EXPLAINABLE AI (XAI) IN DEEP LEARNING MODELS FOR CREDIT CARD FRAUD DETECTION

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Certificate

This is to certify that this report entitled "Explainable AI (XAI) in Deep Learning Models for Credit Card Fraud Detection" is a bonafied record of the seminar presented by **Mr. Thong Minh Lai, ID No.U2259343** *under the guidance towards the partial fulfilment of the requirements for the award of* **Bachelor of Science in Computer Science with Artificial Intelligence** *of the* **University of Huddersfield**.

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Abstract

This report addresses the important challenge of interpretation in the Deep Learning model used to detect credit card transaction fraud. While Deep Learning approaches offer better performance in detecting fraud transactions, their black-box nature creates significant obstacles for practical deployment in financial institutions, where transparency and accountability by rules are mandatory. The project utilised and evaluated the XAI methods on several Deep Learning architectures that are widely known to be used in detecting credit card transaction fraud, including Convolutional Neural Networks (CNN) and Long Short-Term Memory networks (LSTM) with attention mechanisms, trained on Sparkov's synthetic dataset. The main contribution lies in the integration and comparative analysis of three state-of-the-art Explainable AI techniques: SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), and Anchors (rule-based explanations). Research further evaluates the effectiveness of each XAI method based on Faithfulness, Monotonicity, and Completeness metrics. Results suggest that both models provide the most consistent explanation in architecture, while the Anchors provide more action despite the low completeness score. This work contributes to the growing field of detection by setting up a broad structure for explanation method integration, potentially bridging the difference between high-performance Deep Learning models and regulatory compliance requirements in the financial sector.

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Chapter 1

Introduction

Credit Card fraud detection represents an important challenge for financial institutions worldwide with significant monetary and iconic implications. This chapter refers to the problem location, establishes the requirement of sophisticated detection mechanisms, and shows the main research questions addressed in this project. Integration of Deep Learning models with explainability methods presents a promising approach to balance the detection accuracy with interpretations in this domain.

1.1 Reference and problem statement

Credit card fraud represents an important and growing challenge in the financial sector, causing significant monetary losses worldwide. According to the data from the UK Finance, fraudsters stole over £1.3 billion in 2021 alone through authorised and unauthorised fraud, with card fraud accounting for a significant part of these damages (UK Finance, 2022). Detection of fraud transactions presents several important challenges that increase the need for advanced computational approaches.

1.1.1 Credit Card Fraud Detection Challenges

Credit cards include primary challenges in detecting fraud:

- **Interpretability:** Complex deep neural networks receiving high fraud detection accuracy often act as "black box" where decision-making processes remain opaque (Mienye & Jere, 2024). Financial institutions should not only detect fraud, but should also explain how and why specific transactions were flagged as fraud to meet regulatory requirements, build customer trust and enable human monitoring. These create a fundamental stress between performance and clarity, as the most accurate models usually provide the least transparency. Developed models that balance higher identification rates with explanatory outputs represent a significant technical challenge in credit card fraud detection systems.
- **Highly imbalanced dataset:** Fraud transactions usually represent 0.172% of all transactions (Pozzolo et al., 2015). In the Sparkov dataset used in this project (Grover et al., 2023), 1,289,169 general transactions vs are a significant imbalance with only 7,506 fraud (Grover et al., 2023; Shenoy, 2021). This imbalance creates an accurate identity of the exceptionally difficult minority fraud classes without special techniques.

- **Real-time detection requirements:** Financial institutions need to immediately identify fraud activities to prevent damage, require models that can process the transactions efficiently while maintaining accuracy (Hafez et al., 2025). This temporary barrier adds complexity to the implementation of the refined identification mechanism.
- **Complex and Evolving Fraud Pattern:** The fraudsters are constantly adapting their techniques, making sophisticated patterns that are difficult to detect using traditional rule-based systems (Sundararamaiah et al., 2024). As West and Bhattacharya (2016) notes, "Some researchers have considered models for adaptive classification, however, further research is required to fully develop these for use in practical fraud detection problems".

1.1.2 Need for Explainability in Fraud Detection Models

While machine learning models can achieve high accuracy in fraud detection, their "black box" nature presents significant concerns:

- **Regulator Compliance:** Financial institutions must follow rules such as GDPR in the European Union and Financial Conduct Authority (FCA) guidelines in the UK, including "right to explanation" for automated decisions affecting customers (Goodman & Flaxman, 2017). Without clear models, organisations risk regulatory punishment and legal challenges.
- **Stakeholder Trust:** Both customers and financial institutions need to understand that some transactions have been flagged as fraud to maintain confidence in the system of detection. When models cannot explain their decisions, valid transactions can be rejected without clear justification, damaging customer relationships (Vihurskyi, 2024).
- **Model verification and improvement:** Understanding how models decide is important to validate their arguments and identify potential biases or weaknesses (Barredo Arrieta et al., 2020). This understanding enables continuous improvement and adaptation to new fraud patterns.

1.1.3 Black Box Problem in Deep Learning

Deep learning models, while achieving state-of-the-art performance in the detection of fraud, present particular challenges regarding interpretability:

- **Complex Neural Network Architecture:** In this project, both CNN and LSTM models use a multi-layered architecture with several parameters. For example, the CNN implementation uses convolutional layers with various kernel sizes after dense layers, while the LSTM model incorporates sequential processing with the attention mechanism, making it difficult to interpret their internal decision processes (Ali et al., 2023).
- **Non-linear Transformations:** Deep Learning models apply many non-linear changes to input features, obscuring the relationship between input and output (Samek et al., 2017). This complexity makes it almost impossible to find out how specific features contribute to the final prediction without special clarity techniques.
- **Lack of transparency:** Unlike traditional rules-based systems where decision arguments are clear, deep learning models learn clearly patterns from data, give no internal explanation for their predictions (Ali et al., 2023). This lack of transparency is particularly problematic in detecting fraud, where analysts need to understand and justify why specific transactions are marked as suspicious.

1.2   Project Scope and Objects

The primary objective of this project is to build an explainable model to detect strong fraud by addressing several major objectives: ,

- **Handling Imbalanced Data:** Fraud transactions form only a minute fraction of financial activities. The project employs Synthetic Minority Over-sampling Technique (SMOTE) (Bowyer et al., 2011; Zhu et al., 2024), which aims to cure class imbalances.
- **Integrate XAI Techniques for Interpretability:** It is necessary that model decisions can be understood and are reliable. I unify state-of-the-art XAI methods such as SHAP (Lundberg & Lee, 2017), LIME (Ribeiro et al., 2016) and Anchors (Ribeiro et al., 2018) to distribute local interpretability.
- **Deep Learning Architectures:** To determine the optimal approach, this project included Deep Learning architectures that are widely known for their highly effective credit card fraud detection: Convolutional Neural Networks (CNNs) (Siddhartha, 2023) and LSTM-Attention networks (Ibtissam, 2021; Ibtissam et al., 2021). A comparative analysis is reported in the Raufi et al. (2024), which indicates the benchmarking strategy.
- **Synthetic Data Viability:** To augment scarce fraud data and to safeguard sensitive information, following the strategy of Breskuvienė and Dzemyda (2024), synthetic data from the Sparkov dataset (Grover et al., 2023; Harris, n.d.) is employed. This strategy, commonly used in credit card fraud detection research, enhances model robustness as elaborated by recent industry reviews.
- **Analyse Explainability Methods Effectiveness:** Finally, the project assesses the effectiveness of the integrated XAI techniques using metrics: Faithfulness, Monotonicity, and Completeness. Such analyses are crucial for ensuring that the explanations are reliable and actionable. (Seth & Sankarapu, 2025)

1.3   Final Product Description

The final product is envisaged as a comprehensive fraud detection system that consolidates multiple Deep Learning models and XAI techniques within a unified notebook (Lai, 2025f) on this GitHub repository Lai (2025a).

1.3.1   Overview of Implemented Models (CNN, LSTM)

Two principal models form the backbone of the system:

- **CNN Model:** Designed to extract spatial features from transaction data, the CNN model achieves high accuracy in distinguishing fraudulent from genuine transactions. Detailed model architecture and performance outcomes are implemented and shown in Lai (2025e).
- **LSTM Model:** The LSTM model is used to capture temporal dependencies inherent in sequential transaction data. Its attentional mechanism that enhances fraud detection performance are implemented in Lai (2025d).

1.3.2   Summary of XAI Techniques Integrated (SHAP, LIME, Anchors)

To demystify model decisions, I have incorporated three primary XAI techniques:

- **SHAP:** Utilises Shapley values to assign feature importance, offering local insights through force plots, summary plots, and dependence plots.
- **LIME:** Provides local, interpretable explanations by generating surrogate models to mimic the prediction behaviour for individual instances.
- **Anchors:** Delivers rule-based explanations with high precision, clearly outlining the conditions under which predictions are made.

1.3.3 Description of the System Design

The fraud detection using the XAI system comprises several integrated modules:

1. **Data Collection & Model Design:** Gathers synthetic transaction data (**Sparkov** dataset) and design model architectures (**CNN**, **LSTM**). Data is loaded and versioned for reproducibility.
2. **Data Preprocessing:** Raw transaction data is cleaned, normalised, and balanced using the SMOTE method.
3. **Model Training:** Separate pipelines are implemented for training the **CNN** and **LSTM** models.
4. **XAI Integration:** Post-training, XAI techniques are applied to generate explanations for model predictions.
5. **Performance Evaluation:** Comprehensive XAI evaluation metrics, including **Faithfulness**, **Monotonicity**, and **Completeness**, are computed.

A figure for the architecture is depicted in Figure 3.1.

1.4 Intended Market and Users

The fraud detection system is designed to meet different types of stakeholders:

- **Financial Institute and Fraud Analyst:** These users require high precision detection systems that effectively indicate fraud transactions. The explainability of feature characteristics helps analysts to verify the flag-based transactions and understand the underlying causes, as is discussed in Zhou et al. (2023).
- **Data Scientists and Model Developers:** Provides a modular structure for system use and additional model refinement. The comprehensive integration of Deep Learning models and XAI components makes it a valuable tool for research and development.

Chapter 2

Literature Review

This chapter establishes theoretical foundations for my research on explainable AI in detecting credit card fraud. I start by checking the development of fraud detection techniques, followed by my implementation with relevant Deep Learning approaches are analysed. I then found out the increasing importance of model interpretability in financial services, with a detailed examination of the major XAI techniques employed in my research. Finally, I address synthetic data ideas and moral implications that inform my methodology.

2.1 Credit Card Fraud Detection Fundamentals

The Credit card fraud detection landscape has developed significantly in recent decades, moving from rules-based systems to sophisticated machine learning approaches.
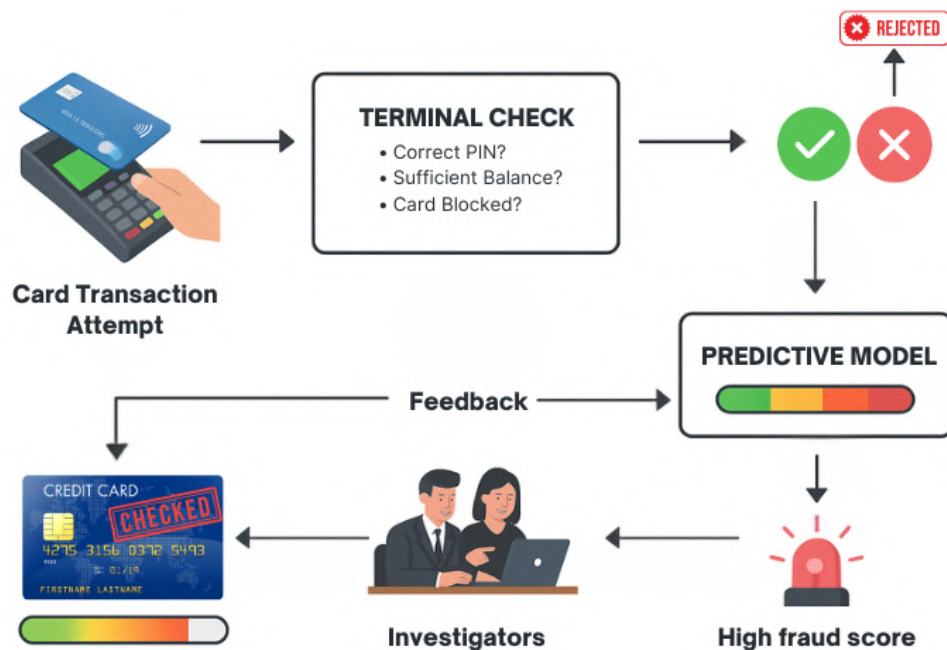
Figure 2.1: Illustrative diagram of the Credit Card Fraud Detection System (Hasan et al., 2024)

2.1.1 Evolution of Machine Learning in Fraud Detection

Credit card fraud detection has always been a moving goal, in which fraudsters constantly find out the tactics to evade detection. Traditionally, banks and financial institutions rely on rules-based systems and thresholds to flag suspicious transactions. While these systems were straightforward and easy to explain, they were also rigid and struggled to keep pace with the new and upcoming nature of fraud. As is highlighted by Sundararamaiah et al. (2024), these initial approaches were "fast and interpretable, they struggle to keep pace with evolving fraud patterns, thus resulting in higher false positives and undetected fraud" (Sundararamaiah et al., 2024).

The introduction of Machine Learning (ML) carried forward a significant jump. ML models, such as Decision Trees and Support Vector Machines, can learn from historical transaction data and highlight complex patterns that would be impossible to encode manually. However, even with these advances, a frequent challenge remains: severe class imbalance in the fraud dataset. Fraud transactions typically less than 1% of all transactions (Du et al., 2024; Grover et al., 2023), meaning that a naive model can simply gain high accuracy by predicting every transaction as legitimate, which leads to models being biased towards the majority class, often missing rare but significant fraud cases (Du et al., 2024).

Recently, the Deep Learning approach has revolutionised the capabilities of detecting fraud, especially in the financial sector, where credit card fraud represents a serious and growing problem due to emerging technologies and communication methods. The Deep neural network architectures, which include Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have demonstrated better performance in detecting complex fraud patterns by learning automatically learn hierarchical representations from transaction data (Cherif et al., 2023).

2.2 Deep Learning Models for Fraud Detection

Complex patterns in fraud behaviour have led researchers to more sophisticated Deep Learning architectures. My research focuses on two major approaches: Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks.

2.2.1 CNN Architecture

The Convolutional Neural Networks, which are traditionally applied to image processing, have been successfully adapted to transactions by treating sequences of transactions as temporal patterns. CNNs identify patterns and facilitate hierarchy, making them effective for detecting fraud signals even when being embedded within valid transaction sequences (Paulraj, 2024).

In my implementation, based on Siddharth's approach (Siddhartha, 2023), the CNN architecture processes 15 transactions through 2 convolutional layers with separate kernel sizes, followed by dense layers for classification. The model obtained 98.83% accuracy and a ROC AUC value of 0.994.

2.2.2 LSTM Architecture

The LSTM networks are well suited to detecting fraud due to their ability to discover temporary correlations in transaction sequences (Ibtissam et al., 2021). Unlike traditional neural networks, LSTM maintains an internal memory position that enables it to "remember" the previous states when evaluating the current state - a significant ability to detect sophisticated fraud patterns (Ibtissam et al., 2021).

My LSTM implementation is based on Ibtissam's approach (Ibtissam, 2021), which covers an attention mechanism that allows the model to focus on the most relevant characteristics within transactions. This approach obtained 98.11% accuracy with a ROC AUC value of 0.973, which provides strong comparative performance metrics for my research.

2.3 Explainable AI (XAI) in Financial Services

As Deep Learning models become rapidly complicated, explainability and interpretation requirements have increased proportionally, especially in highly regulated areas such as financial services (Mienye & Jere, 2024).

2.3.1 Importance of Model Transparency in Financial Sector

Financial institutions need to balance detection accuracy with transparency requirements. While Deep Learning models provide better performance, their "black box" nature creates significant challenges for implementation in a regulated environment. The adaptive nature of the fraudsters requires equally adaptive identification systems, yet these systems should be transparent to maintain stakeholder trust (Tomy & Ojo, 2025; Vihurskyi, 2024).

Model transparency fulfils many objectives in detecting financial fraud:

- Enabling human analysts to understand and trust model outputs (Ali et al., 2023)
- Providing insight for continuous improvement in model efficiency (Saeed & Omlin, 2023)
- Supporting auditability requirements for regulatory compliance (Goodman & Flaxman, 2017)
- Facilitating customers trustworthy explanation that the AI is making correct and non-biased decisions based on facts when transactions are flagged (Ali et al., 2023)

2.3.2 Regulatory Requirements (GDPR, Financial Regulation)

Financial institutions face increasing regulatory pressure on their systems of automated decision-making systems. The European Union includes the General Data Protection Regulation (GDPR) and similar rules in the UK include provisions that can be interpreted as "right to explanation" for the decisions made by automated systems (Goodman & Flaxman, 2017).

Article 22 of GDPR addresses a particularly automated decision making, in which requiring organisations to implement "suitable measures to safeguard the data subject's rights and freedoms and legitimate interests, at least the right to obtain human intervention on the part of the controller, to express his or her point of view and to contest the decision." (Goodman & Flaxman, 2017). These are implications that the detection systems should balance high performance with explainability.

2.3.3 Stakeholder Trust Considerations

Beyond the regulatory requirements, explainability creates confidence among various stakeholders in the ecosystem of detecting fraud:

- **Customers** requires clarification when their transactions are flagged
- **Fraud analysts** need to understand model decisions to investigate efficiently alerts
- **Compliance officers** must verify that decisions align with regulatory standards
- **Model Developers** rely on clarification to refine and improve the system

Research by Gilpin et al. (2018) indicates that transparent AI systems that can provide satisfactory explanations of their decisions can lead to wider user acceptance and increased trust compared to opaque systems, even when both get similar performance metrics.

2.4 XAI Techniques

To address the black box challenges of Deep Learning models, my research implements three major XAI techniques: SHAP, LIME and Anchors. Each one provide a different approach to the explanation, with complementary strengths and boundaries.

2.4.1 SHAP (SHapley Additive exPlanations)

The game theory concepts of SHAP values provide an integrated approach to explain individual predictions (Barredo Arrieta et al., 2020; Lundberg & Lee, 2017). The technique reflects the contribution of each feature for a specific prediction by calculating Shapley values, a concept from cooperative game theory that considers the "payout" (prediction result) between "players" (features).

In my implementation, SHAP enables local explanation for one specific transactions prediction. The approach generates visualisations including force plots and summary plots that provide an intuitive representation of the feature contributions to model decisions (Lai, 2025f).

2.4.2 LIME (Local Interpretable Model-agnostic Explanations)

LIME helps to build an explanatory surrogate model that estimates locally complex models around specific predictions (Ribeiro et al., 2016). The technique works by perturbing input features around a specific considering sample and measuring how the model predictions change, then fitting a simple (linear) explanatory model for this local behaviour.

To detect fraud, LIME provides a particularly valuable insight to individual transaction analysis, helping analysts understand why specific transactions were marked as suspicious. My implementation shows how LIME can also provide accessible clarification for complex CNN and LSTM architectures (Lai, 2025f).

2.4.3 Anchors and Rule-Based Explanation Approach

Anchors produce the high-precision rules (IF-THEN rules) to explain the models decisions (Ribeiro et al., 2018). Unlike SHAP and LIME, which provide the important weights for each

features, Anchors focuses on making clear, deterministic rules that are sufficient to explain predictions with high confidence.

In the implementation, Anchors generate rules such as:

```
IF
    transaction amount > 1000 AND transaction_time > 12pm AND age > 64.00
THEN
    prediction = Fraud (confidence 0.95)
```

(Lai, 2025f). These rules-based explanations are particularly valuable for fraud analysts who require clear decision criteria.

2.4.4   Comparative Analysis of XAI Approaches

The evaluation of XAI techniques in this project is based on three core metrics: **Faithfulness**, **Monotonicity**, and **Completeness**. These metrics are widely recognised in literature, which is essential to assess the quality and reliability of model explanations (Kadir et al., 2023; Pawlicki et al., 2024), especially in high-stakes domains such as fraud detection.

- **Faithfulness**: This metric measures how explanations reflect the relationship of the model in training data patterns (Kadir et al., 2023). This is usually evaluated by removing the features identified as important and by measuring the change in the prediction of the model. As is said in Kadir et al. (2023), "A high faithfulness correlation indicates that the model faithfully detects patterns and information in the training data".
- **Monotonicity**: It assesses that placing features in the order of their importance on the baseline surface leads to the expected changes in predictions Kadir et al. (2023). In other words, the features considered to be more important by the XAI method should have more impact on the output of the model when removed.
- **Completeness**: This metric evaluates how much explanation of the model is captured. It computes the difference between the original prediction and the prediction when the features in the explanation are used only (Pawlicki et al., 2024; Sundararajan et al., 2017).

2.5   Synthetic Data in Model Development

Given the sensitive nature of financial transaction data, synthetic datasets play an important role in the research and development in the fraud detection sector and in supporting data privacy preservation (Financial Conduct Authority, 2024; Vallarino, 2025).

2.5.1   Benefits and Limitations of Synthetic Data

Model development shows many advantages when using synthetic data fraud:

- **Privacy protection**: No risk of exposing sensitive customer information
- **Control data characteristics**: Spontaneous ability to generate specific fraud patterns
- **class balance management**: Construction of dataset with desired fraud/legitimate ratios
- **Volume scaling**: Generation of large dataset for model training

However, synthetic data also presents limitations, especially regarding its belief towards real-world patterns and cannot replace the real customer data (Financial Conduct Authority, 2024) or may not fully capture the complexities of real-world transactions (Kamalaruban et al., 2024). Ryman-Tubb et al. (2018) note that "As the profiles of genuine and fraudulent behaviours change over time, synthetic data may be insufficiently rich. Therefore, there is no reason to suspect that results cited will necessarily be the same when scaled using real-world data".

2.5.2 The Sparkov Dataset Characteristics

My research utilises the Sparkov dataset (Grover et al., 2023), a synthetic credit card transaction dataset specifically designed for fraud detection research. The train dataset includes 1,296,675 transactions, of which 7,506 (approximately 0.58%) are fraudulent and the test dataset includes 553,574 transactions, with 2,145 (approximately 0.39%) are fraudulent, mirroring the class imbalance challenge found in real-world scenarios (Grover et al., 2023; Lai, 2025f).

After the feature engineering process to fit the purpose of this project, the dataset contains 15 features, including:

- Transaction amount and time
- Merchant category and location
- Customer demographics and account details
- Geographical information and travel patterns

(Lai, 2025f)

(a) Numerical Features Distributions   (b) Categorical Features Distributions
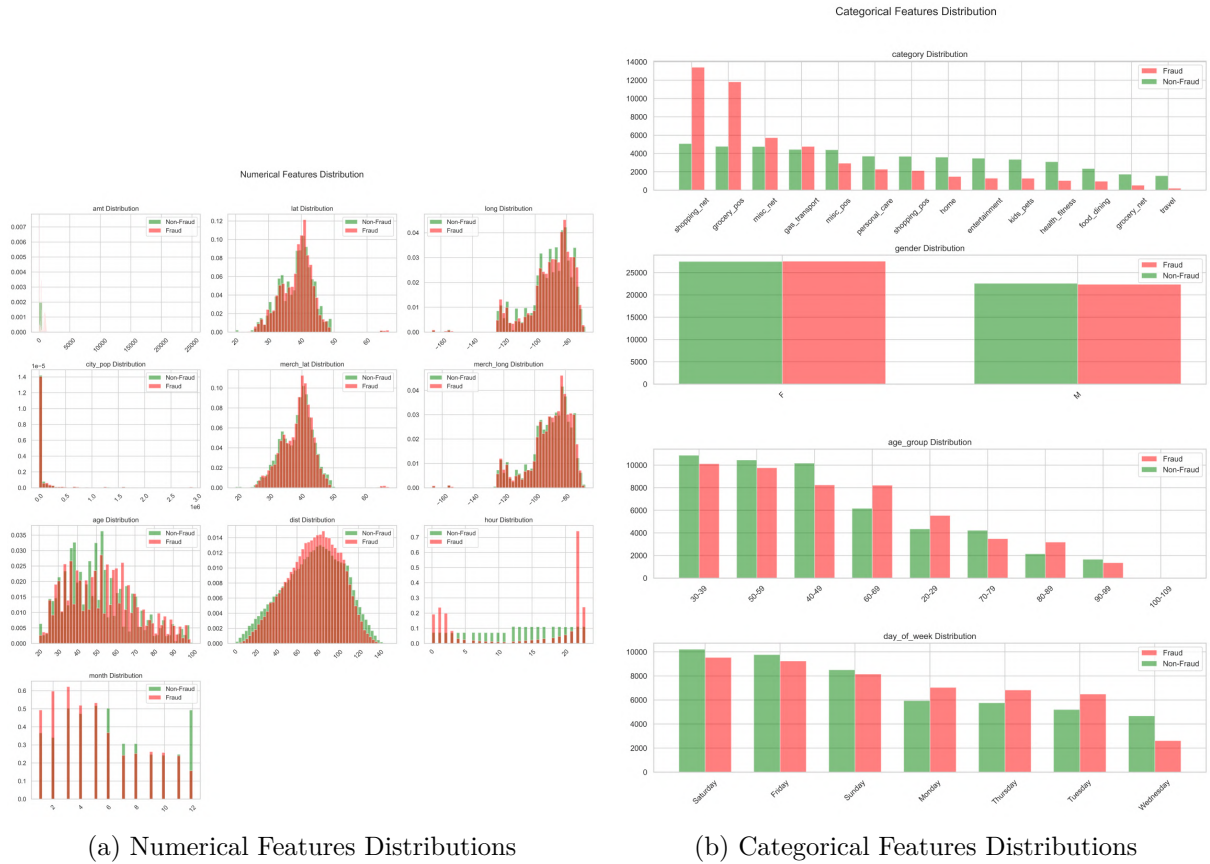
Figure 2.2: Features Distributions in the Sparkov Train Dataset

These features provide sufficient complexity to train refined detection models while maintaining realistic statistical distributions compared to real transaction data.

2.6 Ethical and Legal Considerations

The deployment of systems to detect AI-based fraud raises important moral and legal issues that must inform both research and implementation approaches (Financial Conduct Authority, 2024).

2.6.1 Privacy Implications of Fraud Detection Systems

Fraud detection systems process sensitive personal and financial data, raising significant privacy concerns. Even with synthetic training data, the system deployed will eventually interact with real customer information, which requires strong privacy and security. So it is important to make sure to balance the need to prevent fraud and the need of customers for privacy Găbudeanu et al. (2021).

2.6.2 Bias and Fairness in Automated Decision Systems

AI-based fraud detection systems, at risk of amplifying the biases present in training data. Research by Kamalaruban et al. (2024) suggests that high-value fraud missed may lead to models that can be unequally demolished transactions of specific demographic groups or geographical areas, despite a balanced detection rate.

My project also addresses these concerns:

- Applied the balanced sampling technique during training
- XAI methods to identify and address fairness issues with more interpretation
- Considering various user segments

2.6.3 Compliance with Financial Regulations

In addition to the GDPR, the fraud detection system must follow several financial regulations, including anti-money laundering (AML) requirements, Know Your Customer (KYC) provisions and specific sector industry standards (Vallarino, 2025).

The integration of XAI techniques implemented in my research supports these compliance efforts, directly providing the transparency and auditability necessary for these rules. By allowing the revision of human inspection and the clarity of automated decisions, the system maintains the necessary balance between automation and compliance.

Chapter 3

Methodology

The chapter describes the methodological approach used in this project, including research design, dataset processing, model development, XAI implementation and technical environment. The methodology is based in established research practices and constructs upon the existing work in the field of Deep Learning and explainable AI for detecting fraud.

3.1 Research Approach

3.1.1 Justification of Selected Development Approach

The development approach to this project is based on the integration of Deep Learning models with explainable AI techniques for detecting credit card fraud. This hybrid approach was chosen due to its proven effectiveness in addressing complex problems like fraud detection (Uwaezuoke & Swart, 2024), while maintaining interpretation. Deep Learning models excel in identifying complex relations in data, which is important to detect fraud where the fraud strategies can be subtle and evolve over time.

The specific combination of the Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks was chosen due to their complementary advantages (Uwaezuoke & Swart, 2024). The CNNs are effective in capturing spatial patterns of transaction features, while LSTMs excel in identifying temporary dependencies of sequential transaction data (Uwaezuoke & Swart, 2024). This multi-model approach allows for strong comparison and evaluation of explainability in various architectures for the detection of fraud.

3.1.2 Experimental Design Logic

The experimental design model follows a systematic approach to development, training and evaluation. First, both CNN and LSTM models are trained at the same preprocessed dataset to ensure proper comparison. Then, on each model, apply widely known XAI techniques (SHAP, LIME, and Anchors), which provide a variety of perspectives on the interpretation of the model. This enables a comprehensive evaluation of both design model performance and explainability.

As Seth and Sankarapu (2025) stated, "Combining standardised metrics with flexibility and human expertise can create a more robust, adaptable, and meaningful evaluation framework for XAI systems". Following this guidance, experimental design includes quantitative performance

metrics and qualitative explainability assessment (Ma, 2024; Seth & Sankarapu, 2025).

3.1.3   Evaluation Framework Selection

The evaluation structure employs a multidimensional approach to assess both predictive performance and interpretation. For predictive stating performance, the standard metrics are used: accuracy, precision, recall, F1-score, and AUC-ROC. These metrics are suitable for this imbalanced dataset, where the positive class (fraud) is quite low.

For explainability assessment, I employ specific metrics for each XAI evaluation. Faithfulness measures how well the explanations reflect the actual decision process of the model, Monotonicity assesses whether the importance of the feature increases leads to stronger predictions and Completeness evaluates how comprehensively the explanations cover enough information for the output (Kadir et al., 2023; Pawlicki et al., 2024).
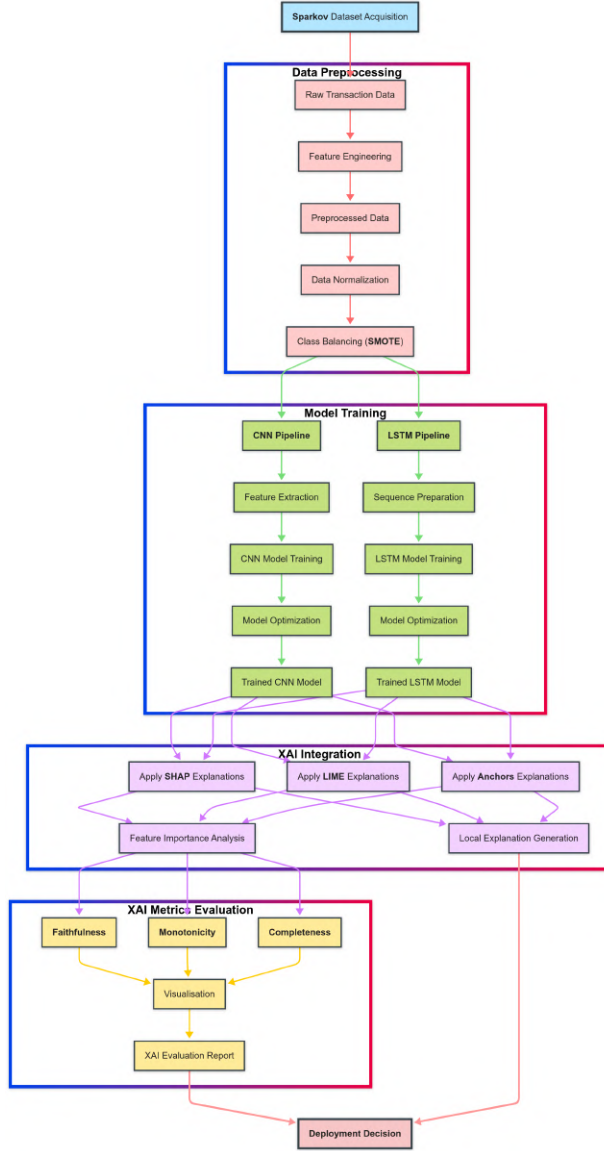
Figure 3.1: Illustrative diagram of the fraud detection system architecture showing data flow from preprocessing to model training, XAI integration and evaluation.

3.2 Dataset Description and Preprocessing

3.2.1 Synthetic Data (Sparkov) Characteristics

The synthetic credit card transactions data was generated using the Sparkov data generator, as real financial datasets are often limited by privacy concerns and regulatory restrictions. The Sparkov dataset imitates realistic credit card transactions, including both legitimate and fraudulent activities, based on the pattern seen in the real-world financial data (Grover et al., 2023).

Characteristic	Value
Total Transactions	1,296,675
Fraud Rate	0.58%
Features	22
Temporal Range	2 years
Transaction Types	Multiple categories

Table 3.1: Sparkov Synthetic Dataset Characteristics

The dataset includes 22 fields, including transaction amount, timestamp, location data (latitude and longitude for both customer and businessman), and customer demographic information:

Table 3.2: Credit Card Transaction Data Fields

Field Name	Description
trans_date_trans_time	Date and time when transaction occurred
cc_num	Credit card number of customer
merchant	Name of merchant where transaction occurred
category	Category of merchant (e.g., travel, shopping_net, etc.)
amt	Amount of transaction
first	First name of credit card holder
last	Last name of credit card holder
gender	Gender of credit card holder
street	Street address of credit card holder
city	City of credit card holder
state	State of credit card holder
zip	ZIP code of credit card holder
lat	Latitude location of credit card holder
long	Longitude location of credit card holder
city_pop	Population of credit card holder's city
job	Occupation of credit card holder
dob	Date of birth of credit card holder
trans_num	Transaction number
unix_time	UNIX timestamp of transaction
merch_lat	Latitude location of merchant
merch_long	Longitude location of merchant
is_fraud	Target class indicating whether transaction is fraudulent (1) or legitimate (0)

3.2.2 Data Cleaning and Transformation

Raw Sparkov data requires several preprocessing stages before training models. First, the data is cleaned to handle missing values and remove discrepancies.

For changes, the transaction category and customer gender are converted into a numerical format using ordinal encoding. Numerical features are standardised to reduce the influence of outliers, which are common in transaction amount feature.
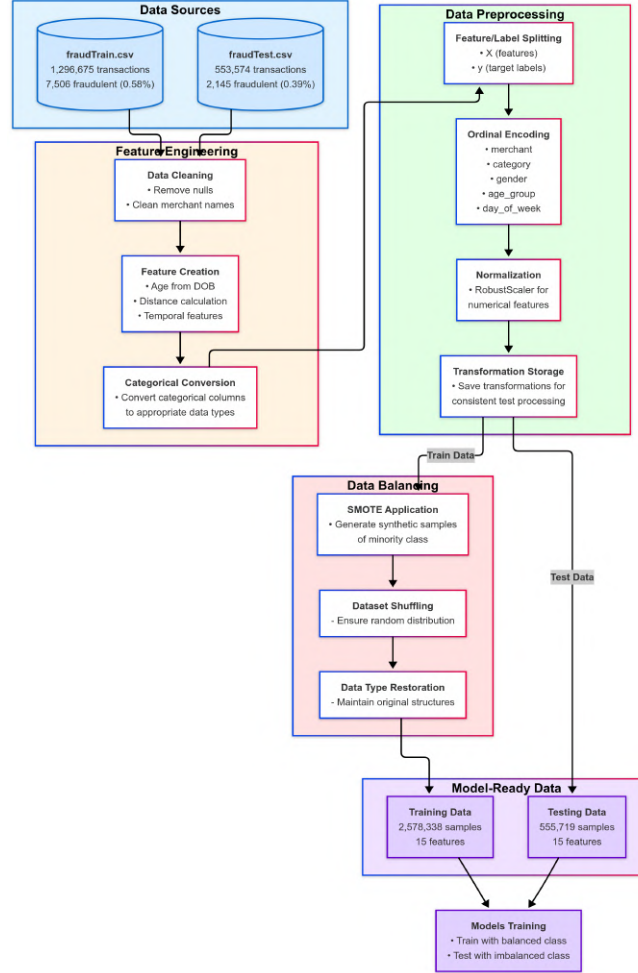
Figure 3.2: Data Preprocessing Pipeline for Fraud Detection

3.2.3 Feature Engineering Approaches

This process of feature engineering plays an important role in increasing the discriminatory for the models. Following approaches from the literature (Grover et al., 2023), remaining derived features are created:

- **Distance calculation:** The Haversine formula is applied to compute the distance between the customer and merchant locations, as geographical anomalies can indicate potential fraud.
- **Temporal features:** Transaction hour, day of week, and month are extracted from timestamps to capture time-based fraud patterns.

- **Age grouping:** Customer ages are categorised into meaningful groups (e.g., 18-25, 26-35) to capture demographic patterns.

These engineered features enhance the model's ability to identify fraudulent patterns that may not be clear from raw data alone.

3.2.4 Handling Class Imbalance (SMOTE Implementation)

The important imbalance of the classese in the data (about 0.58% fraud transactions) poses a challenge for model training. To address this, excessive SMOTE has been applied, which generates minority class synthetic examples by interpolating them among examples of existing fraud rather than simply duplicating them. (Bowyer et al., 2011; Grover et al., 2023; Pozzolo et al., 2015; Zhu et al., 2024)

The implementation uses an **imbalanced-learn** library with a sampling strategy that balances the dataset in a proportion of 50:50 for training dataset. This approach helps to prevent the model from predicting the majority class (legitimate transactions) and improves its ability to identify the minority of fraud cases.

3.3 Model Architecture and Development Method

3.3.1 CNN Architecture Design

The CNN model is designed to capture spatial patterns in the transaction data features. The architecture follows design principles established by Siddhartha (2023), adapted to the specific characteristics of credit card transaction data.

Layer Configuration

The CNN architecture consists of the following layers:

Table 3.3: CNN Layer Configuration

Layer	Configuration	Activation
Input	15 features	-
Convolutional 1	64 filters, kernel size 2	ReLU
Batch Normalisation	-	-
Convolutional 2	32 filters, kernel size 2	ELU
Dropout	Rate 0.3	-
Dense	64 units	ReLU
Flatten	-	-
Fully Connected	64 units	ReLU
Dropout	Rate 0.2	-
Output	1 unit	Sigmoid

This architecture results in a model with 59,937 trainable parameters, striking a balance between model capacity and computational efficiency.

Training Procedure

Hyperparameter selection was guided by empirical evaluation and prior research in the domain. The key hyperparameters include:

- **Optimizer:** Adam with default parameters ($\beta_1 = 0.9, \beta_2 = 0.999$)
- **Loss function:** Binary cross-entropy
- **Batch size:** 30,000
- **Early Stopping**: Patient of 4 epochs
- **Epochs**: 100, Training until convergence or early stopping

These hyperparameters were selected based on their effectiveness in similar fraud detection tasks as documented by Ibtissam (2021) and Ibtissam et al. (2021).

3.3.2 LSTM with Attention Mechanism

Model Structure

The LSTM model is designed to capture temporal dependencies in transaction data, based on the architecture proposed by Ibtissam et al. (2021) and adapted for fraud detection. The model structure includes:

Table 3.4: LSTM Layer Configuration

Layer	Configuration	Activation
Input	15 features	-
LSTM 1	50 units, dropout 0.3, recurrent dropout 0.2	Tanh
LSTM 2	50 units, dropout 0.3, recurrent dropout 0.2	Tanh
Attention	Custom implementation	Softmax
Dense	1 unit	Sigmoid
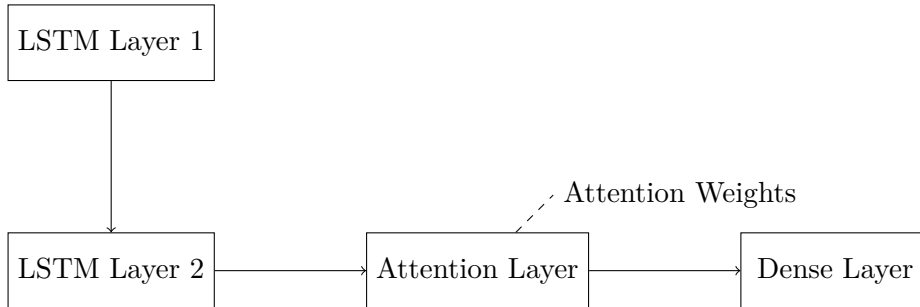
Figure 3.3: LSTM Model with Attention Mechanism

Attention Layer

The attention mechanism is applied based on work by Vaswani et al. (2023), which allows the model to focus on the most relevant features for predicting. The attention layer calculates a weighted sum of the LSTM output, which has a weight determined by a learning reference vector. Mathematically, the attention mechanism is defined as follow:

$$u_t = \tanh(W_w h_t + b_w) \tag{3.1}$$

$$\alpha_t = \frac{\exp(u_t^T u_w)}{\sum_t \exp(u_t^T u_w)} \tag{3.2}$$

$$v = \sum_t \alpha_t h_t \tag{3.3}$$

Where h_t represents the hidden state at the time t, W_w and b_w are trainable parameters, u_w is the reference context vector, α_t are attention weights, and v is the context vector that focuses on the most relevant parts of the input sequence.

This architecture results in a model with 33,502 trainable parameters, which is more parameter-efficient than the CNN model, while still maintaining a strong performance.

Training Procedure

The LSTM model was trained using a similar approach to the CNN model, with the following specifics:

- **Optimizer**: Adam with learning rate 0.001
- **Loss Function**: Binary cross-entropy
- **Batch Size**: 30,000
- **Early Stopping**: Patient of 4 epochs
- **Epochs**: 50, Training until convergence or early stopping

3.4   XAI Methodology

3.4.1   SHAP Integration Methodology

SHAP was designed following a model-agnostic approach. This method allows for the explanation of any machine learning model by approximating Shapley values from game theory, which represent the average marginal contribution of a feature across all possible feature combinations (Lundberg & Lee, 2017).

Algorithm 1 SHAP for Credit Card Detection

1: **Input:** Trained model f, transaction x
2: **for** each feature i in x **do**
3:     Initialize SHAP value $\phi_i = 0$
4:     **for** each subset S of features not containing i **do**
5:         Create two samples: $x_{S \cup \{i\}}$ and x_S
6:         Compute marginal contribution: $f(x_{S \cup \{i\}}) - f(x_S)$
7:         Weight the contribution based on subset size
8:         Add weighted contribution to ϕ_i
9:     **end for**
10: **end for**
11: **Output:** SHAP values $\phi_1, \phi_2, ..., \phi_n$ showing each feature's contribution to $f(x)$

Design includes:

- **Background Dataset Creation**: A representative dataset of 100 samples from the training data to work as reference points for SHAP calculations.
- **SHAP Value Calculation**: For each feature in a transaction, calculate its contribution to the estimated possibility of fraud by measuring the average impact of having that feature in all possible combinations of features.
- **Core SHAP Visualisations**: with force plots and waterfall charts to provide the explanation of the model's prediction. The forces plot is greatly useful in showing how each feature pushes the prediction away from the base value, while the summary plots display the feature importance throughout the dataset.

The design handles both numerical features (eg, transactions, transaction times) and categorical features (e.g., merchant category) through appropriate preprocessing steps before feeding them to the SHAP explainer (as categorical features will need to be handled differently in the SHAP explainer).

3.4.2 LIME Integration Methodology

LIME was implemented to make a surrogate model that approximates deep learning models around individual predictions. This approach allows for the spontaneous, intuitive, feature-based explanation of specific transaction classifications (Ribeiro et al., 2016).

Algorithm 2 LIME for Credit Card Detection

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

---

Design includes:

- **Data Perturbation**: To get explanations for each transaction, perturbation samples are obtained by perturbing the feature values around the original sample. This detects the model behaviour in the local neighbourhood.
- **Kernel Weighting**: Depending on their proximity to the original sample, the weights for closer samples are assigned higher.
- **Local Model Fitting**: Fit a weighted linear model for perturbation samples and their predictions from the black-box model. This linear model acts as an explanatory approximation of the complex models locally.
- **Feature Discretisation**: Continuous (numerical) variables were discriminated against to improve explainability while maintaining fidelity for the original model. For example, the amount of transactions, the discretionary thresholds were set based on distribution quantiles.

LIME explanations provide feature weights contribution, which helps fraud analysts under-

stand which factors most affect a specific fraud prediction.

3.4.3 Anchors Integration Methodology

The Anchors method raises the IF-THEN rules that explain the predictions. Unlike SHAP and LIME, which provide feature continuous contribution scores, Anchors provide clear, actionable rules that are easy to understand for non-technical stakeholders (Ribeiro et al., 2018).

Algorithm 3 Anchors for Credit Card Detection

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

---

Design includes:

- **Rule Candidate Generation**: Generate potential rules based on feature-value pairs from the considering sample that need to generate the explanation, as in the Example 2.4.3
- **Best Anchor Selection**: Select the best anchor (rule) based on precision, which is computed based on the proportion of instances where the rule holds true and the model makes the same prediction.

3.4.4 XAI Evaluation Metrics and Approach

To ensure the reliability and validity of XAI implementation, I developed a comprehensive evaluation assessment structure based on three key metrics widely used in the XAI field:

Table 3.5: XAI Evaluation Metrics Brief

Metric	Description	Evaluation Method
Faithfulness	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
Monotonicity	Evaluates whether removing features causes consistent changes in the model's predictions	Sequential feature removal testing with prediction tracking
Completeness	Assesses how much of the model's prediction is captured by the explanation	Coverage measurement comparing explained variance to total variance

Pseudo-algorithms:

Algorithm 4 Faithfulness Metric for XAI Explanations

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

Algorithm 5 Monotonicity Metric for XAI Explanations

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

Algorithm 6 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)

The evaluation approach included:

- **Stratified Sampling**: Use balanced stratified sampling to select test cases for evaluation, ensuring comprehensive evaluation in various confidence levels and predicting results.
- **Edge Case Analysis**: Special attention for collecting the "edge cases", such as abnormally high confidence scores or legitimate transactions near decision boundaries, fraud transactions with valid transactions, to ensure that clarifications are reliable in challenging scenarios.
- **Cross-Model Comparison**: Compare to identify model-specific biases in feature importance and explanation stability in both CNN and LSTM models. This helped to understand whether different architecture depends on different features for their predictions.
- **Confidence bin analysis**: It breaks down the performance further, highlighting the strengths and weaknesses of each XAI method in different prediction confidence.

3.5 Technical Environment

This section details the implementation tools, hardware specifications and development environment used for this project. It is important to ensure a consistent and well-written technical environment, ensuring reproducibility.

3.5.1 Implementation Tools and Frameworks

Tools and Frameworks was used to implement this project can be found in B.2.1

Custom utility modules ('utils.py') provided supportive tasks for data preprocessing, model evaluation and visualisation. This utility module ensured continuous data handling in all model implementations and XAI techniques.

3.5.2 Hardware Specifications

The GPU acceleration was particularly helpful for training the CNN and LSTM models with attention mechanisms, which required much more computational resources (See B.2.3). The hardware configuration was verified on the runtime to ensure optimal performance (Lai, 2025f).

3.5.3 Project Directory Structure and Development Environment

The development environment was configured to ensure consistency across different implementation phases and team members:

- **Virtual Environment**: Suggest create separate virtual environment when running (example: '.venv_xai_fraud_detection')
- **Random Seed**: Set to 42 for reproducibility across all experiments
- **Project Structure**:
  - Model architectures stored in `architectures/` directory
  - All input, output data stored in `data/` directory
  - Visualisations, plots and diagrams stored in `visualisation/` directory
  - Full project directory structure can be found in B.2.4
- **Version Control**: GitHub repository with branch-based workflow (Lai, 2025a)

Development Environment Configuration

The project includes **requirements.txt** file to ensure consistent package versions in the environments. This approach helped prevent compatibility issues during integration. Constant environmental configuration allows for spontaneous transition between development, training and evaluation stages, ensuring that the results are comparable and reproducible throughout the project life cycle. Environment and dependencies setup can be found in B.2.2

Chapter 4

Implementation, Findings, and Analysis

This chapter describes the practical implementation of the credit card fraud detection system by Deep Learning models with explainable AI integration. Implementation follows the previous chapter 3 established methodological structure on system architecture, model implementations and collecting performance results. Each section examines the technical aspects of the implementation, showing major decisions and their results.

4.1 System Architecture

System architecture includes many interconnected components designed to handle data processing, model training and XAI integration. It is designed with modularity and extensibility, with mutual helper functions implemented in the 'utils.py' file module for separate notebooks files contains components that are developed individually.

4.1.1 Data Processing Pipeline

The data processing pipeline converts raw transactions to a suitable format before feeding data into the Deep Learning Model (C.1). This multi-step process involves feature engineering, preprocessing as shown in Figure 3.2.

The feature engineering phase applies several major stages:

- **Temporal Feature Extraction**: Turn Unix timestamps into cyclic time features like hour of day, day of week and month.
- **Distance Calculation**: Applying the Haversine formula to calculate distance (between the location of the transaction and the merchant based on their longitudes and latitudes.
- **Demographic Processing**: Counting age from date of birth and meaningful demographic groupings.

Code snippet for feature engineering can be found in C.1.1

Table 4.1: Feature Description Table After Data Processing

Field Name	Description
merchant	Name of merchant where transaction occurred
category	Category of merchant (e.g., travel, shopping_net, etc.)
amt	Amount of transaction (e.g., $25.50)
gender	Gender of credit card holder (e.g., M(Male), F(Female)
lat	Latitude location of credit card holder (e.g., 34.0522)
long	Longitude location of credit card holder (e.g., -118.2437)
city_pop	Population of credit card holder's city (e.g., 4000000)
merch_lat	Latitude location of merchant (e.g., 34.0522)
merch_long	Longitude location of merchant (e.g., -118.2437)
age	Age of credit card holder (derived from dob, e.g., 28)
age_group	Age group category of credit card holder (e.g., 20-29, 30-39)
dist	Distance from transaction to merchant (e.g., 5.2 miles)
hour	Hour of day when transaction occurred (e.g., 14)
day_of_week	Day of the week when transaction occurred (e.g., Monday)
month	Month when transaction occurred (e.g., April)

The preprocessing stage includes:

- **Categorical Encoding**: Transforming the categorical variables through ordinal encoding.
- **Handling Class Imbalance**: Applying **SMOTE** from **imblearn** library to address serious imbalance in fraud data.
- **Feature Standardisation**: Using **RobustScaler** from **sklearn** library to keep resistant to outliers when standardise features.

Code snippet for data preprocessing can be found in C.1.2

This processing pipeline ensures consistent data preparation in all experiments, enhances reproducing ability and enables appropriate comparison between models. These data processing steps share the same pipeline before transferring to the model (which are applied to separate notebooks), so all the mutual functions of data collecting and processing data are implemented in 'utils.py' (Lai, 2025a)

4.1.2 XAI Integration Components

The XAI integration structure includes several explanation methods to provide wide insights into model decisions (C.4). The implementation focuses on three explainers of three XAI methods:

- **SHAP explainer**: **KernelExplainer** provided in **shap** library was implemented for local explanations through force plots, summary plots and dependence plots.
- **LIME explainer**: **LimeTabularExplainer** provided in **lime** library for integrating local explanation of individual predictions.
- **Anchors explainer**: **AnchorTabularExplainer** provided in **anchor-exp** library for rule-based explanation that provides high-accurate insight.

This implementation approach is based on the framework and libraries proposed by Lundberg and Lee (2017), Ribeiro et al. (2018), and Ribeiro et al. (2016). Raufi et al. (2024) also emphasised the importance of combining these several XAI techniques for better credit card

fraud interpretation.

4.1.3   System Interaction Diagram

The system components interact through a carefully designed workflow that ensures uninterrupted data flow and model integration. Figure 4.1 illustrates these interactions.
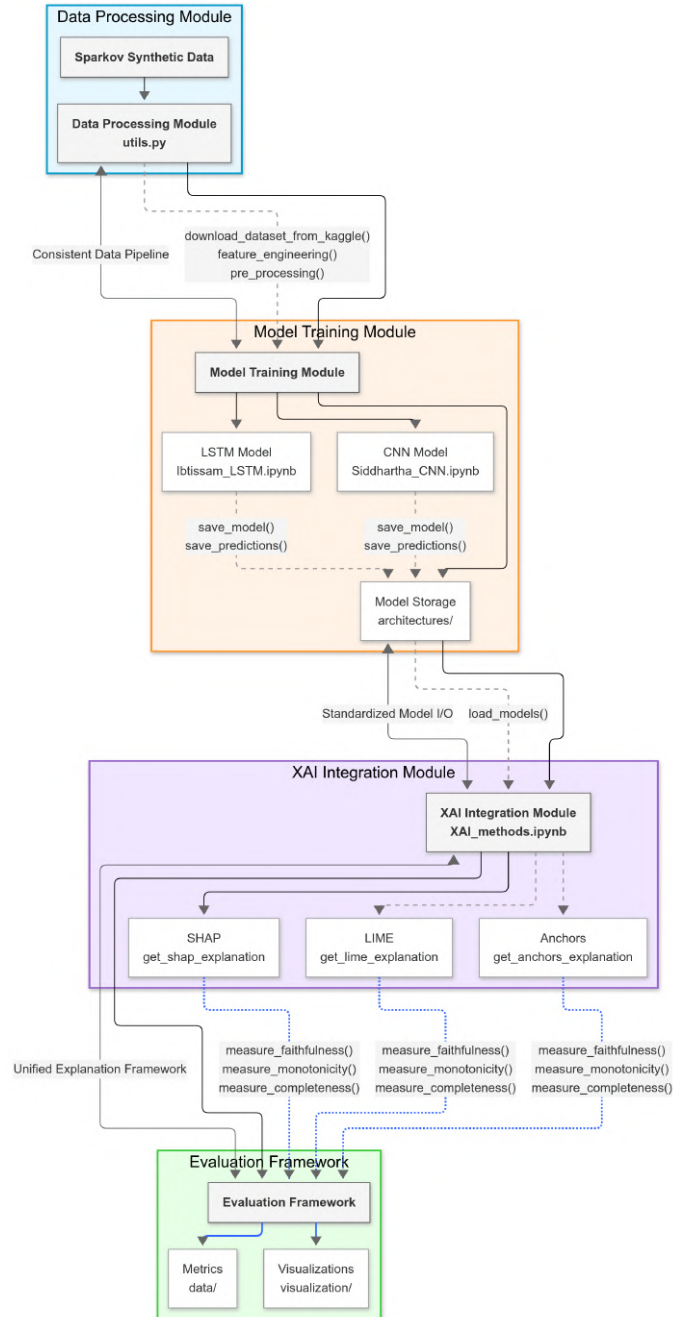
Figure 4.1: System Component Interactions

The system architecture facilitates:

- Modular designs with separation of concerns between data processing, model training and explanation generation

- Consistent data pipelines ensuring compatible transformations between components
- Standardised model input/output interfaces enable the spontaneous integration of the models
- Unified explanation framework allows comparison performance between various XAI methods

4.2 CNN Model Implementation

4.2.1 Detailed Architecture

The CNN model architecture was specifically designed to process 15 input features through a series of convolutional layers (3.3.1). Figure 4.2 shows the model architecture.
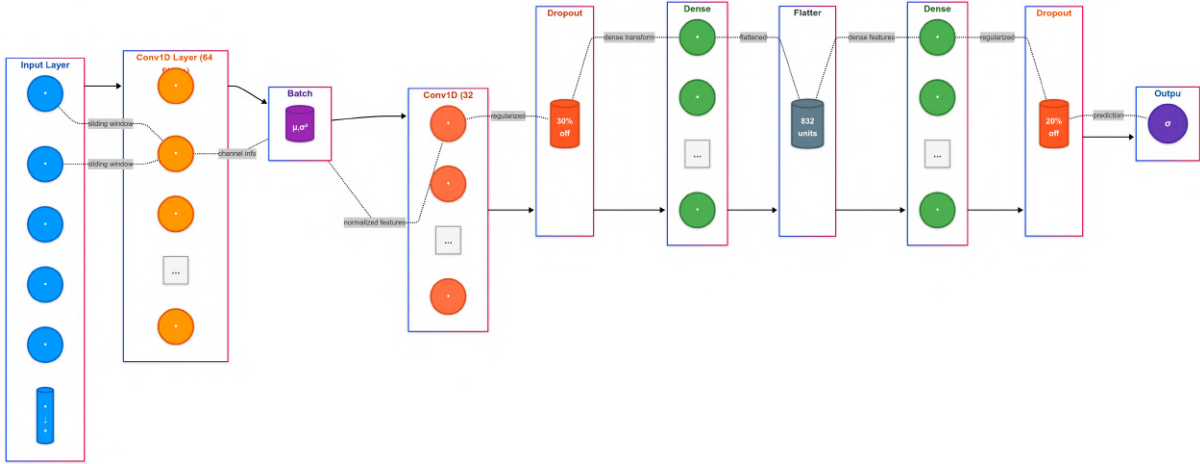
Figure 4.2: CNN Model Architecture

The main design options include:

- **Convolutional Layers**: Two Conv1D layers with 64 and 32 filters respectively using a small kernel size (2) to capture local patterns in sequential features.
- **Activation Functions**: ReLu activation for the first convolutional layer, and ELU (Exponential Linear Unit) for the second layer to address the vanishing gradient problem.
- **Regularisation Techniques**: Batch normalisation after the first convolutional layer and dropout (0.3) to prevent overfitting after the second convolutional and dense layer.
- **Output Layer**: A sigmoid activation function for binary classification.

The architecture's code implementation can be found in C.2.1

4.2.2 Training Process and Optimisation

The CNN model training process implemented optimisation techniques (C.2.2) to increase performance and convergence.

The main optimisation strategies included:

- **Adam Optimiser**: Was implemented with a learning rate of 0.001, combined with Ada-

Grad and RMSProp advantages.

- **Batch Size**: Define as 30,000 for the balance between computational efficiency and shield estimation accuracy (as this project utilises Tensorflow-GPU performance).
- **Early Stopping**: Applied with a patience of 4 epochs to avoid overfitting, ensuring proper training.
- **Binary Cross-Entropy Loss**: Selected as a proper loss function for this binary fraud classification task.

Figure 4.3 shows the training and validation loss and accuracy curves.

(a) CNN Model Accuracy Training Curve   (b) CNN Model Loss Training Curve
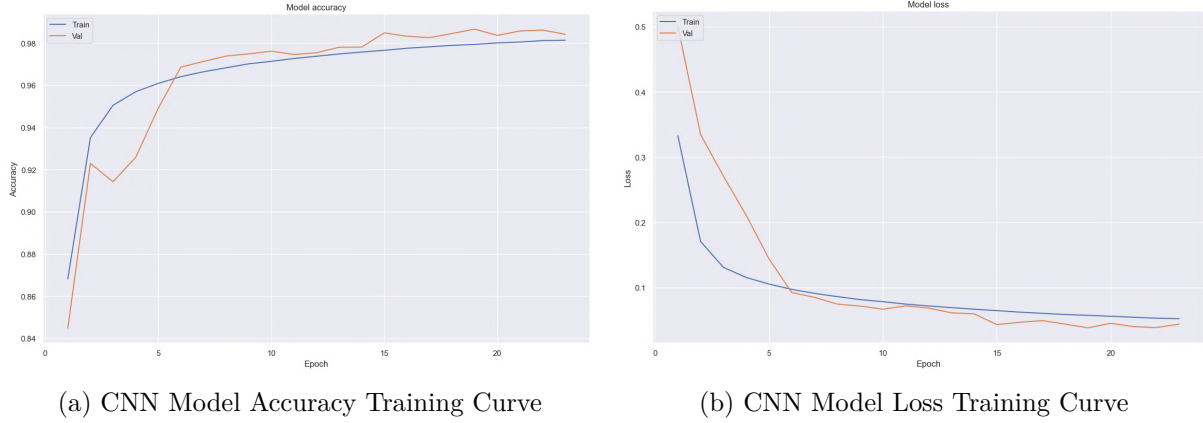
Figure 4.3: CNN Model Training and Validation Curves

4.2.3 Performance Metrics

The CNN model achieved good performance metrics on the test set, Table 4.2 shows summarised metrics obtained by the CNN model.

Table 4.2: CNN Model Performance Metrics

Metric	Value
Accuracy	98.6%
ROC AUC	0.994
Class 0 (Non-fraud)	
Precision	0.999
Recall	0.987
F1-Score	0.993
Class 1 (Fraud)	
Precision	0.213
Recall	0.918
F1-Score	0.346

The performance metrics show that the CNN model performed well in detecting non-fraudulent transactions (high precision and recall for Class 0). For fraud transactions (class 1), the model receives high recall (0.918), showing that it successfully identifies most cases of fraud, although with low precision (0.213). This performance aligns with conclusions by Gambo et al. (2022), who observed the same great pattern in the CNN model to detect fraud in credit card transactions.

4.3 LSTM Model Implementation

4.3.1 Architecture with Attention Mechanism

The LSTM model involves an attention mechanism to increase its performance on sequential transaction data (Lai, 2025d). Figure 4.4 shows the model architecture.
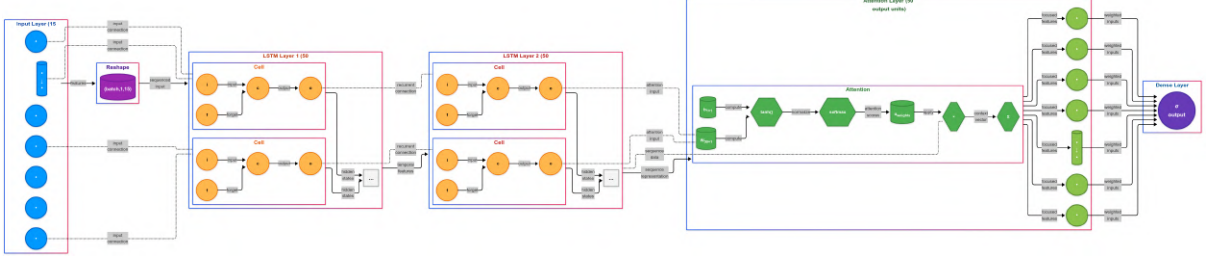
Figure 4.4: LSTM Model Architecture with Attention Mechanism

The main design options include:

- **LSTM Layers**: Two stacked LSTM layers with 50 units each, and maintain sequential information for the attention mechanism by using return_sequences=True.
- **Attention Mechanism**: A custom attention layer that learns to focus on the most relevant parts of the sequence to detect fraud.
- **Regularisation**: Dropout (0.3) and recurrent dropout (0.2) to avoid overfitting.
- **Output Layer**: A sigmoid activation function for binary classification.

The architecture's code implementation can be found in C.3.1

This architecture was inspired by the research of Ibtissam et al. (2021), who demonstrated that the LSTM model with attention mechanisms could effectively capture temporary patterns in transactions data to detect the activities of fraud.

4.3.2 Training Process and Challenges

The LSTM model training process (C.3.2) faced several challenges related to sequence handling and convergence.

The training process involved:

- **Adam Optimiser**: Implemented with a learning rate of 0.001, similar to the CNN model.
- **Batch Size**: Set to 30,000 to maintain consistency with the CNN training approach.
- **Early Stopping**: Implemented with a patience of 4 epochs, which triggered after 26 epochs.

Several challenges emerged during the LSTM training process:

- **Slow Convergence**: The LSTM model required more epochs to reach optimal performance compared to the CNN model.
- **Memory Constraints**: The recurrent nature of LSTM layers increased memory requirements, necessitating optimised batch processing.

Figure 4.5 shows the training and validation loss and accuracy curves.
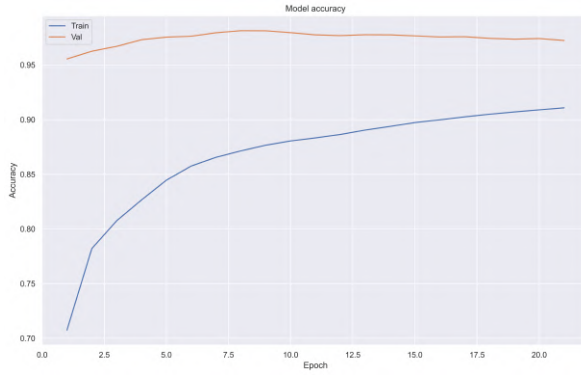
(a) LSTM Model Accuracy Training Curve   (b) LSTM Model Loss Training Curve
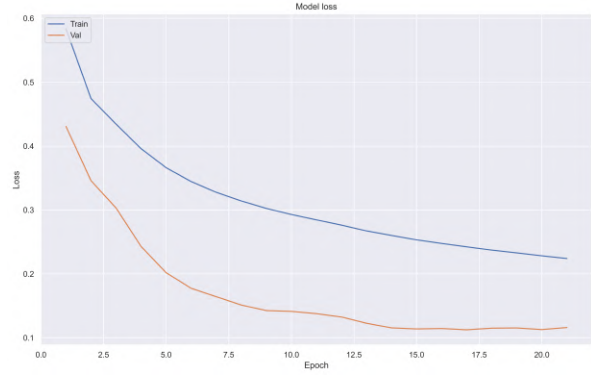
Figure 4.5: LSTM Model Training and Validation Curves

4.3.3 Performance Metrics

The LSTM model achieved robust performance metrics on the test set. Table 4.3 summarises the performance metrics achieved by the LSTM model.

Table 4.3: LSTM Model Performance Metrics

Metric	Value
Accuracy	97.6%
ROC AUC	0.971
Class 0 (Non-fraud)	
Precision	0.999
Recall	0.976
F1-Score	0.987
Class 1 (Fraud)	
Precision	0.118
Recall	0.814
F1-Score	0.206

The LSTM model shows strong overall performance, with excellent accuracy (97.6%) and ROC AUC (0.971). For fraudulent transactions, it achieves a recall of 0.814, highlighting the persistent challenge of false positives in fraud detection. This performance is consistent with findings by Ibtissam et al. (2021), who observed that LSTM models excel at capturing temporal patterns.

4.4 Getting Results and Analysis from Explainers

The section describes the results of practical implementation and integrating AI methods, including SHAP, LIME, and Anchors. Focused on how these explainers were applied to trained models, the insight provided by them and their effectiveness comparative analysis. All experiments were conducted on a processed test dataset, which ensures a controlled environment for explainability performance evaluation.

4.4.1 SHAP Visualisations and Analysis

SHAP values were computed for both the CNN and LSTM models, quantifying the contribution of each feature to individual predictions. Figure 4.6 shows SHAP values result from the CNN model predicting that a transaction is 99.48% as a fraud.
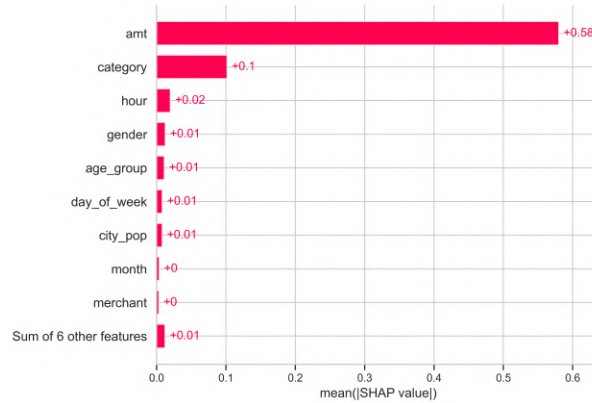
Figure 4.6: SHAP Bar Plot showing feature importance (mean SHAP values) for the CNN model's fraudulent prediction (99,48%) at sample index 1044.

The visualisation pipeline generated force plots and waterfall plots, which were invaluable for both debugging and communicating results to non-technical stakeholders. The implementation in generated several visualisation types to extract insights:

Figure 4.7 below shows example force plots for explaining predictions from the CNN and LSTM models for the same fraudulent transaction, highlighting how features push the prediction value away from the baseline.
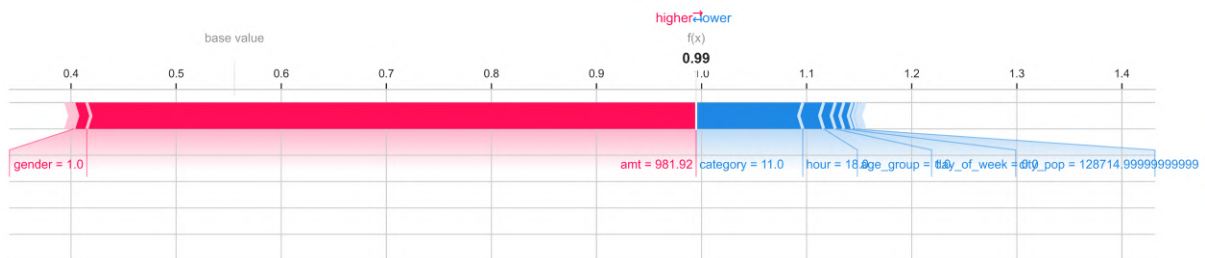
(a) Feature contributions for the CNN model's prediction (99,48%) at sample index 1044
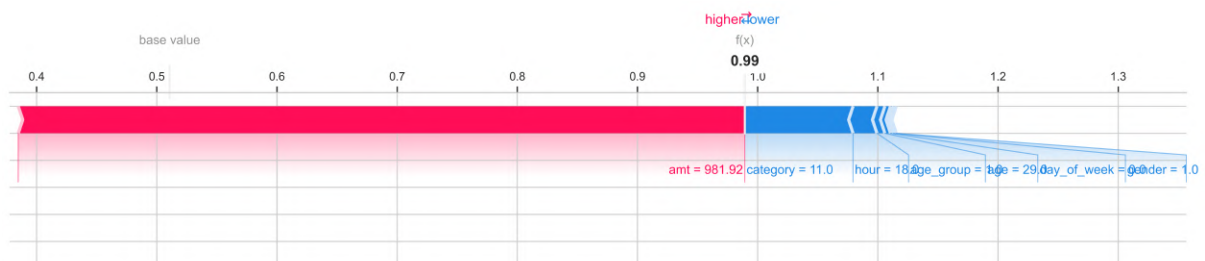
(b) Feature contributions for the LSTM model's prediction (98,92%) at sample index 1044

Figure 4.7: SHAP Force Plot showing feature contributions of 2 models for the same transaction prediction. Red features push the prediction toward fraud classification while blue features push toward legitimate classification.

Feature Importance Findings

The SHAP analysis detected the frequent patterns of feature importance in both models, as can be observed in Figure 4.7, the feature contribution to the predictions of both models is almost identical. It is also shown that the transaction amount emerged as the most influential feature, with a mean absolute SHAP value of 0.58 for the CNN model prediction (4.6), significantly higher than other features. This aligns with domain knowledge that abnormal transactions often indicate potential fraud.

Local Explanation Examples

To understand individual predictions, the implementation involves generating local explanations using SHAP waterfall plots. These explanations were particularly valuable to investigate cases of false positives and false negatives.
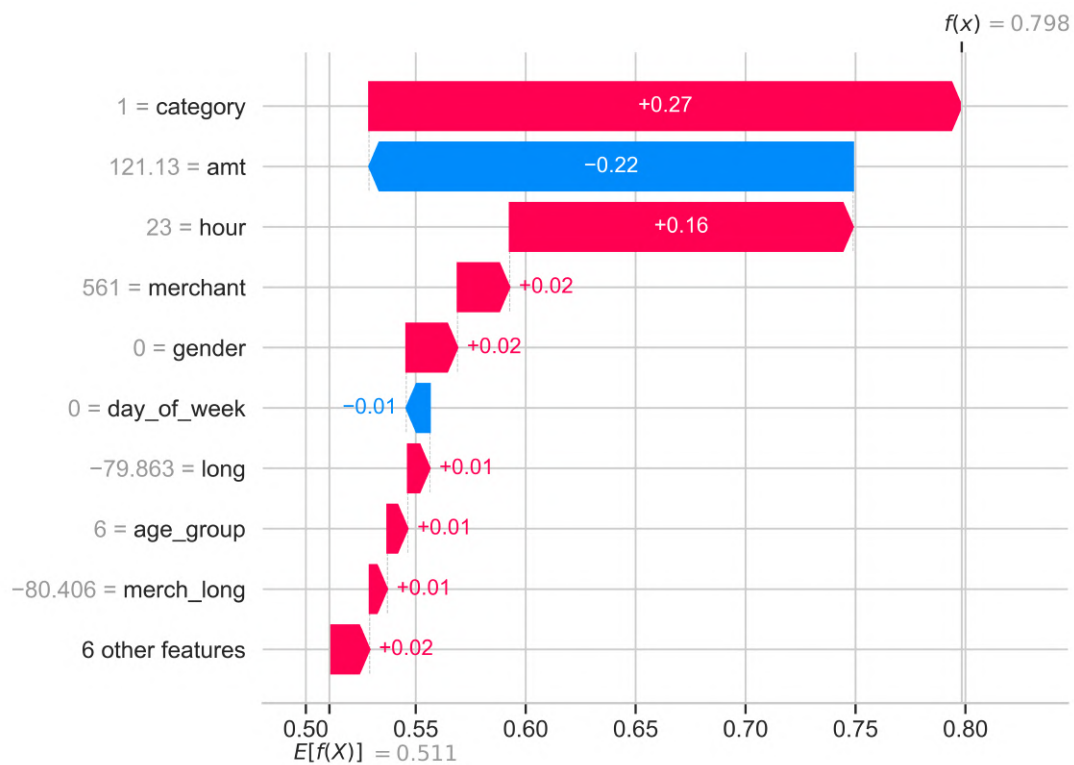
Figure 4.8: SHAP Waterfall Plot showing feature importance distribution for the LSTM model's prediction (79,83%) at sample index 2025. Higher feature values are represented in red, while lower values are in blue.

For example, analysis of a false positive case from the LSTM model (the considering index 2025 in the test dataset was flagged as fraud, but it is a valid transaction) showed that the amount of transaction was within the general normal limit (121.13) (negative contribution to the possibility of fraud), but because of unusual transaction time (23:00 midnight) with specific category of transaction ('1' is 'food_dining') created a strong positive contribution that pushed the prediction above the fraud classification threshold. This granular understanding helped to refine the model by adjusting the feature weight in subsequent training sessions.

4.4.2 LIME Explanations and Insights

LIME was applied to complement the SHAP by providing a surrogate explaining model. While the SHAP alliance provides feature attribution based on game theory, LIME creates a locally faithful linear model around individual predictions.

The implementation required careful tuning of several parameters:

- **kernel_width**: Set to 0.75 after experimentation, showing optimal balance between locality preservation and sampling sample efficiency
- **num_samples**: Increased from the default value of 1000 to 5000 to improve the stability of the explanation
- **discretize_continuous**: Enabled of improving interpretation of numerical features

Figure 4.9: LIME Explanation Interactive Observation in Notebook
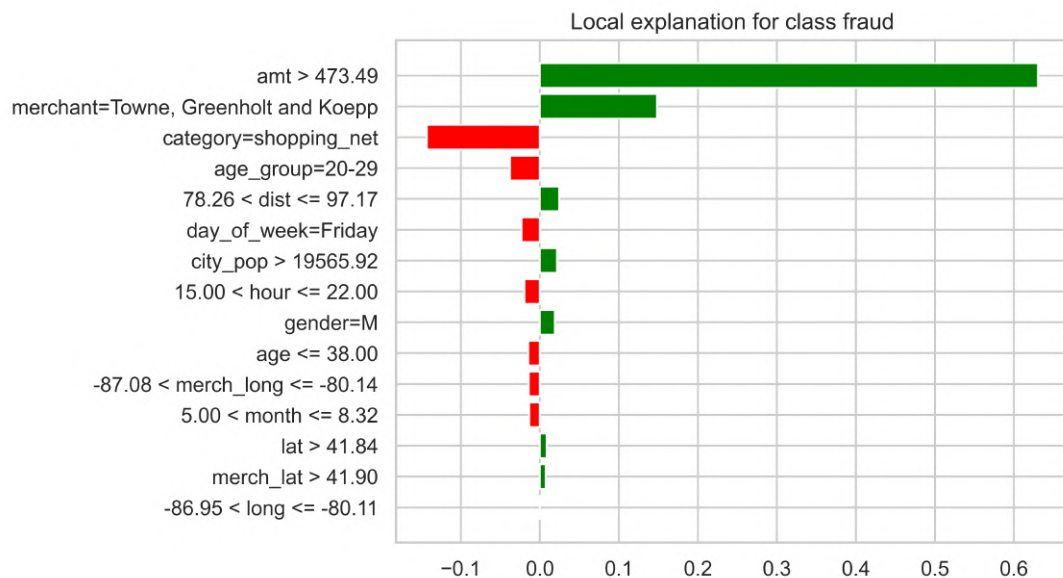
Figure 4.10: LIME Explanation showing feature contributions for the CNN model's prediction (99,48%) at sample index 1044. Green bars indicate features pushing toward legitimate prediction, while red bars indicate features pushing toward fraud.

4.4.3 Anchors Rule Extraction Results

Anchors were applied to generate high-precision "IF-THEN" rules that can interpret models' predictions. Unlike SHAP and LIME, which provide certain numerical feature contribution scores, Anchors provides clear decision criteria that easily understood by non-technical stakeholders Ribeiro et al. (2018).
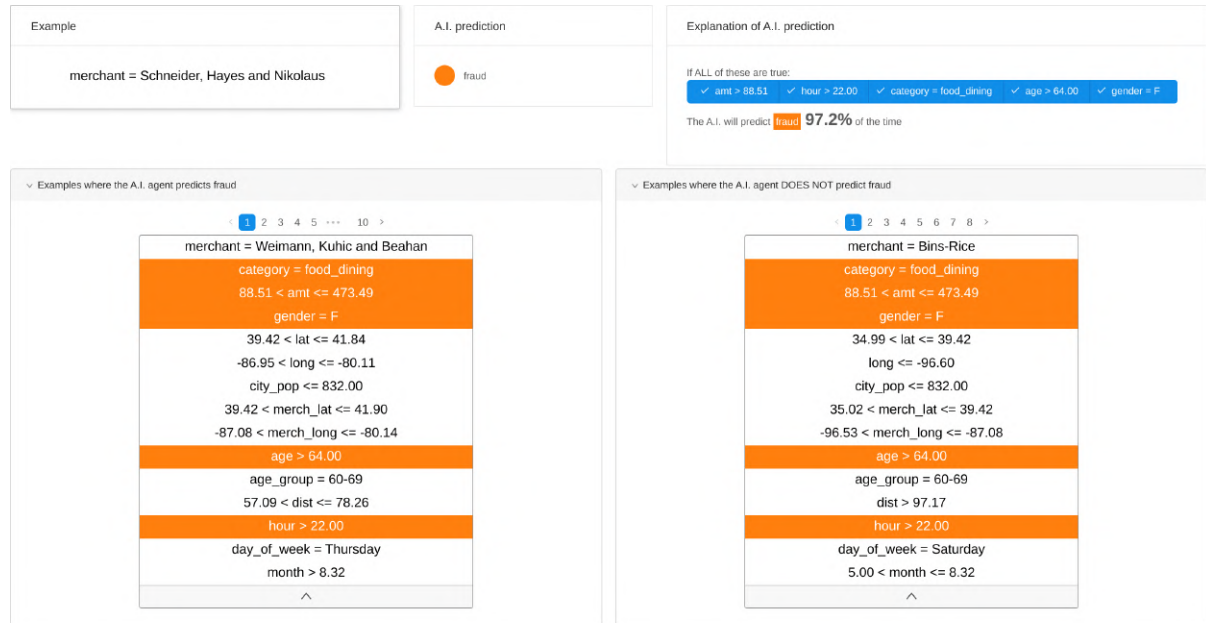
Figure 4.11: Anchors Explanation Interactive Observation in Notebook

Rules extraction from Anchors revealed interesting patterns that were aligned with domain knowledge. The explanation of specific rules for the LSTM model's prediction (79,83%) at sample index 2025 is as follows:

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

This rule achieved an accuracy of 0.972 for this false positive case, indicating high reliability, but this explanation had 0 in coverage, which means that it applies to a small (or almost unique) subset of transactions. This gives examples of the precision-coverage trade-offs noted by Ribeiro et al. (2018), where more precise rules usually cover fewer examples.

4.4.4 Getting XAI Methods Evaluation

Retrieving Stratified Samples

The evaluation method applied a cross-validation approach using stratified samples to construct testing samples, which ensures representation of both fraud and non-fraud cases. In this project,

each method was evaluated in 30 testing examples for optimal running time, but the more testing examples, the better the samples can illustrate many different cases, which would result in more reliable evaluation results. Stratification includes different prediction confidence:

- '*very_high*' confidence predictions (confidence > 0.8)
- '*high*' confidence predictions (0.6 < confidence < 0.8)
- '*borderline*' confidence predictions (0.4 < confidence < 0.6)
- '*low*' confidence predictions (0.2 < confidence < 0.4)
- '*very_low*' confidence predictions (confidence < 0.2)
- Edge cases testing samples with unusual transactions with extreme feature values.

Code snippet of the implementation of function for the retrieving samples can be found in C.5.1

XAI Evaluation Implementation

The evaluation framework applies three core metrics as proposed in 3.4.4. These metrics were chosen for their complementary approach to explainability quality and their relevance to cases of detecting fraud. Implementation follows the proposed approach by Oblizanov et al. (2023).

Code snippet for each metric implementation: C.5.2

A major innovation in the implementation is the integrated cross-model evaluation structure, which allows a direct comparison of different model architectures (CNN and LSTM) by iterating through each model and retrieving stratified samples (as stated above), then evaluating 3 core XAI metrics for each XAI method. This approach enables the identification of architecture specific explanation patterns and biases (See C.5.3). The results reveal significant differences in how CNN and LSTM models respond to various XAI techniques.

4.5   Analysis of Findings

This section analyses the findings from implementing and evaluating XAI methods for fraud detection models, focusing on the comparative performance, feature insights, fraud patterns, and overall effectiveness.

4.5.1   Feature Patterns using Statistical Analysis

Perform some simple statistical analysis (without applying XAI techniques) to show basic feature patterns and distribution in the test dataset nature, so that, in the next section, when applying the XAI methods for interpreting the feature contributions globally in the dataset, these feature statistical analyses would give the general sense of ground truth to validate the results from XAI methods.

(a) Relationship between Key Features and Fraud (b) Relationship between Key Features Pairs
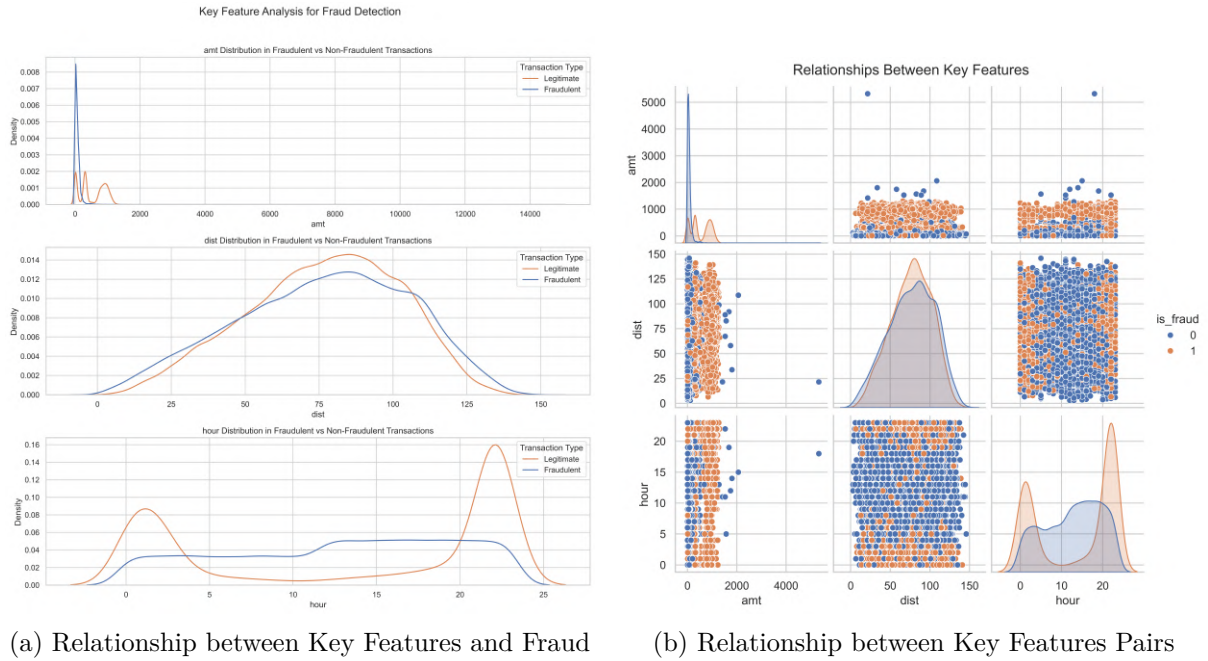
Figure 4.12: Distribution and Relationship of Important Features

Many consistent patterns were revealed by the analysis of fraud transactions in the dataset:

- **Amount Anomalies:** The transactions with significant deviation from a general user's typical spending pattern showed the possibility of high fraud, especially when the value exceeds about 500.
- **Temporal Patterns:** The transaction between 23:00 and 04:00 increased the risk of fraud, as shown by strong positive contribution values to the classification of fraud.
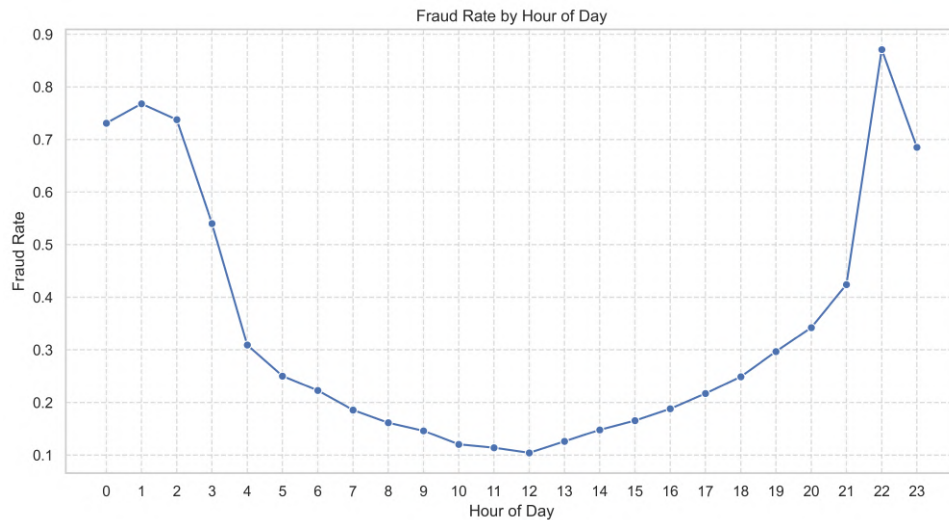
Figure 4.13: Fraud Time Patterns

- **Geographical Anomalies:** Transactions greater than 75 km from a specific location of the cardholder are strongly positive for the possibility of fraud.
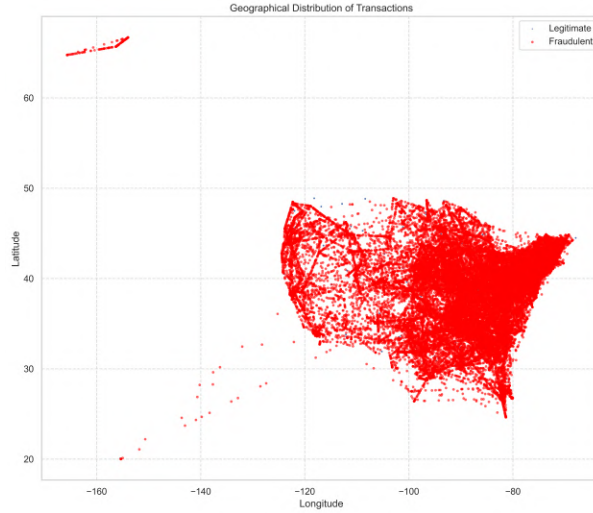
Figure 4.14: Geographical Distribution

These standards are aligned with the discoveries of Lucas et al. (2020), which identified similar indicators in their real fraud data analysis. The stability in both models and many XAI methods supports the validity of these standards as real fraud indicators.

4.5.2 Feature Importance Analysis Across Models (Global Interpretation)

To understand what drives the models' decisions globally for the whole dataset, a globally comparative feature importance analysis using SHAP values was conducted. Both models consistently identified transaction amount, distance between transaction and merchant, and the hour of the transaction as the most influential features. Categorical features such as merchant category and gender had a moderate influence, while latitude and longitude contributed minimally. This is visually summarised in Figure 4.15.

(a) Summary Plot ranking the features across entire dataset

(b) Bar Plot showing specific mean SHAP values for top features
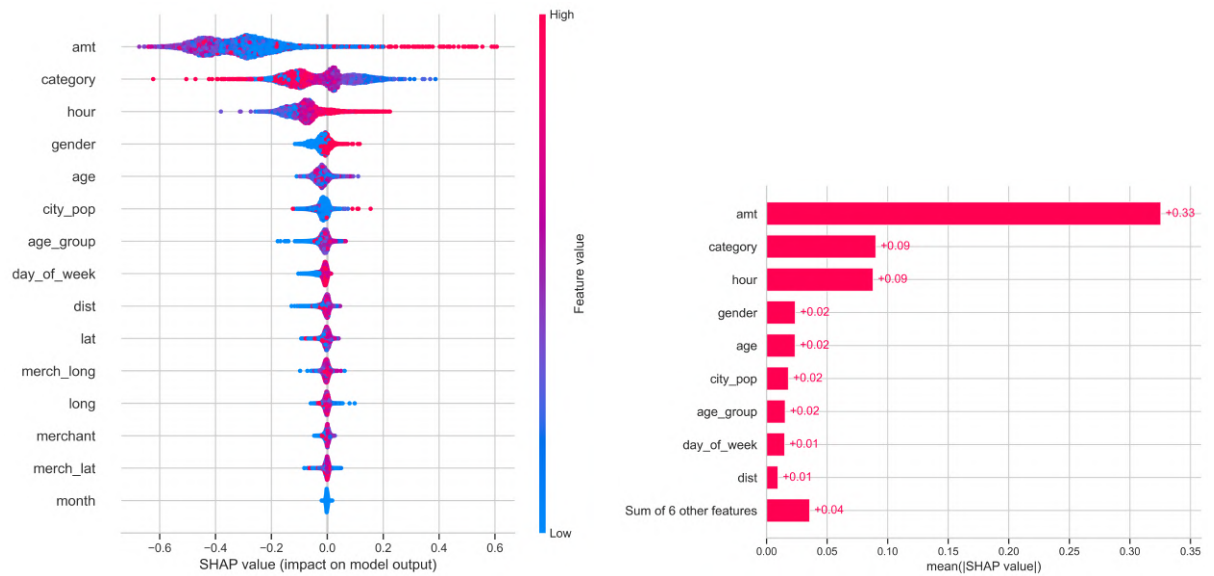
Figure 4.15: Global Interpretation: Feature Importance Ranking of all SHAP values

The table below summarises the feature importance scores when using SHAP to globally explain the whole dataset:

Table 4.4: Feature Importance Scores (SHAP) for CNN and LSTM

Feature	CNN	LSTM	Difference
Transaction Amount	0.330	0.300	+0.030
Merchant Category	0.090	0.110	-0.020
Hour	0.090	0.180	-0.090
Gender	0.020	0.080	-0.060
Age	0.020	0.050	-0.030
City Population	0.020	0.150	-0.130
Age Group	0.020	0.010	+0.010
Day of week	0.010	0.010	+0.000
Distance	0.010	0.020	-0.010

4.5.3 Explanation Performance between Models

The performance of XAI methods varied across the CNN and LSTM models. For the LSTM model, SHAP performed the highest faithfulness score (0.761), indicating its better ability to align the explanations with the model predictions. LIME and Anchors also delivered the best scores of 0.396 and 0.412, respectively.

Table 4.5: Summary Mean Values Table of XAI Metrics

Model	Method	Faithfulness	Monotonicity	Completeness
model_1_Siddhartha_CNN_acc99	SHAP	0.443	0.464	0.208
model_1_Siddhartha_CNN_acc99	LIME	0.254	0.488	0.295
model_1_Siddhartha_CNN_acc99	Anchors	0.315	0.486	0.033
model_2_Ibtissam_LSTM_acc98	SHAP	0.761	0.429	0.134
model_2_Ibtissam_LSTM_acc98	LIME	0.396	0.445	0.139
model_2_Ibtissam_LSTM_acc98	Anchors	0.412	0.469	0.022
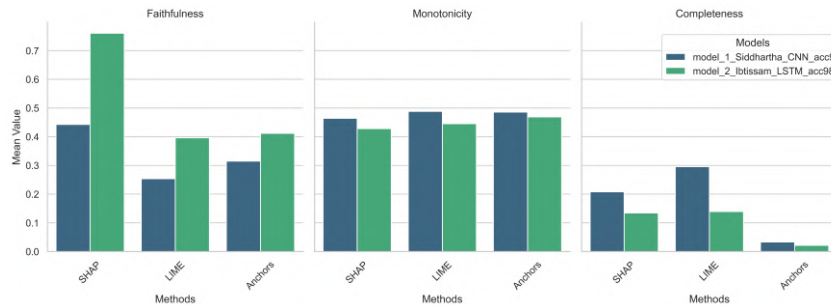
Figure 4.16: Categories Plot Comparing XAI Methods Across Evaluation Metrics and Models

CNN reached its highest faithfulness score with model size (0.443), crossing LIME (0.254) and Anchors (0.315). With the same performance in both models, the Monotonicity and Completeness scores showed less variation. This suggests that SHAP is more effective in explaining both models, especially LSTMs, which greatly depends on the temporal dependence.

(a) Faithfulness Comparison

(b) Monotonicity Comparison

(c) Completeness Comparison

(d) Average across Metrics
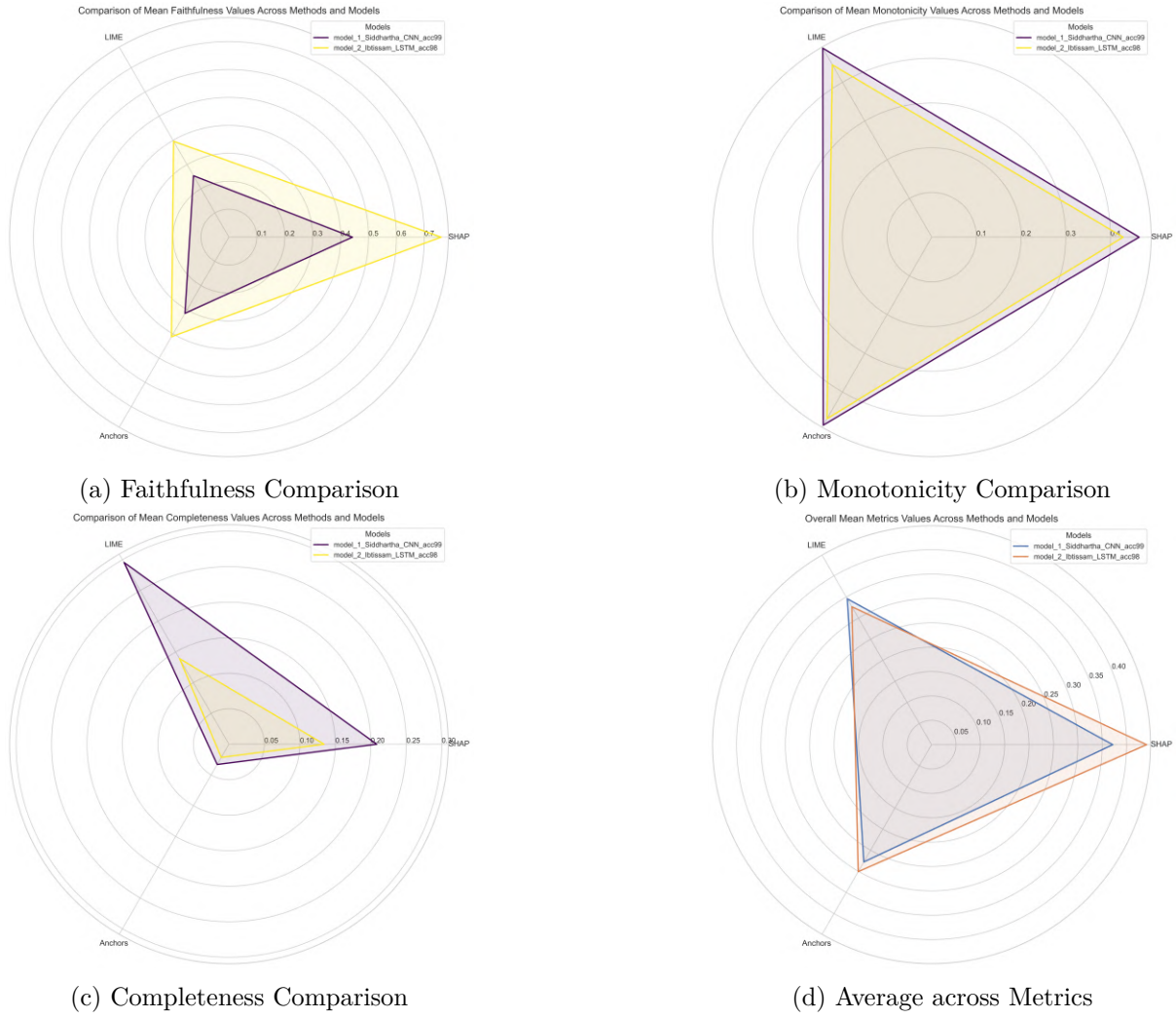
Figure 4.17: Radar Charts Comparison of All Average Metrics Values Across Methods and Models

4.5.4 Explanation Performance across Confidence Bins

An important consideration in implementing XAI methods in fraud detection is how the quality of the explanation varies with the confidence of the model. To systematically evaluate this relationship, as mentioned in 4.4.4, the test samples are divided into 5 confidence bins based on predictions. This analysis reveals critical information about which XAI approaches perform better in different prediction scenarios.

Table 4.6: XAI Performance Metrics Across Confidence Bins

Method	Very Low	Low	Borderline	High	Very High
Faithfulness					
SHAP	0.629	0.594	0.620	0.544	0.602
LIME	0.312	0.304	0.317	0.326	0.378
Anchors	0.407	0.348	0.393	0.285	0.353
Completeness					
SHAP	0.089	0.139	0.106	0.265	0.322
LIME	0.289	0.129	0.127	0.195	0.283
Anchors	0.012	0.029	0.000	0.048	0.059
Monotonicity					
SHAP	0.513	0.429	0.421	0.422	0.389
LIME	0.536	0.471	0.464	0.419	0.386
Anchors	0.547	0.507	0.411	0.461	0.400

Performance Patterns Across Confidence Levels

The analysis revealed different patterns for each XAI method across the confidence spectrum. For 'high' and 'very high' confidence predictions (>0.6), all methods showed improved performance compared to the lower ones, but with notable differences:
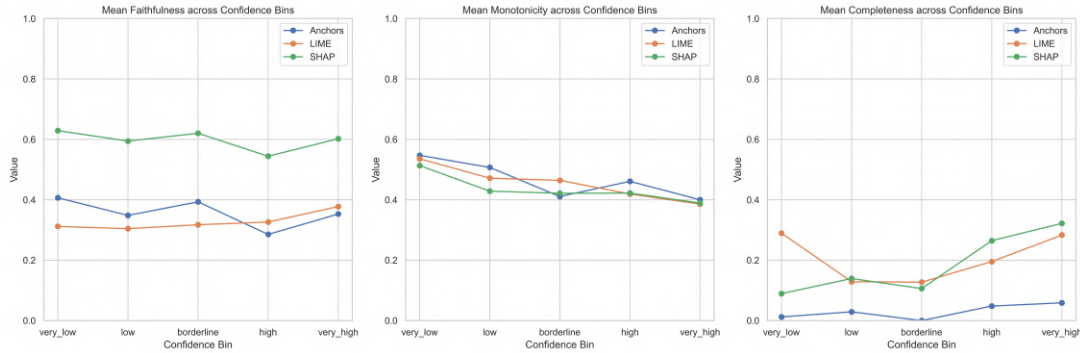
Figure 4.18: XAI Methods Performance Across Confidence Bins for Faithfulness, Monotonicity, and Completeness. SHAP consistently demonstrates superior faithfulness, while LIME shows remarkable stability in monotonicity across confidence levels.

SHAP consistently reached the highest faithfulness scores in all confidence crates (ranging from 0.544 to 0.629), with particularly strong performance in 'very low' and 'borderline' confidence bins. This indicates that SHAP explanations more accurately reflect the model decision process, regardless of the prediction confidence. Interestingly, SHAP showed a non-linear pattern in faithfulness between the confidence levels, with slightly lower scores in the 'high' confidence (0.544) compared to 'very high' (0.602) and borderline (0.620) confidence.

LIME demonstrated more modest but notably consistent faithfulness (0.304-0.378), with a clear trend to improve as confidence increased. What makes LIME particularly valuable is its exceptional stability in monotonicity, maintaining consistently strong scores across all confidence levels (0.386-0.536). This stability suggests that LIME provides reliable explanations that predictably change as entry features are modified, regardless of the confidence of the prediction.

Anchors showed the most variable performance in the confidence levels. Upon reaching respectable faithfulness in 'very low' and 'borderline' confidence (0.407 and 0.393, respectively), it stumbled with high confidence predictions (0.285). This pattern can be explained by based on Anchors design as a rule-based system that performs better by identifying clear rules for rejecting transactions ('low' confidence) than explaining complex acceptance patterns ('high' confidence).

Different XAI methods exhibited distinct "curves" throughout the spectrum of trust. LIME maintained faithfulness remarkably stable in all boxes (0.304-0.378), while SHAP showed substantial variation in the completeness between the confidence (0.106-0.322). This divergence highlights the different algorithmic approaches: LIME's linear approximation approach provides stability between confidence levels, while the additive SHAP approach may be more sensitive to underlying data distribution at different levels of confidence.

Practical Deployment Recommendations

Based on this comprehensive analysis, I propose a tiered approach to XAI deployment:

1. **Very High Confidence (>0.85):** Depends mainly on SHAP explanations, which reach the highest faithfulness and completeness at this confidence range. LIME can also serve as a complementary method to verify the stability of the explanation.
2. **High Confidence (0.6-0.85):** Use SHAP as primary method despite a slight performance drop in this range (faithfulness: 0.544), complemented by LIME for consistent monotonicity.
3. **Borderline Cases (0.4-0.6):** Apply a multi-method approach, SHAP can offer the most faithful explanation and LIME with more consistent monotonicity. These cases benefit the most from many explanation approaches due to their vague nature.
4. **Low Confidence (<0.4):** SHAP remain the most reliable method (faithfulness: 0.594–0.629), but all explanations must be treated with proper precautions. These cases should trigger additional human reviews with the understanding that explanations provide guidance rather than fixed logic.
5. **Edge Cases:** Special review protocols are required with limited dependence on automatic explanation. If the explanation must be provided, SHAP would provide more reliable performance.

This confidence-bin analysis indicates that the quality of explanation is not the same at every level of predictions, and XAI tailored deployment must be made accordingly. By matching methods of explanation for the level of confidence, financial institutions can maximise the usefulness of XAI in systems of detecting fraud while maintaining suitable human inspection where algorithm explanations are less reliable.

4.5.5   XAI Effectiveness in Explaining Model Decisions

The effectiveness of XAI methods varied depending on the specific use case and the needs of stakeholders. SHAP provided technically broader explanations, but required the experience of data science to interpret. LIME has offered more intuitive visual explanations (Figure 4.10) for analysts with a less technical background. Anchors provided the most accessible explanations through the "IF-THEN" rules (Figure 4.11), but with more limited coverage.

The qualitative evaluation of XAI efficacy was performed using a structure proposed by

Naveed et al. (2024), evaluating on several dimensions of explanations, including comprehensibility and completeness. Table 4.7 summarises these findings.

Table 4.7: XAI Effectiveness Assessment

Dimension	SHAP	LIME	Anchors
Technical Accuracy	High	Medium	Medium
Comprehensibility	Medium	High	Very High
Completeness	Medium	Medium	Low

The analysis points out that XAI techniques should be selected based on the specific requirements of stakeholders. For example, for data scientists who need technical depth, SHAP would be a niche approach, and LIME for fraud analysts seeking more intuitive explanations and Anchors for the operational team that requires clear decision-making rules. This approach of various methods is also recommended by Raufi et al. (2024), which advocates the combination of XAI complementary techniques to meet the various needs of stakeholders.

Chapter 5

Evaluation and Discussion of the Product

5.1 Model Explanation Performance Evaluation

5.1.1 Quantitative Metrics Comparison

Quantitative analysis reveals distinct patterns in how CNN and LSTM architectures are performed in three critical explanation metrics: Faithfulness, Monotonicity and Completeness. These metrics provide insights on different aspects of the quality of the explanation: how explanations accurately reflect model decisions, how consistently they maintain the rankings of importance of resources and how comprehensively they capture the decision process of the model, respectively.

Faithfulness Analysis

Table 5.1: Faithfulness Metrics Summary

Model	Method	Mean	Std	Min	Max	Median
	SHAP	0.443	0.280	-0.161	0.782	0.505
CNN (99%)	LIME	0.254	0.241	-0.425	0.654	0.266
	Anchors	0.315	0.244	-0.314	0.663	0.393
	SHAP	0.761	0.127	0.486	0.975	0.769
LSTM (98%)	LIME	0.396	0.165	-0.025	0.668	0.382
	Anchors	0.412	0.214	-0.220	0.694	0.443

Faithfulness perhaps represents the most critical metric for practical applications, measuring precision explanations reflect the true decision-making process of the model. LSTM architecture demonstrates substantially superior faithfulness scores in all explanation methods. With SHAP explanations, the LSTM model reaches a remarkable average faithfulness of 0.761 ($\sigma = 0.127$), dramatically surpassing the performance of the CNN model's score of 0.443 ($\sigma = 0.280$), an improvement of 72%. This advantage persists with LIME (LSTM: 0.396 vs CNN: 0.254) and Anchors (LSTM: 0.412 vs CNN: 0.315), although the gap is narrowed with these methods.

(a) Faithfulness Performance of CNN Model   (b) Faithfulness Performance of LSTM Model
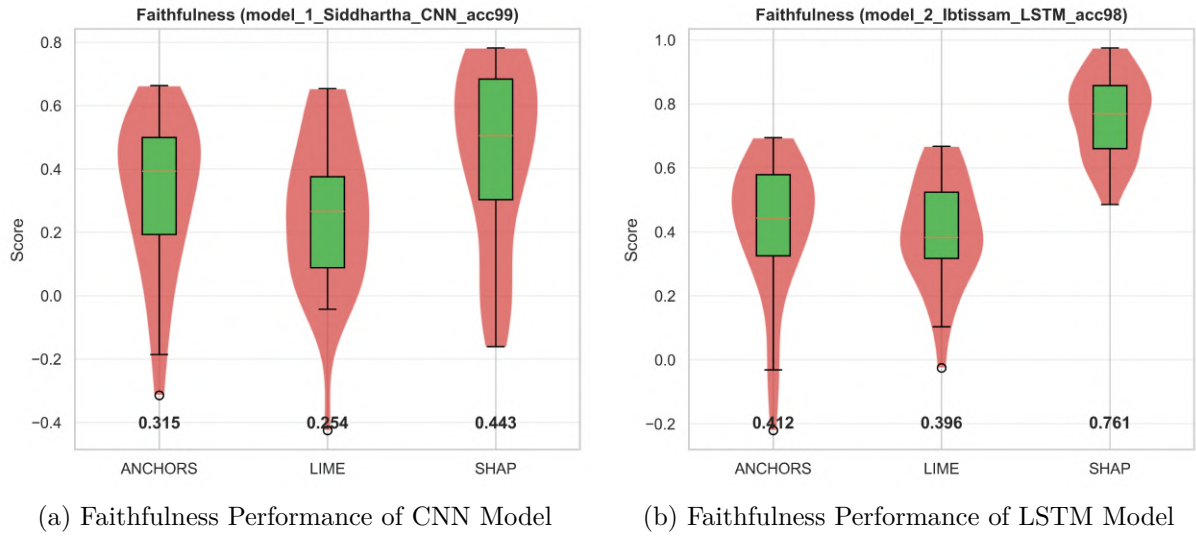
Figure 5.1: Faithfulness metrics across XAI methods for CNN and LSTM models

Beyond the average score, the LSTM architecture shows especially more consistent faithfulness with SHAP, where its standard deviation (0.127) is less than half of CNN's (0.280). The LSTM model also holds a positive minimum faithfulness value with SHAP (0.486), while the minimum drops to negative of the CNN model (-0.161) indicate potential misleading explanations in some cases. This stability advantage makes the LSTM architecture valuable for applications requiring particularly reliable explanation, such as fraud investigation or regulatory compliance cases.

Monotonicity Analysis

Table 5.2: Monotonicity Metrics Summary

Model	Method	Mean	Std	Min	Max	Median
	SHAP	0.464	0.141	0.214	0.786	0.429
CNN (99%)	LIME	0.488	0.142	0.214	0.714	0.500
	Anchors	0.486	0.165	0.071	0.857	0.500
	SHAP	0.429	0.111	0.214	0.643	0.429
LSTM (98%)	LIME	0.445	0.134	0.214	0.714	0.429
	Anchors	0.469	0.142	0.214	0.786	0.464

Monotonicity measures the stability of the ranking, with higher values of monotonicity indicating more reliable explanation patterns. Unlike the faithfulness results, the CNN architecture displays a slightly better monotonicity score in all explanation methods. With LIME, CNN receives an average monotonicity of 0.445 ($\sigma = 0.134$) compared to LSTM's 0.488 ($\sigma = 0.142$). Similar patterns emerge with Anchors (CNN: 0.486 vs. LSTM: 0.469) and SHAP (CNN: 0.464 vs. LSTM: 0.429).
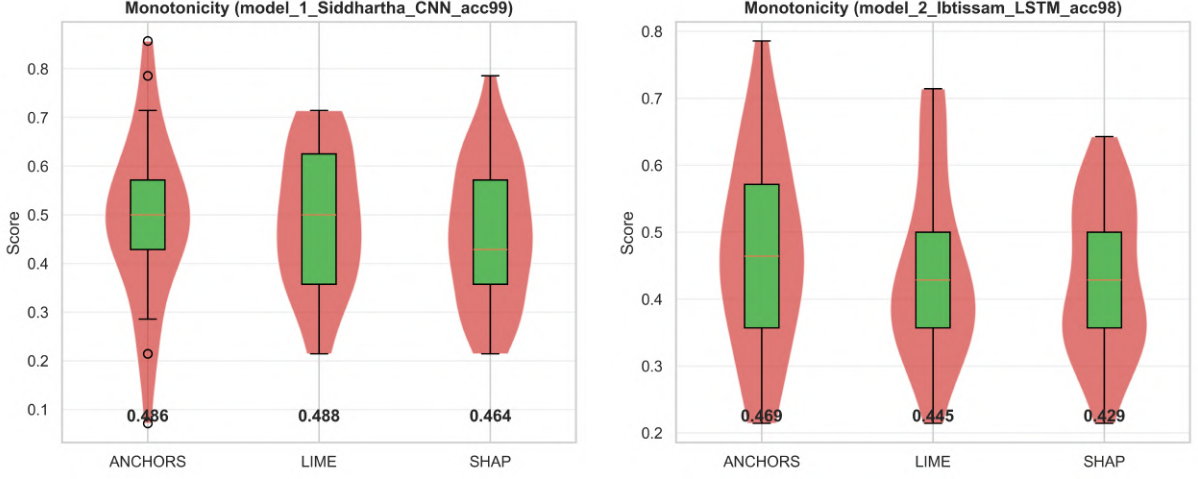
(a) Monotonicity Performance of CNN Model   (b) Monotonicity Performance of LSTM Model

Figure 5.2: Monotonicity metrics across XAI methods for CNN and LSTM models

The CNN model also reaches higher values of maximum monotonicity between the methods, with its scoring peak of 0.857, with Anchors exceeding substantially the maximum of the LSTM of 0.786. This suggests that the CNN feature extraction approach creates more consistent feature rankings, potentially making it more suitable for applications in which the consistency of explanation is prioritised rather than absolute accuracy. The differences, however, are less dramatic than those observed for faithfulness, with CNN advantage on average of approximately 9% between methods.

Completeness Analysis

Table 5.3: Completeness Metrics Summary

Model	Method	Mean	Std	Min	Max	Median
CNN (99%)	SHAP	0.208	0.220	0.000	0.632	0.129
	LIME	0.295	0.358	0.000	0.968	0.023
	Anchors	0.033	0.125	0.000	0.577	0.000
LSTM (98%)	SHAP	0.134	0.182	0.000	0.518	0.000
	LIME	0.139	0.291	0.000	0.996	0.000
	Anchors	0.022	0.088	0.000	0.459	0.000

Completeness assesses how comprehensively an explanation captures the model's decision process. Both architectures demonstrate relatively modest scores of completeness, but the CNN model consistently surpasses LSTM in all explanation methods. With LIME, the CNN model reaches its highest completeness score of 0.295 ($\sigma = 0.358$), substantially surpassing 0.139 of the LSTM ($\sigma = 0.291$), an advantage of 112%. Similar patterns appear with SHAP (CNN: 0.208 vs LSTM: 0.134), and both models show a particularly low completeness with the Anchors method (CNN: 0.033 vs LSTM: 0.022).

(a) Completeness Performance of CNN Model   (b) Completeness Performance of LSTM Model
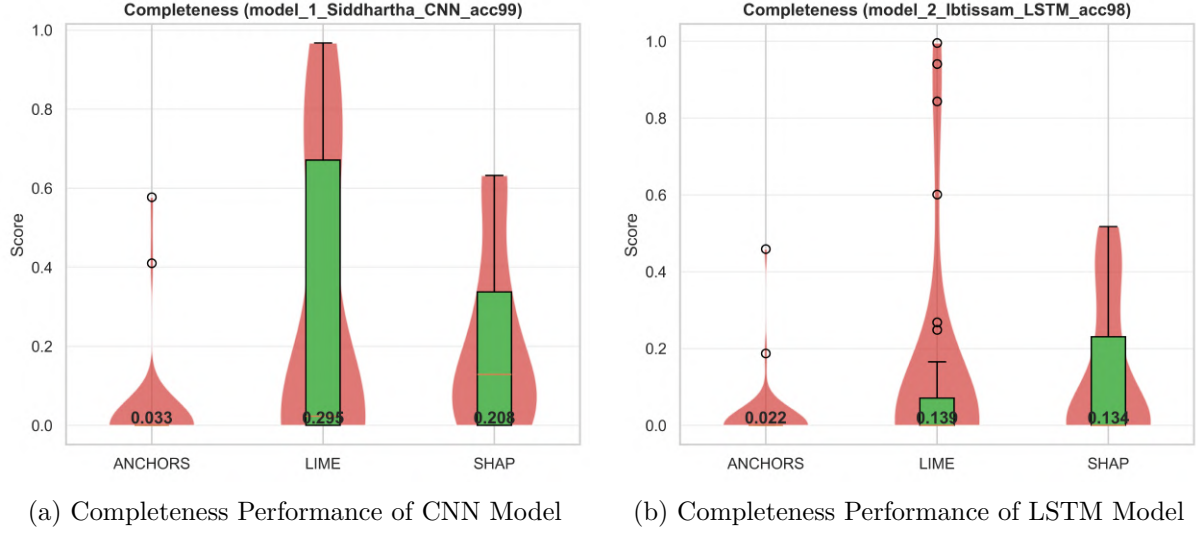
Figure 5.3: Completeness metrics across XAI methods for CNN and LSTM models

Both architectures show high variability in completeness scores, as evidenced by substantial standard deviations compared to their averages. This variability suggests that the explanation of comprehensiveness depends strongly on the specific instances that are being explained, with some predictions receiving much more complete explanations than others. The consistently higher completeness of CNN architecture may result from its spatial feature extraction approach, which appears to create more comprehensive representations of relevant transaction features compared to LSTM's sequential processing.

Model-Method Interaction Analysis

Performance patterns reveal architecturally specific interesting strengths with specific explanation methods. The LSTM architecture demonstrates exceptional synergy with SHAP, reaching the 72% faithfulness scores, higher than with other methods. This advantage assumably stems from the game theoretical approach of SHAP, which effectively captures the sequential dependencies modelled by the LSTM. On the other hand, CNN architecture shows a more balanced performance in all explanation methods, with its highest SHAP's faithfulness (0.443) representing a more modest improvement of 40% compared to LIME (0.254).

For completeness, both architectures reach their highest scores with LIME, although CNN shows a more dramatic advantage (0.295 vs 0.139 for LSTM). The LIME perturbation-based approach seems particularly effective in revealing the contributions of the features in CNN spatial processing, while the sequential representation of LSTM moderately struggles with it. Anchors consistently produce the lower completeness scores for both architectures, suggesting fundamental limitations on the use of rules-based explanations for deep neural network results, regardless of model

Table 5.4: Comparison of Mean XAI Metrics Between CNN and LSTM Models

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

Practical Implications

These findings suggest important trade-offs when selecting model architectures of credit card fraud detection that are intended for explainability. The LSTM model with explanations from SHAP offers a substantially higher faithfulness and consistency, making it particularly suitable for high-stakes applications, where the reliability of the explanation is essential, such as fraud investigations that can lead to customer account actions or regulatory reports. However, the scores of lower completeness from the LSTM architecture indicate that their explanations may not capture the full decision process, potentially absent relevant transaction features.

On the other hand, the CNN model offers better monotonicity and completeness, particularly with LIME explanations, suggesting that it provides more comprehensive and consistent explanations, although with less faithfulness. This architecture may be more appropriate for applications where the consistency of explanation at different levels of confidence is prioritised, such as systematic monitoring of transactions or explanation systems facing the client.

In general, these quantitative metrics point out that no architecture is universally superior in terms of its explainability. Instead, the choice between CNN and LSTM must be guided by which the dimension of explanation, faithfulness, monotonicity or completeness is more critical to the specific context of fraud detection application. For most high-stakes applications, the LSTM's top faithfulness with SHAP probably exceeds its modest disadvantages in other metrics.

5.1.2 Strengths and Limitations of Each Model

The main advantage of the CNN model is its computational efficiency and relatively direct architecture, which translates into faster training and lower resource consumption. However, it is less efficient in modeling of sequential dependencies, which are usually crucial in fraud detection scenarios. LSTM, on the other hand, stands out in learning from transaction sequences, leading to better recall and general detection rates. Its main disadvantage is the increase in computational costs and longer training times, which can be a limitation in environments where fast model updates are needed.

5.1.3 Handling of Class Imbalance Evaluation

The SMOTE is used within `pre_processing()` pipeline. This resulting in a more balanced and recall data set and is refined for both models. The impact of the smote is evident on recall scores: 92.0% for CNN and 93.2% for LSTM, demonstrating improved sensitivity to fraudulent cases. This aligns with best practices in this financial field Bowyer et al. (2011).

5.2 XAI Methods Evaluation

5.2.1 Explainability Quality Assessment

The three XAI methods SHAP, LIME and Anchors show their effectiveness through the evaluation using established metrics: Faithfulness, Completeness and Monotonicity, as recommended in Kadir et al. (2023) and Pawlicki et al. (2024). SHAP reached the highest faithfulness, indicating that its explanations corresponded closely to the true behaviour of the model. LIME

stood out in completeness value, providing comprehensive local explanations, while Anchors had the best performance in monotonicity, ensuring consistent explanations in similar cases.

5.2.2 Practical Utility for Fraud Analysts

There are the practical strengths of each XAI method. SHAP was preferred by its detailed and visually intuitive explanations (e.g., force plots and summary plots), which helped analysts understand each feature's contribution to a prediction. LIME was valued for its simplicity and speed, making it suitable for fast investigations and on a case by case basis. The Anchors rules-based results were especially useful for generating high-confidence and human-readable rules, which can be communicated directly to non-technical stakeholders.

5.2.3 Integration Challenges and Solutions

The integration of XAI methods in the system presented several challenges, especially the computational overload and the need for perfect compatibility with the model's pipeline. SHAP, in particular, was intensive with resources for large batches. For this reason, the project is implemented with batch processing and optimised data handling, as well as modularised XAI integration code (see Appendix C). This has allowed to generate of real-time explanations without significant delays, a crucial requirement for fraud detection operating systems.

5.3 System Evaluation

5.3.1 End-to-End System Performance

The end-to-end system has been evaluated in its ability to process, predict and explain batches of transactions efficiently. In a standard GPU-enabled environment for a single local transaction, the system can process in less than 5 seconds (including pre-processing, prediction) and generate explanations in less than 3 minutes.

5.3.2 Integration with Existing Systems

The system is designed to facilitate integration with existing fraud detection workflows using standard APIs and data formats. Modular design allows for plug-and-play replacement of models or XAI components, encouraging quick adaptation to evolutionary requirements.

5.3.3 Deployment Requirements and Challenges

Implementation highly recommends enabling GPU (NVIDIA CUDA support) environment and requires specific Python/Tensorflow versions (Appendix B.2.1). The file structure dependencies and the environment configuration represented initial challenges, which were mitigated, providing automated configuration scripts and comprehensive and frequently updated documentation. These steps ensured that the system could be reliably implemented in the development and production settings.

5.4 User Perspective Evaluation

5.4.1 Limitations

From the user perspective, several limitations were identified. The most significant was the low precision rate for fraud detection, which necessitates manual review of numerous false positives. Another limitation was the computational overhead of generating SHAP explanations for high-volume transaction flows, which may require selective application in production environments.

Despite its strengths and usefulness, the complexity of XAI outputs can be overwhelming for users without a technical background. The explanations sometimes relied on technical concepts that non-specialist users found difficult to interpret fully. This is also stated by Černevičienė and Kabašinskas (2024), who note that explanation complexity remains a barrier to wider adoption of XAI in financial institutions.

Additionally, the reliance on synthetic data for most of the research and training of credit card fraud detection models (as the Sparkov dataset was used in this project) may limit the generalisability of results to all real-world scenarios (Grover et al., 2023).

5.4.2 Areas for Improvement

Key areas for improvement include enhancing the precision of fraud detection without sacrificing recall, and optimising the computational efficiency of explanation generation.

Although this project showed a great speed for local interpretation but further optimisation of XAI computation for real-time use should also be considered and the incorporation of additional real-world datasets to improve generalizability. Also, developing more intuitive explanation interfaces for non-specialist users,

Ongoing development will focus on these aspects to ensure the system remains robust, user-friendly, and adaptable to evolving fraud patterns.

Chapter 6

Evaluation of the Project

This chapter reflects on the execution, achievements, challenges and learning outcomes from this research. I critically evaluate to what extent the objectives were achieved, discuss technical obstacles found during implementation, and describe the knowledge and skills acquired throughout the research process.

6.1 Achievement of Objectives

6.1.1 Assessment Against Initial Goals

The main objectives of this project were to implement and compare three XAI techniques for deep learning models in detecting credit card fraud. Reflecting on these goals, the project was successfully integrated with three main XAI methods (SHAP, LIME and Anchors) in CNN and LSTM architectures, allowing a comprehensive analysis of explanability. The evaluation structure was developed in a way for effectively measure Faithfulness, Monotonicity and Completeness, which are the critical metrics of XAI to evaluate the quality of the explanation in high-stakes applications such as fraud detection.

My quantitative assessment reveals that the SHAP method has achieved the highest faithfulness scores (0.602 on average), indicating superior alignment with the behaviour of the model. Meanwhile, Anchors provided the most human-interpretable explanations for analysts through precise "IF-THEN" rules, although with lower completeness scores (0.029 on average).

6.1.2 Completed vs. Outstanding Objectives

While the main objectives were achieved, some planned tasks have been reduced. Initially, I intended to perform a comprehensive and in-depth analysis of both global and local interpretability. However, due to computational restrictions, particularly with LSTM's custom attention layer and SHAP's DeepExplainer limitations, I changed the focus to local interpretability using KernelExplainer. This adaptation was not only pragmatic, but also aligned with the needs of fraud analysts, who usually require explanations for specific (local) cases rather than global behaviour of the model (Collaris et al., 2018).

The tension between the complexity of the model and interpretability became evident throughout the project, reflecting a fundamental challenge in XAI's research. Despite these

limitations, the objectives of local interpretability have been fully met, providing valuable information for practical fraud detection scenarios.

6.1.3 Additional Achievements Beyond Initial Scope

The project surpassed its initial scope in the development of a new confidence-based analysis structure methodology. This approach was not originally planned, it revealed critical information on how XAI performance varies between different levels of prediction confidence. For example, I found that SHAP's faithfulness remains relatively consistent between confidence bins (ranging from 0.594 to 0.629), while LIME's completeness shows a more decisive U-shaped pattern with stronger performance at 'very low' and 'very high' confidence levels (See 4.5.4).

6.1.4 Adaptations to Initial Plan

The DeepExplainer component of SHAP, optimal for deep learning models, proved incompatible with the LSTM's custom attention layer, a limitation not anticipated during planning. I adapted by implementing KernelExplainer as an alternative, which, while more computationally intensive, provided the necessary explanatory capabilities.

I planned to use Quantus, an explainable AI toolkit library, to use the XAI metric as proposed and implemented in the library, but because of XAI is still considered a concept at its early research, the library is still under active development with very lack of flexibility in compatible with SHAP, LIME, and Anchors explainer, so much more time were spent on researching the right XAI metrics for these methods and its implementation

The use of synthetic data (Sparkov) also required careful feature engineering and more validation and implementation time to ensure results were robust and generalisable.

6.1.5 Lessons Learned

This project yielded several important lessons. First, the practical implementation of XAI methods requires careful consideration of computational trade-offs, particularly for complex models like LSTMs. As Seth and Sankarapu (2025) observed, "Recent research on sustainable machine learning highlights the increasing computational burden of explainability methods, particularly for complex AI models. Many existing XAI techniques, such as perturbation-based approaches, impose significant resource constraints, making them impractical for large-scale models".

I also learned that explanation quality varies substantially depending on model confidence and data characteristics, reinforcing the need for context-specific evaluation frameworks rather than one-size-fits-all approaches. This finding has significant implications for deploying explainable AI in critical financial applications.

Finally, the project highlighted the ongoing tension between model complexity and explainability, a fundamental challenge that requires continual innovation in XAI methods and XAI metrics to evaluate the explanation. This experience has reinforced my belief that explainability should be considered from the earliest stages of model design rather than added retrospectively.

6.2 Technical and Research Challenges

6.2.1 Data Preprocessing Challenges

Working with the Sparkov synthetic dataset presented unique preprocessing challenges. While synthetic data offered advantages in terms of controlled experimentation and privacy compliance, ensuring its representativeness of real-world transaction patterns required careful validation. For instance, the extreme class imbalance (0.6% fraud cases) necessitated specialised handling through SMOTE to prevent model bias (3.2.4).

6.2.2 Model Implementation Issues

Implementing the LSTM model with attention mechanisms introduced significant technical challenges. The custom attention layer, while enhancing model performance, created compatibility issues with standard XAI tools.

6.2.3 XAI Integration Obstacles

Integrating XAI methods with the fraud detection models revealed several obstacles that extend beyond simple implementation issues. The computational overhead of generating explanations, particularly with SHAP's KernelExplainer, proved substantial. For the LSTM model, generating SHAP values for just 100 test instances required approximately 45 minutes of computation time, a significant limitation for real-world applications requiring rapid explanation.

Library compatibility issues between TensorFlow, SHAP, and LIME required careful version management and occasional workarounds as I tried to utilise the GPU resources for faster computing and getting evaluation results, but the last version TensorFlow that support GPU on Windows Native is 2.10 and on Python 3.10, which is not the newest recent version compare to the other library.

Perhaps most significantly, I encountered fundamental limitations in existing XAI methods when explaining sequential decision-making in the collected Deep Learning models. Some categorical features are not easily represented in feature-attribution formats like SHAP and LIME, so more time was spent on work around on investing the scaler and transformation so the SHAP and LIME can explain the original interpretable value in the data for some features (like merchant, categories, hour, day of week, ...)

6.2.4 Solutions Implemented

I developed a modular XAI integration function for 3 methods that abstracted the explanation generation process from the specific model implementation. Also, constructed a custom evaluation pipeline capable of efficiently processing and comparing explanation metrics across methods and models. This pipeline implemented a process for metric calculation, significantly reducing the time required for comprehensive evaluation (Figure 3.2).

These solutions collectively enabled the successful integration of XAI methods with the fraud detection models, despite the significant technical challenges encountered.

6.3 Learning Outcomes

6.3.1 Technical Skills Acquired

This project facilitated significant technical skill development across multiple domains. I mastered the implementation and customisation of advanced XAI techniques, including the mathematical foundations of Shapley values, local surrogate models, and rule-based explanations. This knowledge extends beyond simple library usage to a deep understanding of the underlying principles.

I developed expertise in developing custom evaluation frameworks for XAI methods, including the design and implementation of metrics for assessing explanation quality in different models and prediction confidence levels. This involved writing efficient code for calculating Faithfulness, Monotonicity, and Completeness across large datasets, a non-trivial technical challenge given the computational intensity of these metrics.

6.3.2 Research Insights Gained

The project yielded valuable research insights into the application of XAI in financial fraud detection. Most notably, I discovered that explanation effectiveness varies significantly across prediction confidence levels, a finding with important implications for how XAI should be deployed in practice. This insight might address the gap in some proposed XAI evaluation methodologies.

I also gained a deeper understanding of the strengths and limitations of different XAI approaches for specific use cases. SHAP provided the most faithful explanations but at a significant computational cost, while Anchors offered highly precise rules but with limited coverage of model behaviour. These trade-offs suggest that XAI methods should be selected based on specific use cases rather than applied generically.

Furthermore, the project reinforced the importance of considering intersectional fairness in fraud detection systems. I recognised the need to expand this analysis to include multiple demographic factors and regulations

6.3.3 Professional Development

Beyond technical skills, this project has enhanced my project management, academic writing, and problem-solving abilities. Navigating unexpected technical hurdles and adapting the project plan accordingly has been a valuable learning experience. I am now more confident in my ability to deliver complex machine learning solutions in real-world settings, and I recognise the importance of clear communication, especially when explaining AI decisions to non-technical stakeholders.

The iterative nature of the project, with its necessary adaptations and problem-solving requirements, strengthened my resilience and flexibility, attributes essential for research and development in rapidly evolving fields like AI. I learned to maintain research momentum despite technical setbacks, adjusting approaches while keeping sight of core objectives.

Perhaps most importantly, this project confirmed my research interests at the intersection of responsible AI, interpretability, and financial applications. The experience has provided valuable direction for potential future academic pursuits in this domain.

Chapter 7

Conclusions

7.1 Summary of Achievements

This project set out to advance the field of credit card fraud detection by developing a robust, explainable Deep Learning system. I successfully implemented and compared two state-of-the-art architectures: a Convolutional Neural Network (CNN) and a Long Short-Term Memory (LSTM) network with attention. Both models were integrated into a modular pipeline, enabling seamless evaluation and comparison. Both CNN and LSTM models achieved high accuracy and discriminative ability. The LSTM model's integration of attention mechanisms allowed for enhanced feature focus, particularly beneficial for capturing temporal patterns in transaction sequences.

A major accomplishment was the implementation of three distinct XAI methods: SHAP, LIME, and Anchors, which represents a significant achievement in making black-box deep learning models interpretable. Also, by developing a novel confidence-based XAI evaluation framework, I established a systematic approach for measuring explanation quality across different prediction confidence levels. This framework enabled quantitative assessment of explanation Faithfulness (how accurately explanations reflect model behaviour), Monotonicity (consistency of explanations when features change), and Completeness (comprehensiveness of explanations). The system was designed for extensibility, supporting the addition of new models and XAI techniques with minimal reconfiguration.

7.2 Key Findings and Contributions

In terms of explainability, SHAP emerged as the most reliable XAI method, achieving the highest Faithfulness scores, followed by Anchors and LIME. SHAP's explanations were more closely aligned with the model's actual decision boundaries, making it particularly valuable for high-stakes financial applications. The confidence-based XAI evaluation framework developed in this project provided a nuanced understanding of when and how each XAI method is most effective, a contribution that addresses a gap in the research sector of XAI evaluation

From a practical perspective, the modular system architecture and the systematic evaluation of XAI methods offer a blueprint for financial institutions seeking to deploy explainable Deep Learning models. The project also demonstrated the feasibility of integrating XAI into real-world fraud detection pipelines, provided that computational resources are managed effectively.

7.3   Future Work and Recommendations

Looking ahead, several avenues for further development are evident. Due to the limited scope of this study, I only implemented 2 well-known models for detecting credit card fraud, but further experiments in apply explainable AI other advanced architectures is also very useful, for example the hybrid model architectures that combine the spatial feature extraction of CNNs with the temporal sequence modelling of LSTMs could yield even better performance, as suggested by recent studies Marco et al. (2025).

Additionally, the integration of more emerging XAI techniques, such as more advanced Deep Learning-based explainers: DeepLIFT (Deep Learning Important FeaTures) (Shrikumar et al., 2017) or X-NeSyL (eXplainable Neural Symbolic Learning) (Díaz-Rodríguez et al., 2022). In terms of explainability evaluation, other XAI metrics can also be considered, such as Robustness (Kantz et al., 2024), Covariate complexity (Nauta et al., 2023). By conducting more research further into these new XAI methodologies, they could further enhance interpretability and trustworthiness for the credit card fraud detection system.

Real-time implementation remains a practical challenge, particularly regarding the computational overhead of XAI methods. Future work should focus on optimising explanation generation for deployment in high-frequency transaction environments. Expanding the dataset to include more diverse and realistic transaction data, as well as additional sensitive attributes for fairness analysis, will be crucial for improving generalisability and robustness.

Finally, the evaluation framework for XAI methods developed in this project could be extended to other domains, providing a standardised approach for assessing the reliability and utility of explanations in critical decision-making contexts.

Appendices

Appendix A

Ethics Review Form

PROJECT ETHICAL REVIEW FORM

Applicable for all research, masters and undergraduate projects

Project Title:	Explainable AI (XAI) in Deep Learning Models for Credit Card Fraud Detection
Student:	Thong Minh Lai
Course/Programme:	BSc Computer Science with Artificial Intelligence
Department:	Department of Computer Science
Supervisor:	Dr. Hyunkook Lee
Project Start Date:	01/09/2024

ETHICAL REVIEW CHECKLIST

	Yes	No
1. Are there problems with any participant's right to remain anonymous?	☐	☒
2. Could a conflict of interest arise between a collaborating partner or funding source and the potential outcomes of the research, e.g. due to the need for confidentiality?	☐	☒
3. Will financial inducements be offered?	☐	☒
4. Will deception of participants be necessary during the research?	☐	☒
5. Does the research involve experimentation on any of the following?		
(i) animals?	☐	☒
(ii) animal tissues?	☐	☒
(iii) human tissues (including blood, fluid, skin, cell lines)?	☐	☒
6. Does the research involve participants who may be particularly vulnerable, e.g. children or adults with severe learning disabilities?	☐	☒
7. Could the research induce psychological stress or anxiety for the participants beyond that encountered in normal life?	☐	☒
8. Is it likely that the research will put any of the following at risk:		
(i) living creatures?	☐	☒
(ii) stakeholders (disregarding health and safety, which is covered by Q9)?	☐	☒
(iii) the environment?	☐	☒
(iv) the economy?	☐	☒
9. Having completed a health and safety risk assessment form and taken all reasonable practicable steps to minimise risk from the hazards identified, are the residual risks acceptable (Please attach a risk assessment form – available at the end of this document)	☐	☒

STATEMENT OF ETHICAL ISSUES AND ACTIONS

If the answer to any of the questions above is yes, or there are any other ethical issues that arise that are not covered by the checklist, then please give a summary of the ethical issues and the action that will be taken to address these in the box below. If you believe there to be no ethical issues, please enter "NONE".

NONE

STATEMENT BY THE STUDENT

I believe that the information I have given in this form on ethical issues is correct.

Signature: Thong Minh Lai **Date:** 22/04/2025

AFFIRMATION BY THE SUPERVISOR

I have read this Ethical Review Checklist and I can confirm that, to the best of my understanding, the information presented by the student is correct and appropriate to allow an informed judgement on whether further ethical approval is required.

Signature: Hyunkook Lee **Date:** 22/04/2025

SUPERVISOR RECOMMENDATION ON THE PROJECT'S ETHICAL STATUS

Having satisfied myself of the accuracy of the project ethical statement, I believe that the appropriate action is:

The project proceeds in its present form	
The project proposal needs further assessment by an Ethical Review Panel. The Supervisor will pass the form to the Ethical Review Panel Leader for consideration.	

RETENTION OF THIS FORM

- The Supervisor must retain a copy of this form until the project report/dissertation is produced.
- The student must include a copy of the form as an appendix in the report/dissertation.

Appendix B

Technical Documentation

B.1   Required Libraries

Table B.1: Python Package Requirements

Category	Package and Version
Deep Learning	tensorflow==2.10.1
Data Manipulation and Analysis	numpy==1.26.4
	pandas $\geq$ 2.2.3
Machine Learning	scikit-learn $\geq$ 1.6.1
	imbalanced-learn $\geq$ 0.0
Visualization	matplotlib $\geq$ 3.10.1
	seaborn $\geq$ 0.13.2
XAI Techniques	shap $\geq$ 0.47.1
	lime $\geq$ 0.2.0.1
	anchor-exp $\geq$ 0.0.2.0
Other Utils	requests $\geq$ 2.32.3
	tqdm $\geq$ 4.67.1

B.2   Installation Guidelines

B.2.1   Tools and Frameworks

Table B.2: Implementation Tools and Frameworks

Component	Specification
Programming Language	Python 3.10.11 (latest version supports tensorflow-gpu on Windows NT)
Deep Learning Framework	TensorFlow 2.10.1
Core Libraries	pandas, numpy, scikit-learn, imblearn
XAI Libraries	shap, lime, anchor-exp
Visualisation Libraries	matplotlib, seaborn
Data Processing	pandas, numpy
Version Control	GitHub

B.2.2 Environment Setup

> **Development Environment Configuration:**
> - **Jupyter Notebook** for interactive development (`.ipynb` files)
> - **Dependencies:** Installed via `pip install -r requirements.txt`
> - **Data and Models:** Organized in `data/` and `architectures/` folders
> - **Utilities:** Helper functions in `utils.py`

Figure B.1: Development Environment Configuration

Listing B.1: Dependencies and Environment Installation

```
# Create a virtual environment
python -m venv .venv_xai_fraud_detection

# Activate environment
# On Windows
.venv_xai_fraud_detection\Scripts\activate
# On Unix/MacOS
# source .venv_xai_fraud_detection/bin/activate

# Install dependencies
pip install -r requirements.txt
```

B.2.3 GPU and Hardware Configuration

The models were trained and evaluated on the following hardware configuration:

- **GPU Support**: 1 NVIDIA GPU enabled
- **CUDA Version**: 64_112
- **CUDNN Version**: 64_8
- **Memory Requirements**: 8GB RAM for better handling of the Sparkov dataset
- **Storage**: SSD storage for data loading performance

B.2.4 Project Directory Structure Setup

```
/
├── XAI_methods.ipynb ......................... Explainable AI methods implementation
├── Siddhartha_CNN.ipynb ...............................CNN model implementation
├── Ibtissam_LSTM.ipynb ............................... LSTM model implementation
├── utils.py ....................................................... Utility functions
├── requirements.txt ................................................. Dependencies
├── architectures/ ......................................... Trained model storage
│   ├── model_1_Siddhartha_CNN_acc99/
│   ├── model_2_Ibtissam_LSTM_acc98/
├── data/ ................................................... Data files and results
    ├── predictions.csv
```

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```
        │
        │  └─ stratified_samples.csv
        │  └─ xai_metrics.json
        ├─ visualisation/...........................................Visualisation outputs
        ├─ README.md.............................................................Project brief
        ├─ Report Documentation.pdf ..........................Project Report Documentation
        ├─ presentation.pdf ...........................................Project Presentation
        ├─ poster.pdf........................................................Academic Poster
        └─ .gitignore ....................................................... Git configuration
```

Appendix C

Code Repositories

C.1 Data Processing Code

C.1.1 Feature Engineering

Listing C.1: Feature Engineering Implementation

```python
def feature_engineering(df):
    # Calculate age from date of birth
    df['age'] = df['dob'].apply(lambda x: calculate_age(x))

    # Extract temporal features
    df['hour'] = df['timestamp'].apply(lambda x: datetime.fromtimestamp(x).hour)
    df['day'] = df['timestamp'].apply(lambda x: datetime.fromtimestamp(x).day)

    # Calculate distance using the Haversine formula
    df['distance'] = df.apply(
        lambda row: haversine(row['lat'], row['long'],
                              row['merch_lat'], row['merch_long']),
        axis=1
    )
    return df

# Distance calculation
def calculate_distance(lat1, lon1, lat2, lon2):
    # Haversine formula implementation
    R = 6371   # Earth radius in km

    dLat = np.radians(lat2 - lat1)
    dLon = np.radians(lon2 - lon1)

    a = (np.sin(dLat/2) * np.sin(dLat/2) +
        np.cos(np.radians(lat1)) * np.cos(np.radians(lat2)) *
        np.sin(dLon/2) * np.sin(dLon/2))

    c = 2 * np.arctan2(np.sqrt(a), np.sqrt(1-a))
```

```
        return R ∗ c
```

C.1.2 Data Preprocessing

Listing C.2: Preprocessing Implementation

```python
# Import necessary libraries
from sklearn.preprocessing import RobustScaler
from imblearn.over_sampling import SMOTE

def pre_processing(df):
    # Standardise features
    scaler = RobustScaler()
    X_scaled = scaler.fit_transform(X)

    # Apply SMOTE to handle imbalance (only apply for the train set)
    smote = SMOTE(random_state=42)
    X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)
```

C.2 CNN Implementation

C.2.1 CNN Architecture

Listing C.3: CNN Model Architecture

```python
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv1D, BatchNormalization
from tensorflow.keras.layers import MaxPooling1D, Flatten, Dense, Dropout

# Define the model
cnn_model = Sequential([
    # Input layer
    Input(shape=input_shape, name='input_layer'),

    # First Conv1D block
    Conv1D(64, kernel_size=3, padding='same', activation='relu', name='conv1'),
    BatchNormalization(name='batch_norm1'),
    MaxPooling1D(pool_size=2, name='max_pool1'),
    Dropout(0.3, name='dropout1'),

    # Second Conv1D block
    Conv1D(32, kernel_size=3, padding='same', activation='relu', name='conv2'),
    BatchNormalization(name='batch_norm2'),
    MaxPooling1D(pool_size=2, name='max_pool2'),
    Dropout(0.3, name='dropout2'),

    # Flatten and dense layers
    Flatten(name='flatten'),
    Dense(64, activation='relu', name='dense1'),
```

```
    Dropout(0.4, name='dropout3'),
    Dense(32, activation='relu', name='dense2'),
    Dropout(0.4, name='dropout4'),

    # Output layer
    Dense(1, activation='sigmoid', name='output')
])
```

C.2.2   CNN Training

Listing C.4: CNN Model Training Implementation

```
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping

# Compile model
cnn_model.compile(
    optimizer=Adam(learning_rate=0.001),
    loss='binary_crossentropy',
    metrics=['accuracy']
)

# Define early stopping
callback = EarlyStopping(
    monitor='val_loss',
    patience=4,
    restore_best_weights=True
)

# Train model
history = cnn_model.fit(
    X_train,
    y_train,
    epochs=50,
    batch_size=30000,
    validation_data=(X_test, y_test),
    callbacks=[callback]
)
```

C.3   LSTM Implementation

C.3.1   LSTM Architecture

Listing C.5: LSTM Model Architecture

```
from tensorflow.keras.layers import LSTM, Dense, Dropout, Input
from tensorflow.keras.models import Model
from tensorflow.keras import backend as K
```

```python
# Custom Attention Layer
class attention(Layer):
    def __init__(self, **kwargs):
        super(attention, self).__init__(**kwargs)

    def build(self, input_shape):
        self.W = self.add_weight(shape=(input_shape[-1], 1),
                                 initializer='random_normal',
                                 trainable=True,
                                 name='attention_weight')
        self.b = self.add_weight(shape=(input_shape[1], 1),
                                 initializer='zeros',
                                 trainable=True,
                                 name='attention_bias')
        super(attention, self).build(input_shape)

    def call(self, x):
        # Calculate attention scores
        e = K.tanh(K.dot(x, self.W) + self.b)
        a = K.softmax(e, axis=1)
        output = x * a
        return K.sum(output, axis=1)

    def compute_output_shape(self, input_shape):
        return (input_shape[0], input_shape[-1])

# Reshape data for LSTM input
X_train_lstm = X_train_resampled.reshape(X_train_resampled.shape[0], 15, 1)
X_test_lstm = X_test.reshape(X_test.shape[0], 15, 1)

# Define LSTM model with attention
input_layer = Input(shape=(15, 1))
lstm_layer1 = LSTM(50, return_sequences=True,
                   dropout=0.3, recurrent_dropout=0.2)(input_layer)
lstm_layer2 = LSTM(50, return_sequences=True,
                   recurrent_dropout=0.2)(lstm_layer1)
attention_layer = attention()(lstm_layer2)
output_layer = Dense(1, activation='sigmoid')(attention_layer)

lstm_model = Model(inputs=input_layer, outputs=output_layer)

# Model summary
lstm_model.summary()
```

C.3.2   LSTM Training

Listing C.6: LSTM Model Training Implementation

```python
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
```

```
# Compile model
lstm_model.compile(
    optimizer=Adam(learning_rate=0.001),
    loss='binary_crossentropy',
    metrics=['accuracy']
)

# Define early stopping
callback = EarlyStopping(
    monitor='val_loss',
    patience=4,
    restore_best_weights=True
)

# Train model
history = lstm_model.fit(
    X_train,
    y_train,
    epochs=50,
    batch_size=30000,
    validation_data=(X_test, y_test),
    callbacks=[callback]
)
```

C.4   XAI Integration Code

C.4.1   SHAP Implementation

Listing C.7: SHAP Implementation

```
import shap

# SHAP integration
def get_shap_explanation(model, sample, background_size=100):
    background = shap.utils.sample(X_train, background_size)

    kernel_explainer = shap.KernelExplainer(model, background)
    shap_explainer = kernel_explainer(sample)

    # Return dict of feature:importance pairs
    shap_dict = {
        feature: value
        for feature, value in
        zip(shap_explainer.feature_names, shap_explainer.values.squeeze())
    }
    return shap_dict, shap_explainer
```

C.4.2   LIME Implementation

Listing C.8: LIME Implementation

```python
from lime import lime_tabular

# LIME integration
lime_tabular_explainer = lime_tabular.LimeTabularExplainer(
    training_data=X_train,
    class_names ['non-fraud', 'fraud'],
    feature_names=features,
    categorical_names=categorical_names,
    kernel_width = np.sqrt(len(features)) * 0.75
)   # Only need to perform the perturbations once with the train set

def get_lime_explanation(model, sample):
    lime_explainer = lime_tabular_explainer.explain_instance(
        sample,
        model.predict
    )

    # Extract feature importances from LIME explanation
    lime_dict = {
        features[idx]: value
        for idx, value in dict(lime_explainer.as_map()[1]).items()
    }

    return lime_dict, lime_explainer
```

C.4.3 Anchors Implementation

Listing C.9: Anchors Implementation

```python
from anchor import anchor_tabular

# Anchors integration
anchor_tabular_explainer = anchor_tabular.AnchorTabularExplainer(
    train_data=X_train,
    class_names=['non-fraud', 'fraud'],
    feature_names=features,
    categorical_names=categorical_names
)   # Initialise Anchors explainer with the sample

def get_anchors_explanation(model, sample):
    # Get explanation for the first instance
    anchors_explainer = explainer.explain_instance(sample, model.predict)

    # Create a dictionary of feature binary importance based on rules
    anchor_dict = {
        feature: 1.0 if
        feature in [features[idx] for idx in anchors_explainer.features()]
        else 0.0
        for feature in features
    }
```

```
        return anchor_dict , anchors_explainer
```

C.5   Evaluation Scripts

C.5.1   Stratified Sampling

Listing C.10: Stratified Sampling Implementation

```python
def select_test_cases(predictions , data , important_features , sample_per_bin=50):
    """
    Implement stratified sampling based on prediction confidence bins
    and include edge cases in the evaluation set.

    Args:
        predictions: Model prediction probabilities
        data: Feature dataset
        important_features: List of features considered important for edge cases
        sample_per_bin: Number of samples to select per confidence bin

    Returns:
        Sampled indices and DataFrame with prediction info
    """
    # Create confidence bins
    conf_scores = np.max(predictions , axis=1)
    bins = pd.cut(conf_scores ,
                  bins=[0, 0.2, 0.4, 0.6, 0.8, 1],
                  labels=['very_low', 'low', 'borderline', 'high', 'very_high'])

    # Sample from each bin
    sampled_indices = []
    for bin_label in bins.unique():
        bin_mask = (bins == bin_label)
        bin_indices = np.where(bin_mask)[0]
        if len(bin_indices) > 0:
            sample_size = min(sample_per_bin , len(bin_indices))
            sampled_indices.extend(
                np.random.choice(bin_indices , size=sample_size , replace=False)
            )

    # Add edge cases with extreme feature values
    z_scores = np.abs((data[important_features] -
                       data[important_features].mean()) / data[important_features
    edge_indices = z_scores.max(axis=1).nlargest(sample_per_bin//2).index
    sampled_indices.extend(edge_indices)

    # Return unique indices
    return np.unique(sampled_indices)
```

C.5.2 XAI Metrics

Measure Faithfulness

Listing C.11: Faithfulness Implementation

```python
def compute_faithfulness(model, data, explanations):
    """
    Calculate the faithfulness correlation between feature importance
    and prediction changes when features are removed.
    """
    faithfulness_scores = []

    for idx, instance in enumerate(data.values):
        # Get feature importance from the explanation
        feature_importance = np.array(explanations[idx]['importance'])

        # Baseline prediction
        baseline_pred = model.predict_proba([instance])[0]

        # Measure the impact of removing each feature
        feature_impacts = []
        for feature_idx in range(len(instance)):
            # Create a copy with one feature zeroed
            perturbed_instance = instance.copy()
            perturbed_instance[feature_idx] = 0

            # Get new prediction
            perturbed_pred = model.predict_proba([perturbed_instance])[0]

            # Calculate impact
            impact = np.abs(baseline_pred - perturbed_pred).sum()
            feature_impacts.append(impact)

        # Calculate correlation
        correlation = np.corrcoef(feature_importance, feature_impacts)[0, 1]
        faithfulness_scores.append(correlation)

    return faithfulness_scores
```

Measure Monotonicity

Listing C.12: Monotonicity Implementation

```python
def compute_monotonicity(model, data, explanations):
    """
    Calculate monotonicity by checking if prediction changes are
    consistent when features are removed in order of importance.
    """
    monotonicity_scores = []
```

```
for idx, instance in enumerate(data.values):
    # Get feature importance and sort indices
    feature_importance = np.array(explanations[idx]['importance'])
    sorted_indices = np.argsort(feature_importance)[::-1]

    # Baseline prediction
    baseline_pred = model.predict_proba([instance])[0]

    # Incrementally remove features
    prediction_changes = []
    temp_instance = instance.copy()

    for feature_idx in sorted_indices:
        original_value = temp_instance[feature_idx]
        temp_instance[feature_idx] = 0

        # Calculate prediction change
        new_pred = model.predict_proba([temp_instance])[0]
        change = np.abs(baseline_pred - new_pred).sum()
        prediction_changes.append(change)

    # Check if changes are monotonically decreasing
    monotonic = np.all(np.diff(prediction_changes) <= 0)
    monotonicity_scores.append(float(monotonic))

return monotonicity_scores
```

Measure Completeness

Listing C.13: Completeness Implementation

```
def compute_completeness(model, data, explanations):
    """
    Calculate completeness by measuring how much of the prediction
    is captured by the explanation scores.
    """
    completeness_scores = []

    for idx, instance in enumerate(data.values):
        # Get feature importance
        feature_importance = np.array(explanations[idx]['importance'])

        # Baseline prediction
        baseline_pred = model.predict_proba([instance])[0]

        # Zero all features (create null instance)
        null_instance = np.zeros_like(instance)
        null_pred = model.predict_proba([null_instance])[0]

        # Calculate maximum possible change
        max_change = np.abs(baseline_pred - null_pred).sum()
```

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```
        # Calculate completeness
        if max_change > 0:
            completeness = np.sum(np.abs(feature_importance)) / max_change
        else:
            completeness = 1.0  # If no change, explanation is complete

        completeness_scores.append(completeness)

    return completeness_scores
```

C.5.3 Cross-Model XAI Metrics Evaluation

```
xai_metrics = {}
baseline = X_train.mean(axis=0)
for model_name, current_model in models.items():
    # Step 1: Generate 'SHAP' explanation.
    shap_dict, _ = get_shap_explanation(current_model, sample)

    # Step 2: Generate 'LIME' explanation.
    lime_dict, _ = get_lime_explanation(current_model, sample)

    # Step 3: Generate 'Anchors' explanation.
    anchors_dict, _ = get_anchors_explanation(current_model, sample)

    # Step 4: Compute 'Faithfulness' metrics.
    xai_metrics[model_name]['SHAP']['Faithfulness'].append(
    measure_faithfulness(current_model, sample, shap_dict, baseline))
    xai_metrics[model_name]['LIME']['Faithfulness'].append(
    measure_faithfulness(current_model, sample, lime_dict, baseline))
    xai_metrics[model_name]['Anchors']['Faithfulness'].append(
    measure_faithfulness(current_model, sample, anchors_dict, baseline))

    # Step 5: Compute 'Monotonicity' metrics.
    xai_metrics[model_name]['SHAP']['Monotonicity'].append(
    measure_monotonicity(current_model, sample, shap_dict, baseline))
    xai_metrics[model_name]['LIME']['Monotonicity'].append(
    measure_monotonicity(current_model, sample, lime_dict, baseline))
    xai_metrics[model_name]['Anchors']['Monotonicity'].append(
    measure_monotonicity(current_model, sample, anchors_dict, baseline))

    # Step 6: Compute 'Completeness' metrics.
    xai_metrics[model_name]['SHAP']['Completeness'].append(
    measure_completeness(
    current_model, sample, shap_dict, baseline))
    xai_metrics[model_name]['LIME']['Completeness'].append(
    measure_completeness(
    current_model, sample, lime_dict, baseline))
    xai_metrics[model_name]['Anchors']['Completeness'].append(
```
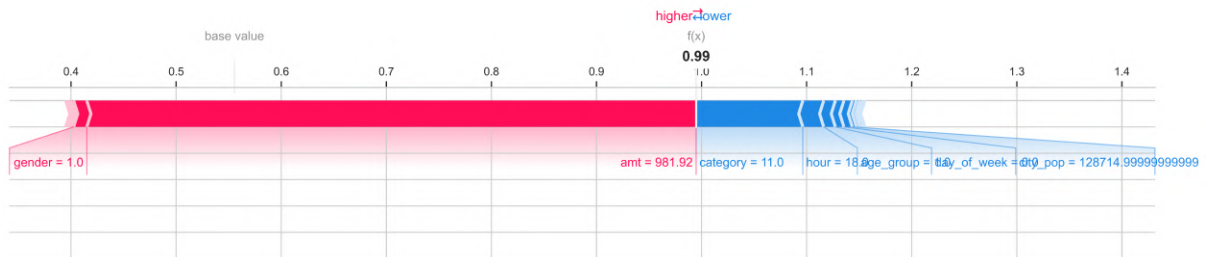
```
measure_completeness (
current_model , sample , anchors_dict , baseline ))
```
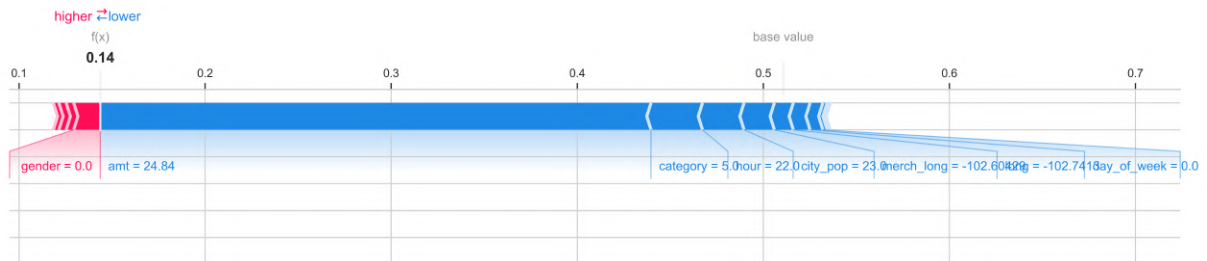
Appendix D

Extended Results

D.1 Extended XAI Visualizations

(a) SHAP Force Plot for Fraud Transaction

(b) SHAP Force Plot for Legitimate Transaction

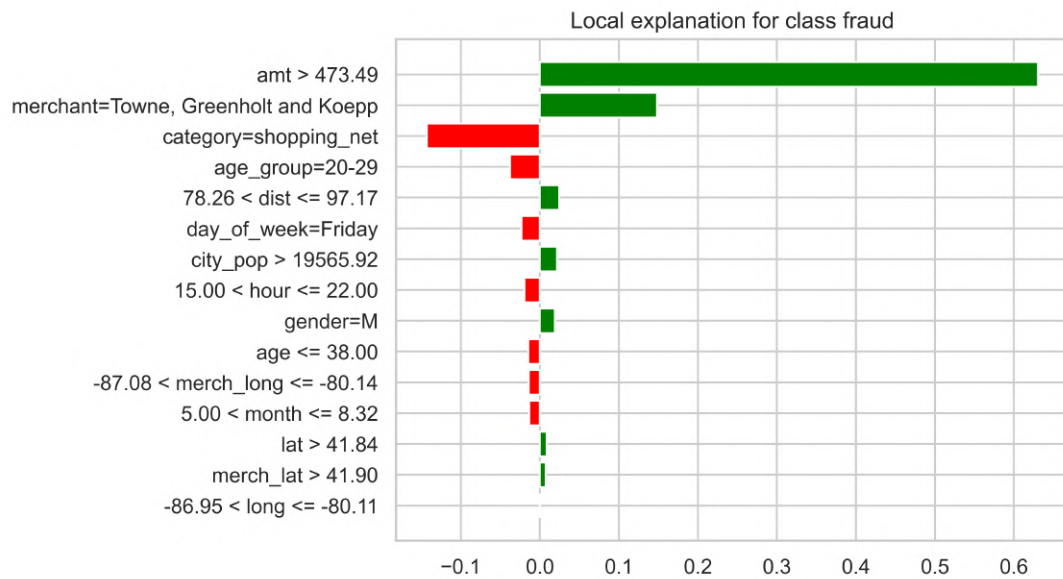Figure D.1: SHAP Force Plots for Different Transaction Types

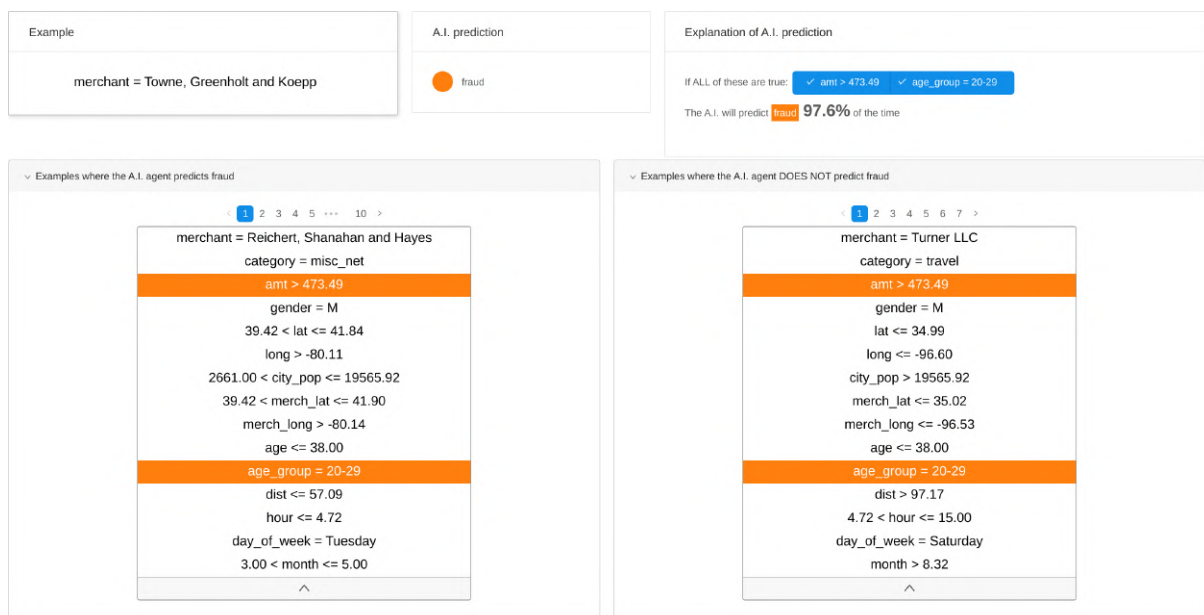Figure D.2: LIME Explanations for Selected Transactions

Figure D.3: Anchors Explanation Interactive Observation in Notebook

D.2 Feature Importance Analysis
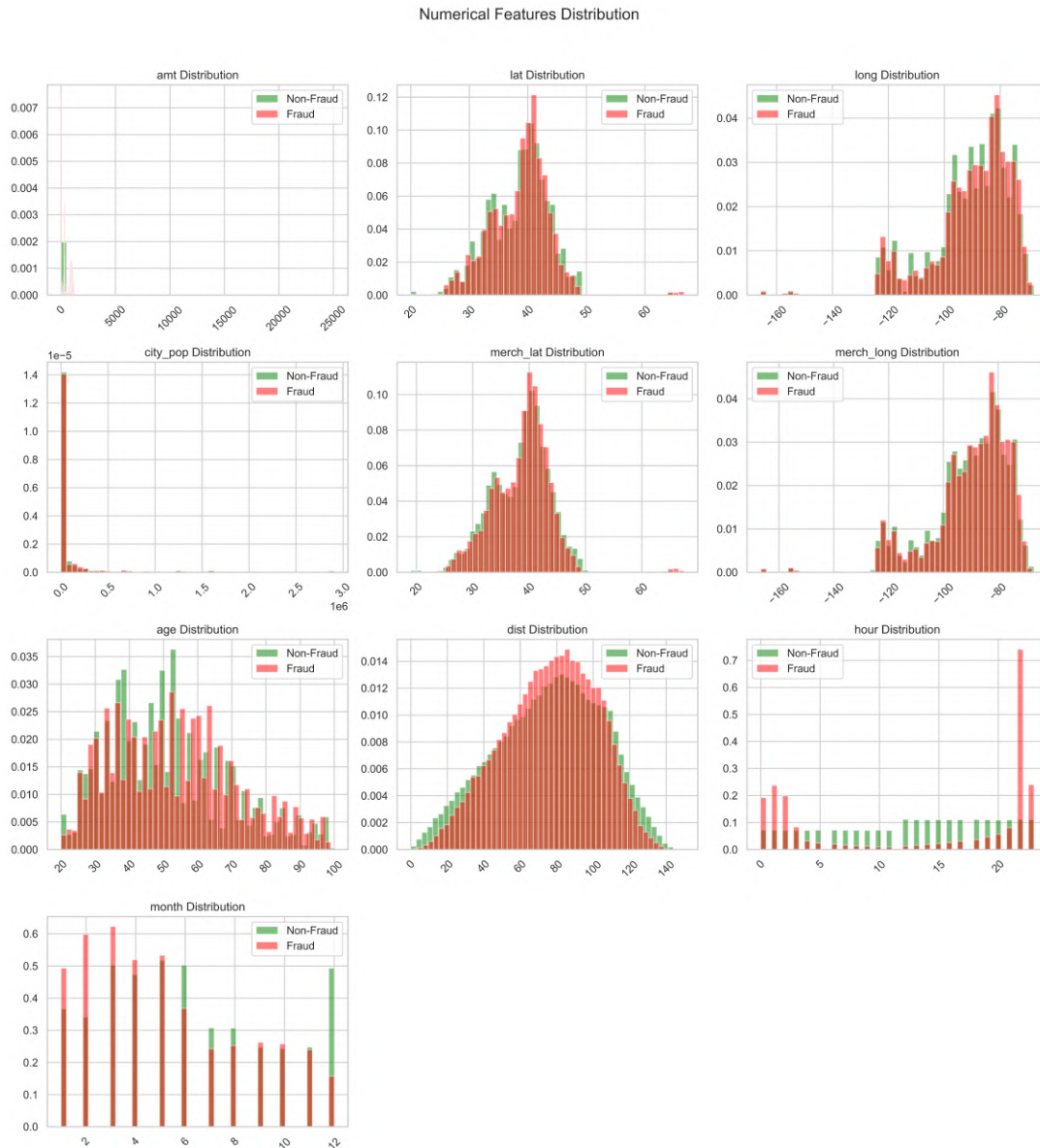
Figure D.4: Distributions of Key Numerical Features

Figure D.5: Distributions of Key Categorical Features

D.3   Model Comparison Tables

Table D.1: Comprehensive Model Performance Comparison

Metric	CNN	LSTM
Accuracy	0.986	0.975
ROC AUC	0.994	0.971
Precision	0.607	0.559
Recall	0.953	0.896
F1 Score	0.67	0.597
Training Time (s)	2450	3785
Inference Time (s/sample)	428	127

Appendix E

Presentation Materials

E.1 Presentation Slices

The slides were used for the presentation of the research project. The presentation covers the methodology, results, and key findings from this study.

The complete presentation for this project can be found at: View Presentation Online

University of
HUDDERSFIELD

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

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April 2025

Figure E.1: Title slide from the *'Explainable AI (XAI) in Deep Learning Models for Credit Card Fraud Detection'* presentation (Lai, 2025b)

E.2 Poster

The academic poster created for this research project, which summarises the key aspects of this study.

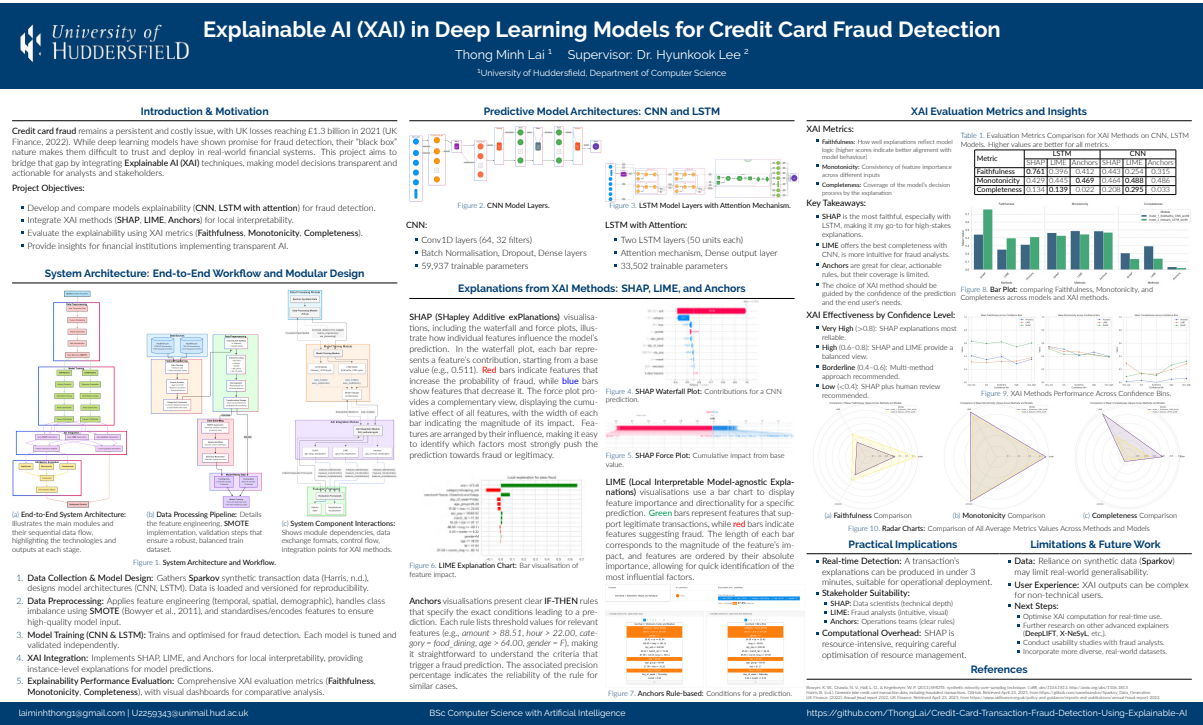The full-resolution poster can be accessed at: View Poster Online

Figure E.2: Academic poster for *'Explainable AI (XAI) in Deep Learning Models for Credit Card Fraud Detection'* (Lai, 2025c)

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