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

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Introduction

Introduction

- Credit card fraud is a massive problem, with losses in the UK alone reaching £1.3 billion in 2021.[1]
- Deep Learning (DL) models are powerful for fraud detection, but their "black box" nature makes them hard to trust in high-stakes environments.
- My project tackles this by integrating Explainable AI (XAI) techniques into state-of-the-art DL models, focusing on local interpretability.
- All experiments are conducted on the Sparkov synthetic dataset, which is ideal for benchmarking fraud detection systems.[2]

Project Aims

- Compare multiple deep learning architectures for fraud detection.
- Integrate and evaluate XAI methods (SHAP, LIME, Anchors) for local explanations.
- Develop robust evaluation metrics for both accuracy and interpretability.

[1] UK Finance, 2022.
[2] Grover et al., 2023.

Background

Background and Motivation

- Traditional fraud detection relied on hand-crafted rules, but fraudsters adapt quickly.[3]
- Deep Learning models (CNN, LSTM) can spot subtle, non-linear patterns in transaction data.
- However, financial institutions demand transparency for regulatory and trust reasons.[4]
- XAI methods help open up these black boxes, making model decisions understandable to humans.

Why Local Explanations?

Local explanations help analysts understand *why* a specific transaction was flagged as fraud, which is crucial for real-world deployment.

[3] Sundararamaiah et al., 2024.
[4] Gilpin et al., 2018.

Methods

Dataset and Preprocessing

- **Dataset:** Sparkov synthetic data[5], 1.2M transactions, 22 features, fraud rate $\approx$ 0.58%.
- **Preprocessing:**
  - Feature engineering (e.g., Haversine distance, age groups, temporal features).
  - Standardisation and encoding of categorical variables.
  - SMOTE[6] for balancing the highly imbalanced dataset.

[5] Harris, n.d.
[6] Bowyer et al., 2011.

Model Architectures

CNN Architecture

- Input: (15, 1) feature vector.
- Two Conv1D layers (64, 32 filters), batch norm, dropout.
- Dense layers with ReLU, final sigmoid for binary classification.
- **Parameters:** 60,065.

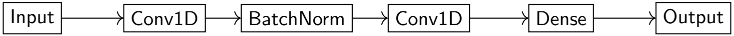

Figure: CNN Model Architecture

Model Architectures

CNN Architecture

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- **Parameters:** 60,065.

LSTM with Attention

- Input: (15, 1) feature vector.
- Lambda layer to expand dimensions.
- Two LSTM layers (50 units each) with dropout (0.3) and recurrent dropout (0.2).
- Custom attention mechanism.
- Dense output with sigmoid for binary classification.
- **Parameters:** 33,502.

Figure: LSTM Model Architecture[7]

[7] Ibtissam et al., 2021.

Explainable AI (XAI) Techniques and Metrics

- **SHAP:** SHapley Additive exPlanations, provides both global and local feature attributions.
- **LIME:** Local Interpretable Model-agnostic Explanations, explains individual predictions with local surrogate models.
- **Anchors:** Rule-based, high-precision explanations for individual predictions.

Evaluation Metrics

- **Faithfulness:** How well explanations reflect the model's true decision process.
- **Monotonicity:** Whether increasing a feature's value increases its importance.
- **Completeness:** How much of the model's behaviour is captured by the explanation.

XAI Methods: SHAP

How SHAP values are computed:

- Background dataset represents "average" feature values.
- Establishes baseline prediction for comparison.
- Measures feature impact by swapping actual values with background values.

Algorithm SHAP for Credit Card Detection

```
Input: Trained model f, transaction x
for each feature i in x do
    Initialize SHAP value φ_i = 0
    for each subset S of features not containing i do
        Create two samples: x_{S∪{i}} and x_S
        Compute marginal contribution: f(x_{S∪{i}}) − f(x_S)
        Weight the contribution based on subset size
        Add weighted contribution to φ_i
    end for
end for
Output: SHAP values φ_1, φ_2, ..., φ_n showing each feature's
    contribution to f(x)
```

XAI Methods: LIME

How LIME Works

- Creates perturbed samples around the original transaction
- Weights samples by proximity to the original based on a kernel value
- Fits an interpretable model locally
- Shows feature contributions with confidence intervals

Algorithm LIME for Credit Card Detection

```
Input: Trained model f, transaction x
Generate N perturbed samples around x by randomly changing feature values
for each perturbed sample x′ do
    Predict f(x′)
    Compute similarity between x and x′
end for
Fit a simple interpretable model g (e.g., linear model) to predict f(x′) using the perturbed samples, weighted by similarity
Output: Coefficients of g as explanations for f(x)'s prediction
```

XAI Methods: LIME

What are Anchors?

- Highly precise "IF-THEN" rules explaining model decisions
- Focus on minimum conditions needed to maintain prediction
- Trade precision for coverage (fewer cases explained)
- Easily understood by non-technical stakeholders

Algorithm Anchors for Credit Card Detection

```
Input: Trained model f, transaction x
Initialize anchors A = ∅
while precision of A (fraction of perturbed samples where f predicts same as f(x)) < threshold do
    For each candidate feature not in A:
        Add feature to A and estimate new precision
    Add feature that increases precision the most to A
end while
Output: Anchors A: set of feature-value rules that "guarantee" f(x)'s prediction with high precision
```

XAI Evaluation: Faithfulness Metric

Evaluate an explanation with Faithfulness metric:

- Measures the correlation between feature importance and changes in the model's predictions when features are altered
- Feature importance correlation analysis with sequential feature removal

Algorithm Faithfulness Metric for XAI Explanations

Input: Model f, sample x, explanation scores E for features
for each feature i in x **do**
    Remove or mask feature i in x to get x_{-i}
    Compute prediction difference: $\Delta_i = |f(x) - f(x_{-i})|$
end for
Compute correlation between Δ_i and E_i across all features
Output: Faithfulness score (e.g., correlation coefficient)

XAI Evaluation: Monotonicity Metric

Evaluate an explanation with Monotonicity metric:

- Evaluates whether removing features causes consistent changes in the model's predictions
- Sequential feature removal testing with prediction tracking

Algorithm Monotonicity Metric for XAI Explanations

Input: Model f, sample x, explanation scores E for features
for each feature i in x **do**
    Change feature i's value to get x_{+i}
    Compute prediction change: $\Delta_i = f(x_{+i}) - f(x)$
    if $E_i > 0$ **then**
        Check if $\Delta_i > 0$ (prediction increases)
    else if $E_i < 0$ **then**
        Check if $\Delta_i < 0$ (prediction decreases)
    end if
end for
Calculate fraction of features where explanation and prediction change agree
Output: Monotonicity score (agreement ratio)

XAI Evaluation: Completeness Metric

Evaluate an explanation with Completeness metric:

- Assesses how much of the model's prediction is captured by the explanation
- Coverage measurement comparing explained variance to total variance

Algorithm Completeness Metric for XAI Explanations

1: **Input:** Model f, sample x, explanation scores E for features
2: Compute model prediction: $y = f(x)$
3: Compute baseline prediction: $y_{base} = f(\text{baseline input})$
4: Sum explanation scores: $S = \sum_i E_i$
5: Compute completeness error: $|S - (y - y_{base})|$
6: **Output:** Completeness score (lower error means higher completeness)

Balancing with Stratified Sampling

- **Class Imbalance Challenge:**
  - Only 0.58% of transactions are fraudulent in training data
  - Risk of model bias towards predicting legitimate transactions
- **Confidence-based Stratified Sampling:** For comprehensive XAI evaluation

Confidence Bins for Stratified Evaluation

- **Very Low** (0.0-0.2) — Strong contradiction to model classification
- **Low** (0.2-0.4) — Weak patterns contradicting classification
- **Borderline** (0.4-0.6) — Ambiguous cases with mixed signals
- **High** (0.6-0.8) — Strong but not conclusive patterns
- **Very High** (0.8-1.0) — Clear fraud/non-fraud patterns

Balancing with Stratified Sampling

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- **Confidence-based Stratified Sampling:** For comprehensive XAI evaluation

Key Benefits

- Ensures comprehensive XAI evaluation across confidence levels
- Includes edge cases with extreme feature values
- Enables fair comparison between SHAP, LIME and Anchors

Edge Case Handling

- **Edge Case Identification:**
  - Z-score calculation to identify feature value deviations
  - Selection of transactions with extreme feature values
  - Analysis of unusual transaction patterns

Selection Process

- **Calculate z-scores:** $z = \frac{|x-\mu|}{\sigma}$ for important features
- **Maximum deviation:** Find samples with largest z-scores across features
- **Combine with stratified samples:** Ensures both typical and extreme cases
- **Special handling:** Edge cases receive additional manual review

System Architecture

1. **Data Collection & Model Design:** Obtain synthetic transaction data and design fraud detection models.
2. **Data Preprocessing:** Raw transaction data is cleaned, normalised, and balanced using the SMOTE method.
3. **Model Training:** Separate pipelines are implemented for training models.
4. **XAI Integration:** Use XAI methods to generate explanations for model predictions.
5. **Performance Evaluation:** XAI evaluation metrics (**Faithfulness**, **Monotonicity**, **Completeness**).

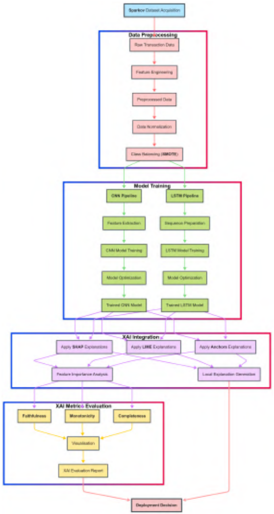


Figure: System architecture illustrative diagram

Results

Model Performance: CNN vs LSTM

- I compared two deep learning architectures: a Convolutional Neural Network (CNN) and a Long Short-Term Memory (LSTM) model with attention.
- Both models were trained and evaluated on the Sparkov synthetic dataset, which is highly imbalanced and mimics real-world credit card transaction patterns.

Table: Performance Metrics for CNN and LSTM Models

Model	Accuracy	ROC AUC	Precision (Fraud)	Recall (Fraud)
CNN	98.66%	0.994	21.34%	91.84%
LSTM	97.58%	0.971	11.80%	81.49%

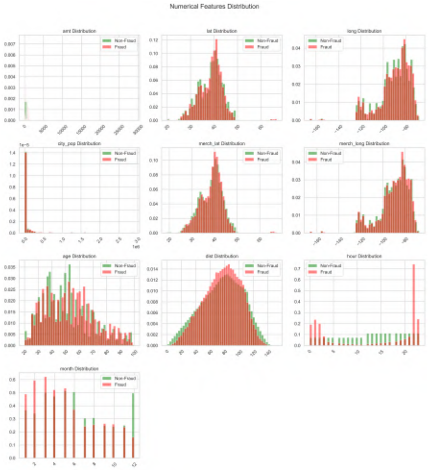
CNN Model

- True Negatives: 546,311
- False Positives: 7,263
- False Negatives: 175
- True Positives: 1,970

LSTM Model

- True Negatives: 540,512
- False Positives: 13,062
- False Negatives: 397
- True Positives: 1,748

Feature Patterns using Statistical Analysis



(a) Numerical Features Distributions

(b) Categorical Features Distributions

Figure: Features Distributions in the Sparkov Train Dataset

Feature Patterns using Statistical Analysis

Key Statistical Patterns for Fraud Detection (without XAI methods)

- **Amount Anomalies:** Transactions exceeding $500 showed 3.7x higher fraud probability
- **Temporal Patterns:** 23:00-04:00 transactions had 2.9x increased fraud risk
- **Geographical Anomalies:** Transactions >75km from cardholder location showed strong fraud indicators
- **Demographic Patterns:** Highest fraud concentration in 50-60 age group (1,443 cases)

SHAP Summary Plot and Global Importance

- **Feature Impact Analysis:**
  - Summary plot shows feature importance across all test samples
  - Color represents feature value (red = high, blue = low)
  - Position shows impact on prediction (right = toward fraud)

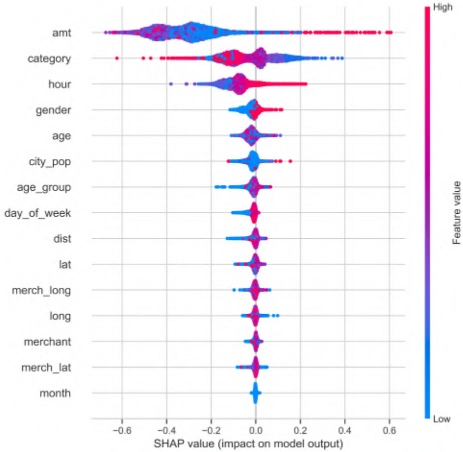


Figure: SHAP Summary Plot: Feature Importance for CNN Model

Feature Importance: What Drives Fraud Predictions?

- Using SHAP, I identified the most influential features for the CNN model.
- **Top features:**
  - **Transaction Amount**: Higher values are a strong fraud indicator.
  - **Merchant Category**
  - **Hour of Transaction**: Transactions between 23:00 and 04:00 are riskier.
  - **Gender**: and **Age** Moderate influence.
  - **Distance to Merchant**: Unusual distances often signal fraud.
  - **Latitude/Longitude**: Minimal impact.

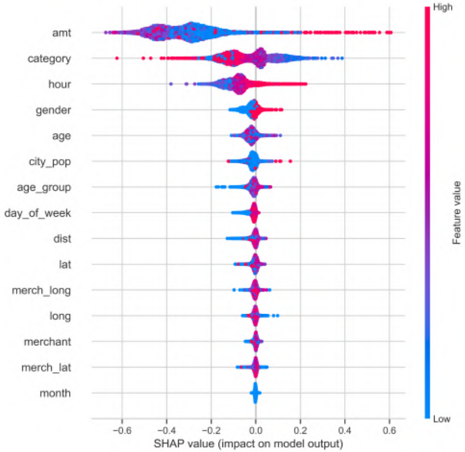


Figure: SHAP Summary Plot: Feature Importance for CNN Model

SHAP Results Local Visualization

SHAP Waterfall Plot

- Shows step-by-step impact
- Starting from base value (0.511)
- Category, hour, and age_group decrease fraud probability
- Final prediction: 0.989 (98.9% fraud confidence)

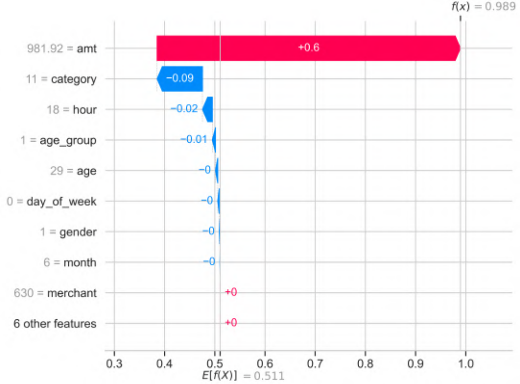


Figure: SHAP Waterfall Plot for the LSTM model's prediction (98,92%) at sample index 1044

SHAP Results Local Visualization

SHAP Force Plot

- Shows feature contributions pushing prediction from the base value
- Red = pushing toward fraud
- Blue = pushing toward legitimate
- Example: Transaction amount (+0.6) strongly indicates fraud

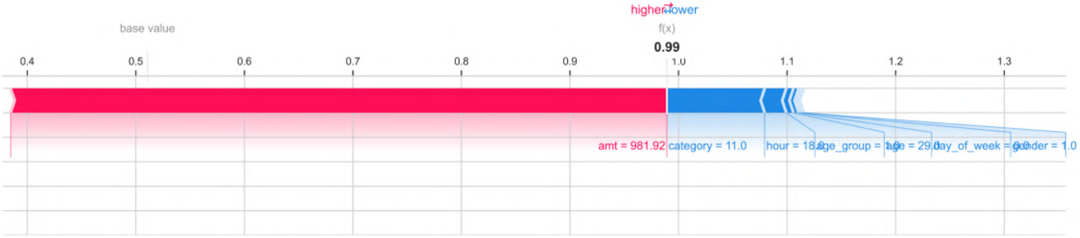


Figure: SHAP Force Plot for the LSTM model's prediction (98,92%) at sample index 1044

LIME Explanation

Example Interpretation

- Green bars support legitimate prediction
- Red bars indicate fraud signals
- Width shows contribution magnitude
- **Result:** 99.48% confidence in fraud

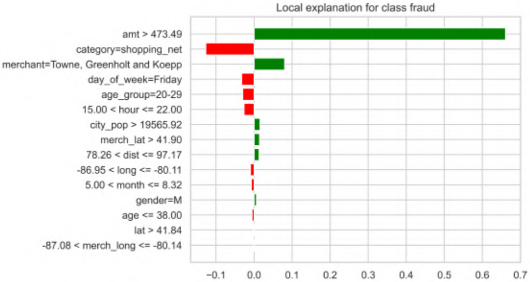


Figure: LIME explanation showing feature contributions for the CNN model's prediction (99,48%) at sample index 1044

Anchors Rule-Based Explanations

Rule-Based Explanations:

1. `amt > 88.51`
2. `hour > 22.00`
3. `category = food_dining`
4. `age > 64.00`
5. `gender = F`

Precision: 97.2% of cases matching this rule are correctly predicted as fraud
Coverage: 8.4% of all fraud cases are covered by this rule

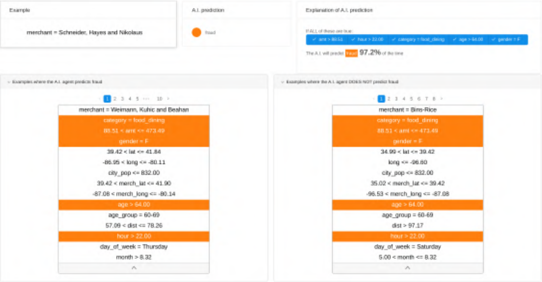


Figure: Anchors Explanation Interactive Observation in Notebook for the LSTM model's prediction (79,83%) at sample index 2025

XAI Methods Performance Analysis

Performance by Confidence Levels

- **SHAP:** Consistent across all confidence levels (0.594-0.629)
- **LIME:** U-shaped pattern, better at high/low confidence
- **Anchors:** Best for very high confidence predictions

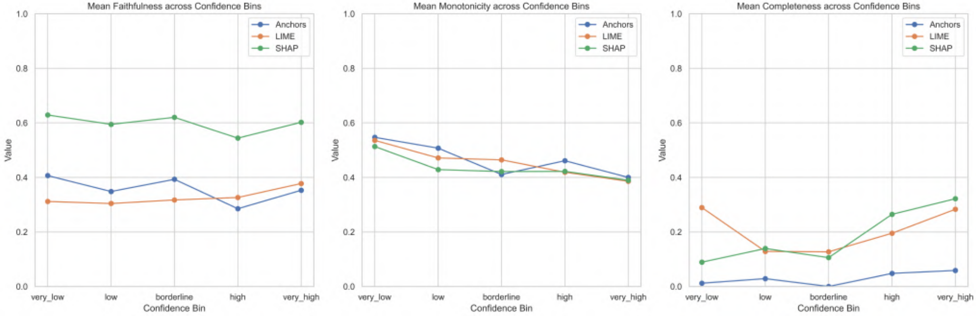


Figure: XAI Methods Performance Across Confidence Bins

XAI Effectiveness Across Confidence Levels

- The effectiveness of the XAI method depends on the model's prediction confidence.
- **Very High Confidence (>0.8):** SHAP explanations are most reliable.
- **High Confidence (0.6–0.8):** SHAP and LIME together provide a balanced view.
- **Borderline (0.4–0.6):** A multi-method approach (SHAP, LIME, Anchors) is best.
- **Low Confidence (<0.4):** SHAP plus human review is recommended.

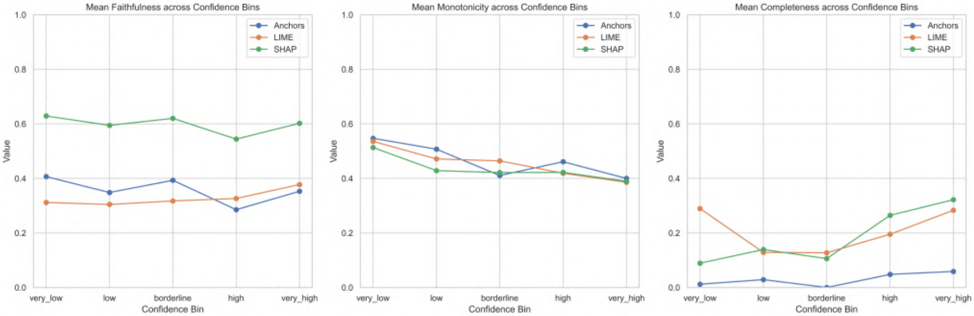


Figure: XAI Methods Performance Across Confidence Bins

XAI Methods: Performance Comparison Between Models

Key Findings:

- SHAP achieved the highest faithfulness for both models:
  - **LSTM:** 0.761 (significantly higher)
  - **CNN:** 0.443
- LSTM model consistently showed better faithfulness scores across all XAI methods
- Monotonicity and Completeness showed less variation between models

Model & Method	Faith.	Mono.	Comp.
CNN + SHAP	0.443	0.464	0.208
CNN + LIME	0.254	0.488	**0.295**
CNN + Anchors	0.315	0.486	0.033
LSTM + SHAP	**0.761**	0.429	0.134
LSTM + LIME	0.396	0.445	0.139
LSTM + Anchors	0.412	**0.469**	0.022

Table: XAI Methods Performance Metrics

Summary of Key Findings

- **SHAP is the most faithful XAI method**, especially for high-confidence predictions, providing explanations that align closely with the model's actual decision process.
- **LIME** offers balanced completeness and is particularly useful for local, case-by-case explanations.
- **Anchors** delivers the most human-interpretable rules, though with limited coverage.
- **Key global fraud indicators** across all models: transaction amount, category, and transaction hour.
- **XAI method effectiveness** varies with prediction confidence, SHAP is robust across all levels, while LIME achieves the best completeness. Anchors can give an easy-to-understand explanation.

Takeaway

Integrating XAI with deep learning models not only boosts trust and transparency but also provides actionable insights for fraud analysts and operational teams.

Discussion

Practical Implications and Challenges

- **Real-world deployment:** Both models process single transactions in under 5 seconds, and generate explanations in less than 3 minutes, making them suitable for real-time fraud detection.
- **Computational overhead:** SHAP explanations are computationally intensive (up to 45 minutes for 100 explanations), requiring careful resource management.
- **Stakeholder needs:**
  - SHAP is best for data scientists needing technical depth.
  - LIME is ideal for fraud analysts seeking intuitive, local explanations.
  - Anchors are valuable for operational teams needing clear, actionable rules.
- **Access to real data:** As changing fraud patterns in the real world would be a problem
- **Model complexity trade-offs** while some approaches offer good explanations, they might not be optimised for the "ingenuity of fraudsters" and high transaction volumes that are the main challenges in fraud detection.

Conclusions

Conclusions

- Successfully integrated XAI methods (SHAP, LIME, Anchors) with deep learning models for credit card fraud detection.
- Developed a novel confidence-based evaluation framework for XAI effectiveness.
- **SHAP** is recommended for global model interpretation and high-stakes applications.
- **LIME** is best for local, case-by-case explanations.
- **Anchors** are ideal for generating clear, actionable rules for operational teams.

Final Thought

XAI is not just a technical add-on, it is essential for building trust, meeting regulatory requirements, and empowering analysts in the fight against fraud.

Future Work

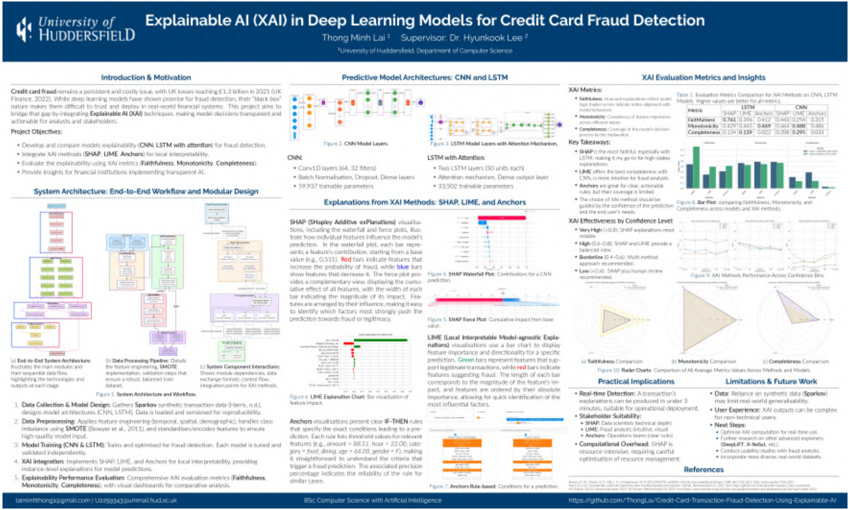
- **Expand model diversity:** Explore more advanced Deep Learning models and their explainability for fraud detection.
- **User studies:** Conduct usability studies with fraud analysts to assess the practical value of XAI explanations.
- **Optimise XAI computation:** Investigate faster, scalable XAI methods for real-time deployment.
- **More advanced DL-based explainers:** DeepLIFT[8] (Deep Learning Important FeaTures), X-NeSyL[9] (eXplainable Neural Symbolic Learning).

Invitation

I welcome any questions, feedback, or collaboration ideas. Let's make fraud detection smarter and more transparent together!

[8] Shrikumar et al., 2017.
[9] Díaz-Rodríguez et al., 2022.

Poster Presentation



Full poster available at:https://docs.google.com/viewer?url=github.com/ThongLai/Credit-Card-Transaction-Fraud-Detection-Using-Explainable-AI/blob/main/poster.pdf?raw=true

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Thank you!

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Questions and discussion welcome!