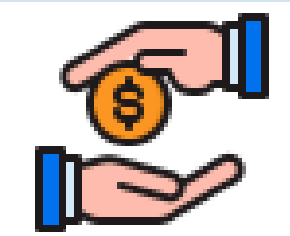


Fraud Risk & Transaction Overview

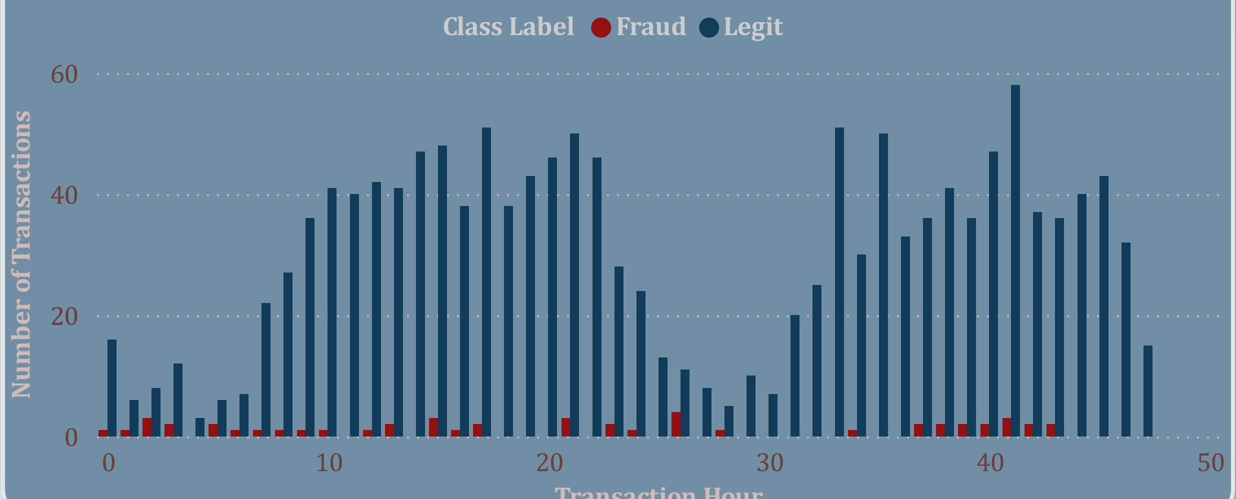
1500	50	3.3%	109.43
Total Transactions	Fraudulent Transactions	% Fraud Transactions	Avg Fraud Amount

High-Value Transactions Overview

Transaction Id	Transaction Amount	Transaction Time	Class Label	SHAP Value-V4	SHAP Value-V14	SHAP Value-V17
0	18.45	128204	Legit	-5.03	-2.93	0.51
1	253.86	152310	Legit	-4.21	-3.17	1.04
2	42.22	77762	Legit	2.31	-4.90	-0.12
3	134.16	60385	Legit	-0.02	-2.80	-0.64
4	2.00	126948	Legit	-4.27	-2.06	0.02
5	647.47	116737	Legit	-4.58	-1.45	-0.27
6	17.45	53263	Legit	-2.09	-4.87	0.77

Transaction Amount Distribution by Label

Transaction Volume by Hour and Fraud Classification



FRAUD RISK SUMMARY & INSIGHTS

- 1500 test transactions analyzed
- ~3.3% predicted as FRAUD
- Fraud transactions often occur between 9 AM – 12 PM
- High-value frauds typically exceed $1,000
- Average fraud transaction = $109.43
- Legit transactions dominate the volume but not always the value

Monitor peak fraud hours & large transactions more closely

Reset Filters

Fraud Classification

Select all | Fraud | Legit

Transaction Hour

- Select all
- 0
- 1
- 2
- 3
- 4

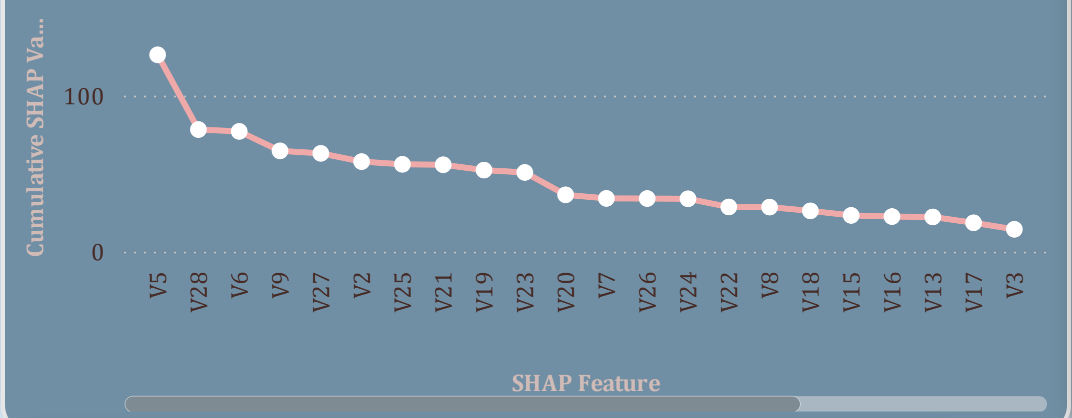
Transaction Amount

- Select all
- 0.00
- 0.01
- 0.12
- 0.22
- 0.49

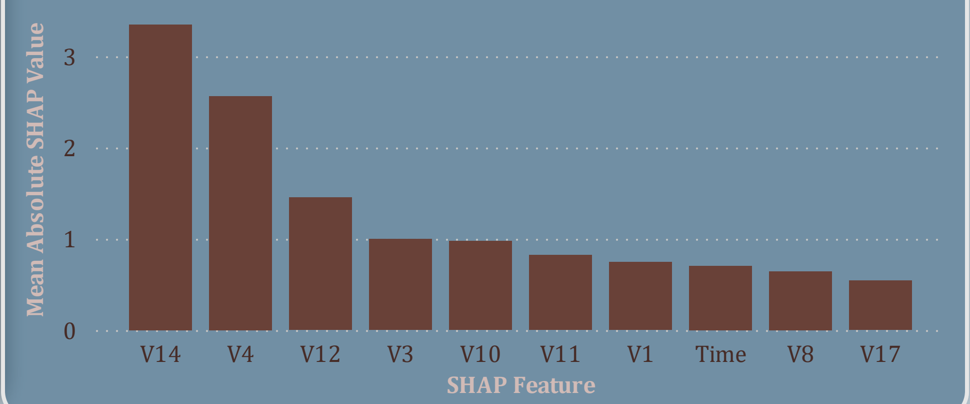
Global Drivers of Fraud: SHAP Feature Insights

1500	50	3.3%	109.43
Total Test Transactions	Fraudulent Transactions	% Fraud Transactions	Avg Fraud Amount

Cumulative SHAP Contribution of Features



Top 10 Fraud-Risk Drivers Based on SHAP



Reset Filters

Fraud Classification

Select all | Fraud | Legit

SHAP Range

10.78 | 29.35

Transaction Amount

- Select all
- (Blank)
- 0.00

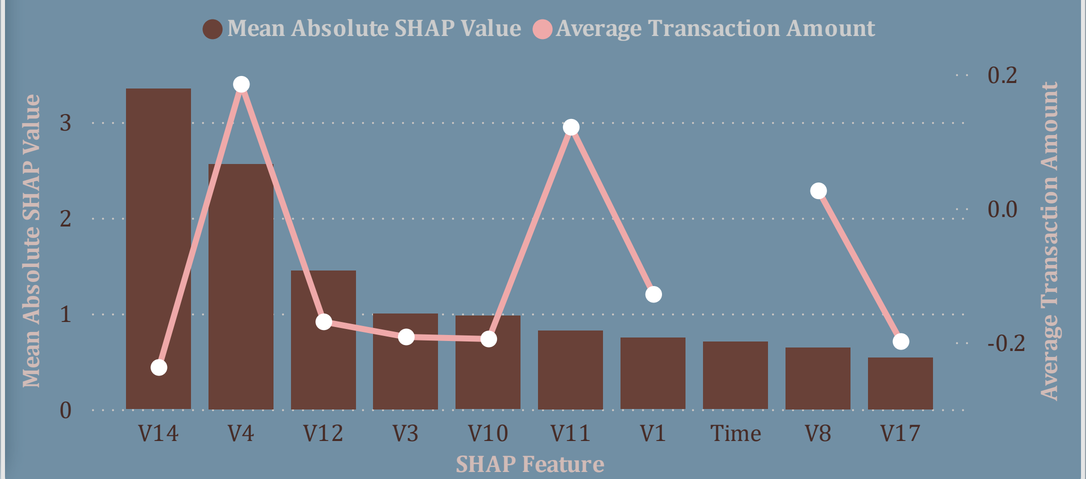
SHAP Feature

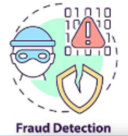
- Select all
- Time
- V1
- V10

GLOBAL SHAP FEATURE INSIGHTS

- SHAP values explain **how much each feature influences** a prediction.
- Features with **higher average SHAP values** contribute more strongly to identifying fraud.
- Combine SHAP with business logic to spot impactful fraud patterns.

Feature Importance vs Monetary Risk (Avg Amount)





Fraud Detection & SHAP Explainability Dashboard

✅ Conclusion

- This project demonstrates how a machine learning model, empowered by SHAP explainability, can identify fraudulent transactions with high precision even when fraud comprises only 3.3% of total records.
- The model's interpretability adds substantial business value: instead of just flagging fraud, it explains **why** a transaction is suspicious — using top contributing features like **V14, V4, and V3**.
- SHAP visualizations provided both global and local interpretability, building trust in the model's decision-making.
- Fraud transactions were found to spike during **9 AM to 12 PM**, indicating a possible time-based vulnerability.
- While **legitimate transactions dominate by volume**, fraudulent transactions often carry **higher monetary value**, increasing the cost of undetected fraud.
- The integration of SHAP values with real-time transaction monitoring offers a **scalable, explainable, and regulatory-compliant** fraud risk system.

💡 Business Recommendations

1. **Prioritize High-Risk Time Windows**: Allocate fraud monitoring resources heavily between **9:00 AM to 12:00 PM**, where fraud attempts are statistically more frequent.
2. **Set Threshold Alerts for High Amounts**: Since many fraud cases exceed **$1,000**, configure additional review layers for large-value transactions.
3. **Deploy SHAP-Based Rule Filters**: Use SHAP value thresholds to flag transactions with high-risk feature contributions — particularly **V14, V4, and V3**.
4. **Train Risk Teams Using SHAP Explanations**: Equip fraud analysts and business teams with dashboards that explain model decisions using SHAP visuals — enhancing both **trust and actionability**.
5. **Retrain Models Regularly**: Schedule model retraining cycles (e.g., monthly) to adapt to evolving fraud tactics, using SHAP drift detection to pinpoint feature shifts.
6. **Integrate Hybrid Review Workflows**: Route SHAP-high transactions to human reviewers in borderline cases — enabling intelligent **AI + Human** collaboration.

💥 Business Impact

- Over $6,700 in potential fraud losses were identified and could be prevented, as the model successfully detected 50 fraudulent transactions, each averaging approximately $134.6 in value.
- SHAP explainability enables regulatory compliance and transparency, especially critical under 2025 standards like the EU AI Act and U.S. financial industry audit mandates, ensuring the model is both auditable and trustworthy.
- Stakeholders across fraud, finance, and compliance teams can now make better decisions, as the visual SHAP explanations demystify model predictions and allow even non-technical users to understand why a transaction is flagged as fraud.
- Resource optimization is achieved through targeted fraud monitoring, allowing fraud analysts to focus efforts on specific hours (9 AM – 12 PM) and high-value transactions, both statistically shown to carry greater fraud risk.

📖 Professional Project Storytelling

In a digital financial landscape where fraud evolves faster than traditional defenses, this project provides a powerful solution: interpretable AI-based fraud detection.
Using real-world transaction patterns and advanced model explanations, we identified that only 3.3% of transactions were fraudulent, yet these few carried significant monetary risk. Our model doesn't just score transactions — it tells a story for each prediction. Why was a transaction flagged? What features triggered concern? Which hour of the day is most dangerous?
SHAP values empower analysts with these answers. Our dashboard breaks the black box by showing which variables like V14, V4, and V3 drive fraud decisions. We learned that frauds spike mid-morning, and high-value frauds can quietly slip past unless we look beyond frequency and into feature risk.
This dashboard isn't just a model showcase. It's a strategic risk tool, equipping finance teams to defend profit margins, analysts to act with evidence, and executives to comply with 2025 AI transparency mandates.

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