem:

- The **Generator** creates synthetic transaction data from random noise
- The **Discriminator** learns to distinguish real vs synthetic data
- This adversarial training produces high-quality synthetic fraud data

> ***Result:*** *Our model learns from 10x more fraud examples without collecting more real fraud cases.*

2️⃣ Random Forest Classifier

Our production model analyzes **22 real-time features** per transaction:

Feature Category	Examples
Behavioral	Transaction frequency, amount deviation from history
Recipient Risk	Trust score, verification status, blacklist status
Contextual	Transaction hour, geo-location anomalies
Device	Device fingerprint, VPN/proxy detection
Historical	Past fraud complaints, account age

Technical Architecture

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│                     React Frontend (Vite)                   │
│          Real-time UI with Socket.IO + Framer Motion        │
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                       │ REST API + WebSocket
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│                  Flask Backend (SocketIO)                   │
│   • Feature extraction from transaction context             │
│   • Real-time risk scoring                                  │
│   • Firebase authentication                                 │
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│                 AI Prediction Engine                        │
│   • Pre-trained Random Forest (scikit-learn)                │
│   • 22-feature normalization pipeline                       │
│   • Probability-based risk levels (LOW/MEDIUM/HIGH)         │
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ML Pipeline Architecture

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║                              TRAINING PIPELINE                           ║
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║  ┌─────────────┐    ┌──────────────────────────────────────────────────┐ ║
║  │ Raw Dataset │    │                GAN Training Module               │ ║
║  │  (CSV/DB)   │───▶│  ┌──────────────┐      ┌──────────────┐          │ ║
║  │             │    │  │  Generator   │◀────▶│ Discriminator│          │ ║
║  │ • Fraud: 1% │    │  │(Creates fake │      │(Detects fake │          │ ║
║  │ • Safe: 99% │    │  │ fraud data)  │      │   vs real)   │          │ ║
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║                     │  │  Synthetic   │                                │ ║
║                     │  │  Fraud Data  │                                │ ║
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║                     ┌────────────────────┐                               ║
║                     │ Augmented Dataset  │                               ║
║                     │ • Fraud: ~50%      │                               ║
║                     │ • Safe: ~50%       │                               ║
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║  │                      Random Forest Training                          │║
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║  │  │ (100 max    │ │ (100 max    │ │ (100 max    │ │ (100 max    │     │║
║  │  │   depth)    │ │   depth)    │ │   depth)    │ │   depth)    │     │║
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║  │                     │  Ensemble Voting Model  │                      │║
║  │                     │   (best_rf_model.pkl)   │                      │║
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║                             INFERENCE PIPELINE                           ║
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║  ┌──────────────────┐                                                    ║
║  │ New Transaction  │                                                    ║
║  │ ──────────────── │                                                    ║
║  │ sender: user@upi │                                                    ║
║  │ receiver: x@upi  │                                                    ║
║  │ amount: ₹50,000  │                                                    ║
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║   │                     Feature Extraction Engine                            │ ║
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║   │  │ Behavioral  │ │  Recipient  │ │ Contextual  │ │ Historical  │        │ ║
║   │  │  Features   │ │   Profile   │ │   Signals   │ │    Data     │        │ ║
║   │  │ (5 values)  │ │ (6 values)  │ │ (5 values)  │ │ (6 values)  │        │ ║
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║   │                     │   22-Feature Vector      │                         │ ║
║   │                     │   [0.2, 0.8, 0.1, ...]   │                         │ ║
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║   │                   Random Forest Prediction                               │ ║
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║   │         │         best_rf_model.pkl                │                     │ ║
║   │         │     model.predict_proba(features)        │                     │ ║
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║   │         │  Probability: [0.15, 0.85]               │                     │ ║
║   │         │  → 85% chance of fraud                   │                     │ ║
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║   │                      Risk Level Classification                           │ ║
║   │                                                                          │ ║
║   │   Probability < 30%   ──▶ ✅ LOW RISK     ──▶  Approve                    │ ║
║   │   Probability 30-70%  ──▶ ⚠️ MEDIUM RISK  ──▶  Warn + Proceed             │ ║
║   │   Probability > 70%   ──▶ 🛑 HIGH RISK    ──▶  Block + Explain            │ ║
║   │                                                                          │ ║
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Key Differentiators

What Others Do	What We Do
Rule-based thresholds	ML-driven pattern recognition
Block & frustrate users	Risk levels with explanations
Batch processing	Real-time prediction (<100ms)
Fixed fraud patterns	GAN-generated evolving patterns
Binary yes/no	Probability scores + risk factors

Demo Highlights

Scenario	Recipient	Result
✅ Send to trusted merchant	trusted.merchant@upi	LOW risk, instant approval
⚠️ Send to suspicious account	suspicious.account@upi	WARNING with risk factors displayed
🛑 Send to known fraud actor	fraud.actor@upi	BLOCKED with explanation

> *"The user sees WHY their transaction is flagged — building trust, not frustration."*

Impact & Metrics

Model Accuracy

~94%

on test data

False Positive Rate

<5%

minimal user friction

Inference Time

<50ms

per transaction

Features Analyzed

22

real-time signals

Vision

Integrate SafePayAI as a **middleware layer** for any payment platform — protecting millions of users with AI-powered, explainable fraud detection.

Q&A Preparation

Potential Question	Answer
Why Random Forest over Deep Learning?	Interpretability + speed. We can explain which features triggered a flag, and inference is instant without GPU.
How does the GAN help?	It synthetically generates realistic fraud scenarios, solving the 1:1000 class imbalance without overfitting.
What about privacy?	All predictions happen locally on transaction metadata — no card/account numbers are stored or transmitted.
How scalable is this?	Flask + pre-loaded model can handle thousands of requests/sec. For production, we'd add Redis caching and load balancing.

> ***Closing Statement:*** *"SafePayAI doesn't just detect fraud — it **anticipates** it. By combining generative AI for training and ensemble models for prediction, we've built a system that evolves as fast as the fraudsters do. The future of payment security isn't just reactive. It's predictive."*

Research References

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