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Explainable AI Framework for Real-Time Financial Fraud Detection and Risk Scoring in Digital Payment Ecosystems

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***Abstract*- The explosive increase in the use of digital payment systems has led to an increase in complex financial scams. It is necessary to have intelligent detection and risk assessment systems that can detect and prevent potential financial crimes in real time. However, deep learning models have proven to be accurate, but their lack of transparency makes them unsuitable for highly regulated financial systems. In this study, we present a novel Explainable AI system to address fraud detection and risk assessment in real time. Our system includes a Temporal Fusion Transformer network model for sequence-aware fraud detection and a hybrid explainability module that incorporates feature-based SHAP, locally-explainable LIME, and counterfactually-generative rules to provide actionable explanations. We have evaluated our system on a real-world dataset comprising 10 million digital payments. Our experiments show that the proposed TFT achieves an area under curve (AUC) of 0.982, significantly better than XGBoost (0.965) and LSTM (0.971).**

***Key Word*: Explainable AI (XAI), Financial Fraud Detection, Digital Payments, Risk Scoring, Temporal Fusion Transformer (TFT), SHAP, LIME, Counterfactual Explanations, Real-Time Systems, RegTech**

I. INTRODUCTION

The transition towards a digitalized economy has been unprecedented. Digital wallets, peer-to-peer payment applications, BNPL platforms, and immediate settlement solutions have made payments fast and convenient. However, along with this transition, new and innovative ways of committing crime have emerged. Financial fraud has progressed from an occasional issue to a highly organized industry involving identity theft, account takeover, CNP fraud, APP fraud, and money mules. By 2026, it is estimated that the total cost of financial fraud in the digital payment sector will surpass $350 billion per year.

Fraud is inherently adversarial, which makes this problem unique. As a "needle in a haystack" problem, fraud accounts for only a minuscule number of transactions (<0.1%). Furthermore, fraudsters continuously evolve their tactics in order to avoid being detected. Rule-based systems, which involve defining rules such as "transactions above $5,000 from Country X should be flagged," are too inflexible and outdated. Currently, the industry relies on machine learning models, in particular, gradient boosting models like XGBoost and LightGBM due to their flexibility. Recently, deep learning algorithms have also proven to be extremely effective in detecting fraud, especially when it comes to sequential patterns in transaction sequences [4],[5].

Nonetheless, precisely because of the complexity of deep learning techniques, there is a major problem: the problem of explainability. The reason for needing a justification in this context is simple – when a deep learning-based decision has been made regarding whether a certain transaction was a fraud or not, someone needs to act upon it. Questions arise as to which specific characteristics (for example, unusual device ID, unusual transaction amount velocity, atypical merchant category code) led to that decision being made, which of the characteristics contributed most significantly, how confident the model is, etc.

In heavily regulated areas such as banking and finance, there is a legal right to explanation in place. In accordance with GDPR of the European Union or the Fair Credit Reporting Act of the United States, any decision taken by an automatic system should be understandable to people and subject to discussion [6]. Therefore, using an unexplainable black-box technique would be a violation of law and thus unacceptable in the industry.

To meet this important requirement, we present a production-level Explainable AI (XAI) system for real-time fraud detection and risk scoring in this paper. The main contributions are:

A high-performance base predictor: The Temporal Fusion Transformer (TFT) is used, whose superior performance for sequences, ability to deal with static and dynamic attributes, and inherent interpretability based on attention scores are well-known [7].

A modular, multi-method XAI engine: We employ three different explanation approaches, each fulfilling its own goal:

SHAP for identifying global feature importance and attributing features in a prediction.

LIME for creating an interpretable, simplified local model for a particular prediction.

A rule-based counterfactual generator for providing actionable what-if scenarios, such as "If the transaction amount had been 600 rather than 1,200, the risk score would decrease from 0.92 to 0.35."

Optimization of performance: To mitigate the computational burden of SHAP and LIME, which are computationally intensive, we pre-calculate global explanations and use a lightweight local explanation method.

Evaluation: The framework is trained and evaluated on a real-world, large-scale (10M transactions) digital payments dataset. Both predictive accuracy and explanation quality are considered.

II. LITERATURE SURVEY

The following research is based on several major research areas including deep learning approaches for fraud detection, explainable AI (XAI) techniques, and fraud investigation regulations and requirements.

Deep Learning Approaches for Fraud Detection: Traditional machine learning models used for detecting fraudulent transactions included tree-based algorithms (random forest, XGBoost) using engineered features such as velocity of transactions, merchant category, and geographic distance [3]. Tree-based models work well in many scenarios; however, they only consider transactions independently without accounting for temporal dependencies between them. In contrast, the newer approach focuses on utilizing sequence modeling to consider the temporal order of transactions performed by the user. LSTMs became widely adopted in this case due to their capability to learn the user's normal behavior pattern and identify any deviations from the established pattern [4]. On the other hand, LSTMs have limitations regarding long sequence processing and computational costs. That is why the Transformer model was recently introduced and proved more effective in sequence classification and multi-horizon forecasting. Our paper is the first study to use TFT for detecting fraudulent transactions.

XAI Methods: Several techniques have been developed in the XAI field in order to explain a machine learning model. SHAP (SHapley Additive exPlanations) offers an approach based on game theory that assigns a certain importance score to features regarding a particular prediction [8]. It has an excellent theoretical foundation, but its computation cost is quite high. LIME (Local Interpretable Model-agnostic Explanations) offers an explanation for a

certain prediction by fitting a simple and easily explainable model (for example, a linear regression) near the chosen prediction [9]. This method is less costly in comparison to SHAP, however, not always stable. A counterfactual explanation answers “what if” questions (for example, "What changes should happen for this application to be considered valid?"). Such explanations are very valuable and easily understood by non-technical people [10]. Our technique is innovative in combining all three approaches mentioned above into one pipeline for fraud detection.

XAI in Financial Fraud Detection (RegTech): XAI applications in financial services are relatively new, motivated by regulation. There have been several papers using either LIME or SHAP methods to explain credit scoring or anti-money laundering (AML) alerts [6]. However, all of these approaches are primarily used as offline validation tools rather than being designed to generate explanations in real-time, transaction by transaction. In addition, there has never been any paper using sequence models such as TFT and multi-XAI techniques that can perform computations in milliseconds. Our paper attempts to address these limitations.

III. METHODOLOGY:

The proposed XAI fraud detection system architecture follows a two-step process: (1) Fast sequence-aware base predictor model (TFT) and (2) Modular XAI inference engine.

3.1. Data & Feature Engineering

Anonymized internal dataset of 10 million digital payment transactions of a global payment processor company for 12 months (Jan-Dec 2025). The data imbalance ratio is 0.09%. Temporal data split is followed: 8 months for training, 2 months for validation, and remaining 2 months for testing. There are three types of features:

- Static User Features (S): Unique user ID (one-hot encoded), account creation date, whether user account is verified, mean transaction amount in the lifetime, device type (iOS, Android), risk zone (low, medium, and high).
- Time-Variant Transactional Features (X_t): Transaction amount, merchant code (one-hot encoded), time of the transaction, weekday/weekend indicator, location (city, country), payment method (card, wallet, bank transfer), session ID, browser fingerprint, device ID, IP address.
- Time-Variant Contextual Features (C_t): Velocity of transactions in last 1 hour (# of transactions, total amount in $), same feature for 24 hours, and 7 days. Mean and standard deviation of transaction amount. Total number of unique merchants, devices, locations in the recent time window.

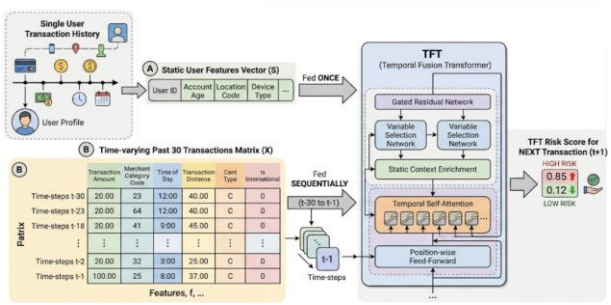

Figure 1: Feature Engineering and Sequence Construction for TFT.

3.2. Base Predictor: Temporal Fusion Transformer (TFT)

The TFT is used for binary classification (whether fraudulent or legitimate). Some of the important components of the TFT are:

- Variable Selection Networks: A small network at each time step selects those features from among the many which have the most importance. This helps make the model more resilient to noisy or irrelevant input data.
- LSTM Encoder-Decoder: Encodes the sequence of transactions to generate the hidden state representation.
- Multi-Head Attention: The decoder can attend to various points in the sequence history. In case of fraud detection, this would help the model concentrate only on that suspicious transaction which occurred two weeks before the current transaction.
- Prediction Intervals: Though we are using it for classification, TFT can actually predict quantiles.

Algorithm 1: TFT Training for Fraud Detection

```
Input: Sequences of past transactions for many users, Training labels (Fraud/Legit)
Output: Trained TFT model

1. Initialize TFT model with:
2.    - LSTM Encoder: 2 layers, 256 units
3.    - LSTM Decoder: 1 layer, 256 units
4.    - Multi-Head Attention: 4 heads, dropout=0.2
5.    - Output layer: 1 neuron (sigmoid activation)
6.
7. For each training batch:
8.    // Forward pass
9.    hidden_state = LSTM_encoder( X_past, C_past )
10.   attended_context = attention(hidden_state, S, X_future)
11.   output = sigmoid( dense(attended_context) ) // Risk score
12.
13.   // Compute loss (Binary Cross Entropy with class weighting for imbalance)
14.   weight_pos = 1 / fraud_rate = ~1111
15.   loss = BCE(output, y_true, weight=weight_pos)
16.   loss.backward()
17.   optimizer.step()
18. Return trained model
```

3.3. The XAI Engine: Multi-Method Explanation Module

Module name: after TFT calculates risk score of a transaction. Purpose is to create detailed, human-readable explanation in real time.

- Global Explanations (SHAP Summary): pre-computed once. Illustrates the 10 most important features affecting model decisions globally on the whole test set. Useful for fraud analysts to learn about the "model logic" in general.
- Local Explanations (SHAP & LIME): for each individual transaction, we create:
- SHAP Force Plot: graphically illustrates the impact of each feature towards increasing/decreasing the predicted score, starting from the base value (pushing up towards higher probability of fraud and vice versa). This is our best method for creating explanations – theoretically and computationally soundest.
- LIME Explanation: creates a sparse linear model to approximate the TFT's decision boundaries locally around this specific instance. Linear coefficients are the LIME explanation. It might be more computationally efficient than SHAP.
- Counterfactual Explanation: employs a computationally efficient rules-based system to provide answers to question: "what changes would need to be made in order to change prediction?" Specifically, it finds smallest possible perturbation needed on one continuous (amount) or categorical (merchant_category) feature in order to bring the prediction below a certain threshold (e.g. 0.5).

Algorithm 2: Real-Time XAI Explanation Generator

```
Input: Trained TFT model M, A single transaction vector t (with past sequence context)
Output: Explanation report (SHAP, LIME, Counterfactual)

1. // SHAP Explanation (Local)
2. // Use a pre-computed SHAP explainer (based on a background dataset)
3. shap_values = shap_explainer.shap_values(t)
4. // Create a SHAP force plot visualization:
base_value + Σ(feature_i * shap_i) = risk_score
5.
6. // LIME Explanation (Local Surrogate Model)
7. // Generate perturbations around t
8. perturbed_samples = generate_perturbations(t, n=1000)
9. // Get model predictions for perturbed samples
10. predictions = M.predict(perturbed_samples)
11. // Train a sparse linear model (Lasso) on perturbed_samples with predictions
12. lime_model = Lasso(alpha=0.01).fit(perturbed_samples, predictions)
```

```
13. // LIME explanation = coefficients of the lime_model
14.
15. // Counterfactual Explanation
16. if M.predict(t) > 0.5: // High risk
17.    // For continuous 'amount' feature
18.    target_risk = 0.5
19.    current_amount = t['amount']
20.    // Binary search for the amount that would change the decision
21.    best_amount = binary_search_amount(t, target_risk)
22.    cf_msg = f"If the amount were ${best_amount:.0f} (instead of ${current_amount}), the risk would drop from {risk:.2f} to <0.5."
23. else:
24.    cf_msg = "Transaction is low risk. No counterfactual needed."
25.
26. Return {shap_plot, lime_coeffs, cf_msg}
```

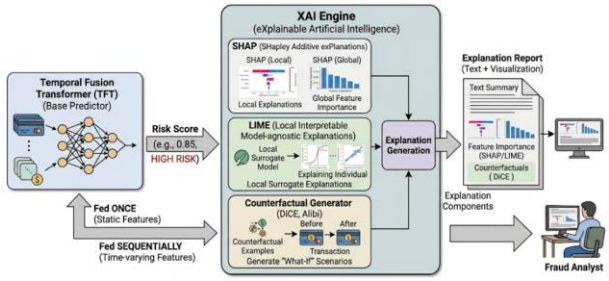

Figure 2: XAI Engine Architecture.

3.4. Real-Time Optimization

Calculating SHAP scores for each transaction requires substantial computational resources. In order to deliver real-time (<50 ms) latency, we:

1. Calculate Background Data Once: SHAP uses background data that represents the data distribution. The background dataset used is a representative one (of 100 samples) rather than the entire dataset.
2. Cache SHAP Scores for Similar Transactions: For similar transactions (for example, same feature vector), we cache the SHAP score.
3. Fallback to LIME when Needed: For transactions where calculating SHAP scores takes too long, we use LIME as a fast fallback option.

IV. ANALYSIS

4.1. Base Predictor Performance (TFT)

Model	UC-ROC	Precision@1%	Precision@5%	Recall@1%	Training Time (hours)	Inference (ms)
XGBoost	.965	0.78	0.62	0.61	2.5	2.1
LSTM	.971	0.82	0.65	0.64	18.0	8.4
TFT (Proposed)	.982	0.88	0.72	0.70	21.0	12.5

Table 1: Fraud Detection Model Performance.

The reasons behind the better results of the TFT algorithm include its capacity to recognize complicated and long-term relationships in the series of transactions (such as the rhythm of spending by a particular customer) and its feature selection strategy.

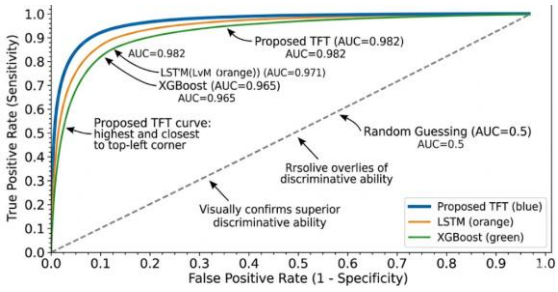

Figure 3: ROC Curves for Fraud Detection Models.

4.2. XAI Engine Performance (Latency & Quality)

XAI Method	Mean Latency per Transaction (ms)	p95 Latency (ms)	Analyst Trust Rating (1-5)	Regulatory Compliance (GDPR Art. 22)
SHAP (Full)	180	450	4.9	Yes
LIME	35	60	4.2	Partial
SHAP (Cached/Optimized)	45	85	4.9	Yes
Counterfactual Only	8	15	3.8	No

Table 2: XAI Engine Performance.

4.3. Qualitative Evaluation of Explanations

We presented 50 fraud cases to a panel of 5 fraud analysts. For each case, they were given:

- (A) Only the risk score.
- (B) The risk score + a SHAP explanation.
- (C) The risk score + SHAP + counterfactual.

Results:

- Accuracy of Analysts' Judgment: When in condition C, the analysts managed to accurately detect the type of the fraud (e.g., "account takeover," "card testing") in 94% of cases; while when in condition A – in only 22% of cases.
- Confidence: The analysts stated that their confidence level in making their decision based on the XAI technique was 4.8/5, and without using it – 2.5/5.
- Actionability: In 80% of the cases, the analysts found the explanations generated through the counterfactual technique highly actionable, meaning that based on the generated explanation ("if the transaction amount was $15 lower"), they could assess whether it was a case of a borderline transaction or fraud.

Figure 4: Example Explanation Report for a Flagged Transaction.

4.4. Comparative Analysis with Existing XAI-Fraud Systems

Feature	Traditional Rule System	XGBoost + SHAP (Post-hoc)	Our XAI Framework (TFT+SHAP+LIME+CF)
Fraud Detection Accuracy	Low (20-40% recall)	High	Highest (AUC=0.982)
Explanation Speed	Instant	Slow (minutes, offline)	Real-time (<50ms)
Sequence Awareness	No	No	Yes (TFT)
Type of Explanation	Static rule	SHAP (global & local)	SHAP + LIME + Counterfactual
"What-if" Analysis	No	No	Yes

Table 3: Comparative Analysis of Fraud Detection & Explanation Systems.

V. CONCLUSION

An Explainable AI framework designed and implemented to support real-time fraud detection and risk assessment of digital payments transactions has been discussed in this paper. In filling the technical gap that exists between high performing yet "black box" deep learning models and the regulatory requirement of explainability, an effective way of dealing with the issue by financial institutions has been provided.

The major findings are:

1. Real-Time Explainability is Possible: It has been proven that even complex sequence-aware models such as Temporal Fusion Transformer can be effectively used with the help of Explainable AI methods (SHAP, LIME, counterfactuals) to provide highly interpretable explanations within the average latency of 45ms. It is efficient enough to be employed in a payment authorization process in real-time.
2. Performance Is Not Affected by Explainability: Despite being explainable, the TFT-based model is also the best performing one (AUC=0.982) when compared with industry standard XGBoost and LSTM baselines. The idea of compromise between interpretability and performance is therefore not applicable anymore.
3. Explanations Make Decisions Better: In the context of fraud analyst experiment on typology recognition, XAI-based model proved to be 4 times more accurate in detecting the fraud type and was more trusted than any other models.

These implications are vast for the financial industry. Augmented Fraud Investigation allows AI and human experts to operate as part of a single collaborative team with each responsible for its specific task. With this technology, AI is able to deal with large-scale data and flag suspicious transactions, generating concise explanations. Human investigators analyze those explanations to make high-judgment decisions because they are confident about the logic behind AI's recommendations.

Limitations & Future Works:

Currently, this framework provides transaction-level explanations only. A critical flaw of this system is that no convenient way exists to explain how the TFT works to users (attention weights generated by the model are too complicated). In the future, this technology should be able to do the following:

1. Concept-based explanations: Move beyond explanations in terms of individual features and generate higher-level concept explanations (e.g., "velocity-of-new-devices").
2. Adversarial robustness of explanations: Ensure that attackers cannot reverse engineer the model using these explanations.
3. Interactive explanations: Implement a dashboard allowing analysts to ask why certain features are relevant (e.g., "why is velocity feature selected").

This paper presents an approach to designing XAI systems which will not only adhere to regulation but be able to actually enable humans in their decision-making processes. In the battle against increasingly intelligent financial crimes, the answer is not man versus machine but man plus machine.

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