Explainable AI (XAI) in Deep Learning Models for Credit Card Fraud Detection

Thong Minh Lai [1] Supervisor: Dr. Hyunkook Lee [2]

[1]University of Huddersfield, Department of Computer Science

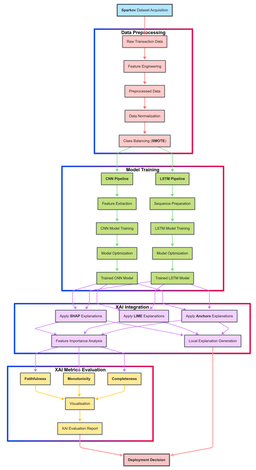
Introduction & Motivation

Credit card fraud remains a persistent and costly issue, with UK losses reaching £1.3 billion in 2021 (UK Finance, 2022). While deep learning models have shown promise for fraud detection, their "black box" nature makes them difficult to trust and deploy in real-world financial systems. This project aims to bridge that gap by integrating **Explainable AI (XAI)** techniques, making model decisions transparent and actionable for analysts and stakeholders.

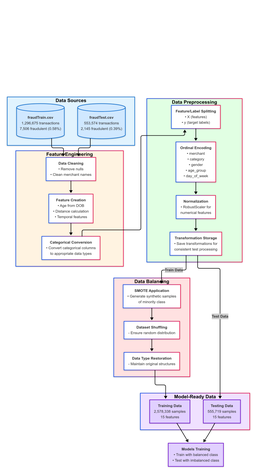
Project Objectives:

- Develop and compare models explainability (**CNN**, **LSTM with attention**) for fraud detection.
- Integrate XAI methods (**SHAP**, **LIME**, **Anchors**) for local interpretability.
- Evaluate the explainability using XAI metrics (**Faithfulness**, **Monotonicity**, **Completeness**).
- Provide insights for financial institutions implementing transparent AI.

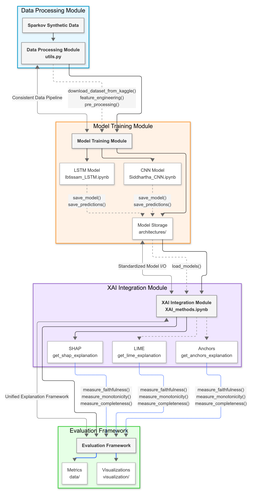
System Architecture: End-to-End Workflow and Modular Design



(a) **End-to-End System Architecture:** Illustrates the main modules and their sequential data flow, highlighting the technologies and outputs at each stage.



(b) **Data Processing Pipeline:** Details the feature engineering, **SMOTE** implementation, validation steps that ensure a robust, balanced train dataset.



(c) **System Component Interactions:** Shows module dependencies, data exchange formats, control flow, integration points for XAI methods.

Figure 1. **System Architecture and Workflow.**

1. **Data Collection & Model Design:** Gathers **Sparkov** synthetic transaction data (Harris, n.d.), designs model architectures (CNN, LSTM). Data is loaded and versioned for reproducibility.
2. **Data Preprocessing:** Applies feature engineering (temporal, spatial, demographic), handles class imbalance using **SMOTE** (Bowyer et al., 2011), and standardises/encodes features to ensure high-quality model input.
3. **Model Training (CNN & LSTM):** Trains and optimised for fraud detection. Each model is tuned and validated independently.
4. **XAI Integration:** Implements SHAP, LIME, and Anchors for local interpretability, providing instance-level explanations for model predictions.
5. **Explainability Performance Evaluation:** Comprehensive XAI evaluation metrics (**Faithfulness**, **Monotonicity**, **Completeness**), with visual dashboards for comparative analysis.

Predictive Model Architectures: CNN and LSTM

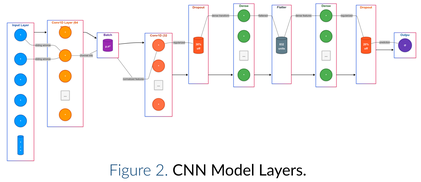


Figure 2. CNN Model Layers.

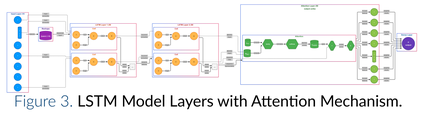


Figure 3. LSTM Model Layers with Attention Mechanism.

CNN:

- Conv1D layers (64, 32 filters)
- Batch Normalisation, Dropout, Dense layers
- 59,937 trainable parameters

LSTM with Attention:

- Two LSTM layers (50 units each)
- Attention mechanism, Dense output layer
- 33,502 trainable parameters

Explanations from XAI Methods: SHAP, LIME, and Anchors

SHAP (SHapley Additive exPlanations) visualisations, including the waterfall and force plots, illustrate how individual features influence the model's prediction. In the waterfall plot, each bar represents a feature's contribution, starting from a base value (e.g., 0.511). Red bars indicate features that increase the probability of fraud, while blue bars show features that decrease it. The force plot provides a complementary view, displaying the cumulative effect of all features, with the width of each bar indicating the magnitude of its impact. Features are arranged by their influence, making it easy to identify which factors most strongly push the prediction towards fraud or legitimacy.

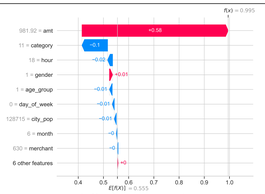


Figure 4. **SHAP Waterfall Plot:** Contributions for a CNN prediction.

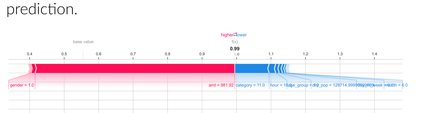


Figure 5. **SHAP Force Plot:** Cumulative impact from base value.

LIME (Local Interpretable Model-agnostic Explanations) visualisations use a bar chart to display feature importance and directionality for a specific prediction. Green bars represent features that support legitimate transactions, while red bars indicate features suggesting fraud. The length of each bar corresponds to the magnitude of the feature's impact, and features are ordered by their absolute importance, allowing for quick identification of the most influential factors.

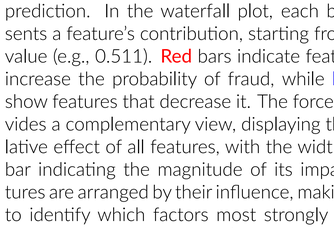


Figure 6. **LIME Explanation Chart:** Bar visualisation of feature impact.

Anchors visualisations present clear **IF-THEN** rules that specify the exact conditions leading to a prediction. Each rule lists threshold values for relevant features (e.g., *amount > 88.51*, *hour > 22.00*, *category = food_dining*, *age > 64.00*, *gender = F*), making it straightforward to understand the criteria that trigger a fraud prediction. The associated precision percentage indicates the reliability of the rule for similar cases.

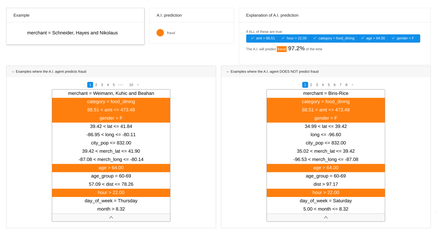


Figure 7. **Anchors Rule-based:** Conditions for a prediction.

XAI Evaluation Metrics and Insights

XAI Metrics:

- **Faithfulness:** How well explanations reflect model logic (higher scores indicate better alignment with model behaviour)
- **Monotonicity:** Consistency of feature importance across different inputs
- **Completeness:** Coverage of the model's decision process by the explanation

Key Takeaways:

- **SHAP** is the most faithful, especially with LSTM, making it my go-to for high-stakes explanations.
- **LIME** offers the best completeness with CNN, is more intuitive for fraud analysts.
- **Anchors** are great for clear, actionable rules, but their coverage is limited.
- The choice of XAI method should be guided by the confidence of the prediction and the end user's needs.

XAI Effectiveness by Confidence Level:

- **Very High** (>0.8): SHAP explanations most reliable.
- **High** (0.6–0.8): SHAP and LIME provide a balanced view.
- **Borderline** (0.4–0.6): Multi-method approach recommended.
- **Low** (<0.4): SHAP plus human review recommended.

Table 1. Evaluation Metrics Comparison for XAI Methods on CNN, LSTM Models. Higher values are better for all metrics.

Metric	LSTM			CNN		
	SHAP	LIME	Anchors	SHAP	LIME	Anchors
Faithfulness	**0.761**	0.396	0.412	0.443	0.254	0.315
Monotonicity	0.429	0.445	**0.469**	0.464	**0.488**	0.486
Completeness	0.134	**0.139**	0.022	0.208	**0.295**	0.033

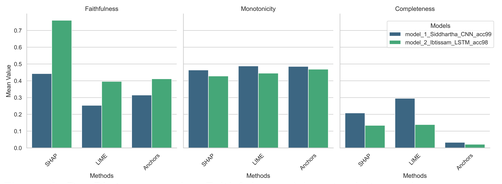


Figure 8. **Bar Plot:** comparing Faithfulness, Monotonicity, and Completeness across models and XAI methods.

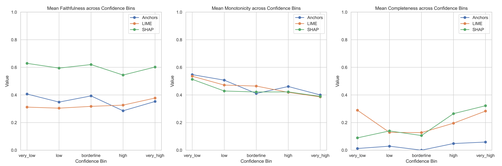
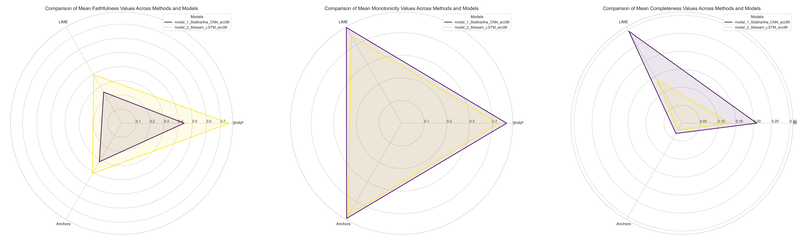


Figure 9. XAI Methods Performance Across Confidence Bins.



(a) **Faithfulness** Comparison (b) **Monotonicity** Comparison (c) **Completeness** Comparison

Figure 10. **Radar Charts:** Comparison of All Average Metrics Values Across Methods and Models

Practical Implications

- **Real-time Detection:** A transaction's explanations can be produced in under 3 minutes, suitable for operational deployment.
- **Stakeholder Suitability:**
  - **SHAP:** Data scientists (technical depth)
  - **LIME:** Fraud analysts (intuitive, visual)
  - **Anchors:** Operations teams (clear rules)
- **Computational Overhead:** SHAP is resource-intensive, requiring careful optimisation of resource management.

Limitations & Future Work

- **Data:** Reliance on synthetic data (**Sparkov**) may limit real-world generalisability.
- **User Experience:** XAI outputs can be complex for non-technical users.
- **Next Steps:**
  - Optimise XAI computation for real-time use.
  - Further research on other advanced explainers (**DeepLIFT**, **X-NeSyL**, etc.).
  - Conduct usability studies with fraud analysts.
  - Incorporate more diverse, real-world datasets.

References

Bowyer, K. W., Chawla, N. V., Hall, L. O., & Kegelmeyer, W. P. (2011).SMOTE: synthetic minority over-sampling technique. *CoRR, abs/1106.1813*. http://arxiv.org/abs/1106.1813

Harris, B. (n.d.). *Generate fake credit card transaction data, including fraudulent transactions*. GitHub. Retrieved April 23, 2025, from https://github.com/namebrandon/Sparkov_Data_Generation

UK Finance. (2022). *Annual fraud report 2022*. UK Finance. Retrieved April 23, 2025, from https://www.ukfinance.org.uk/policy-and-guidance/reports-and-publications/annual-fraud-report-2022

laiminhthong1@gmail.com | U2259343@unimail.hud.ac.uk

BSc Computer Science with Artificial Intelligence

https://github.com/ThongLai/Credit-Card-Transaction-Fraud-Detection-Using-Explainable-AI