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

A seminar report submitted to University of Huddersfield
in partial fulfilment of degree of

BSc. Computer Science

with

Artificial Intelligence

by

Thong Minh Lai

Student ID: U2259343

University of Huddersfield

DEPARTMENT OF COMPUTER SCIENCE

SCHOOL OF COMPUTING AND ENGINEERING

April 2025

DEPARTMENT OF COMPUTER SCIENCE

SCHOOL OF COMPUTING AND ENGINEERING

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**.*

Dr. Hyunkook Lee
Professor and Supervisor
Sch. of Comp & Engg
Huddersfield

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.

Contents

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, 2025d) 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 (2025c).
- **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 (2025b).

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 XAI system comprises several integrated modules:

1. **Data and Model Collection:** Obtaining synthetic transaction data and collecting fraud detection models architectures.
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.

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 provides 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 the cooperative game theory that considers the "payout" (prediction result) between "players" (features).

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

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 fits a simple (linear) explanatory model for this local behavior.

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, 2025d).

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
   time_since_last_transaction < 5 minutes AND
   different_country = True
THEN prediction = Fraud (confidence 0.95)
```

(Lai, 2025d). 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".

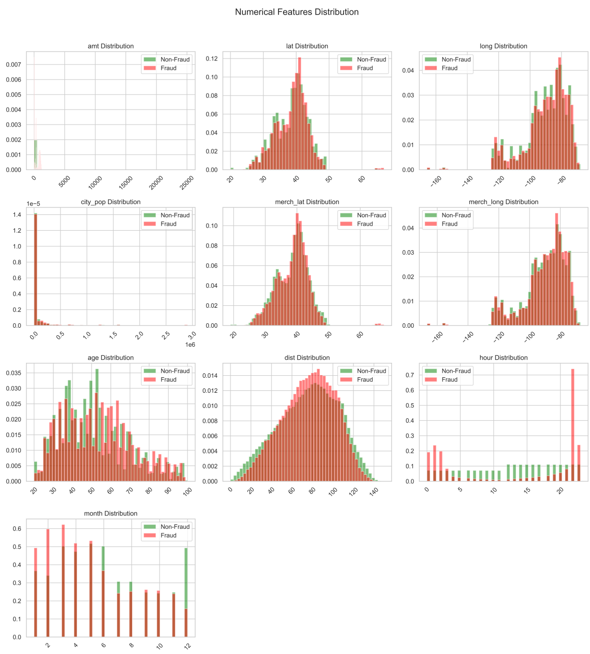
2.5.2 The Sparkov Dataset Characteristics

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, 2025d).

After feature engineering so it can 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, 2025d)



(a) Numerical Features Distributions

(b) Categorical Features Distributions

Figure 2.1: 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).

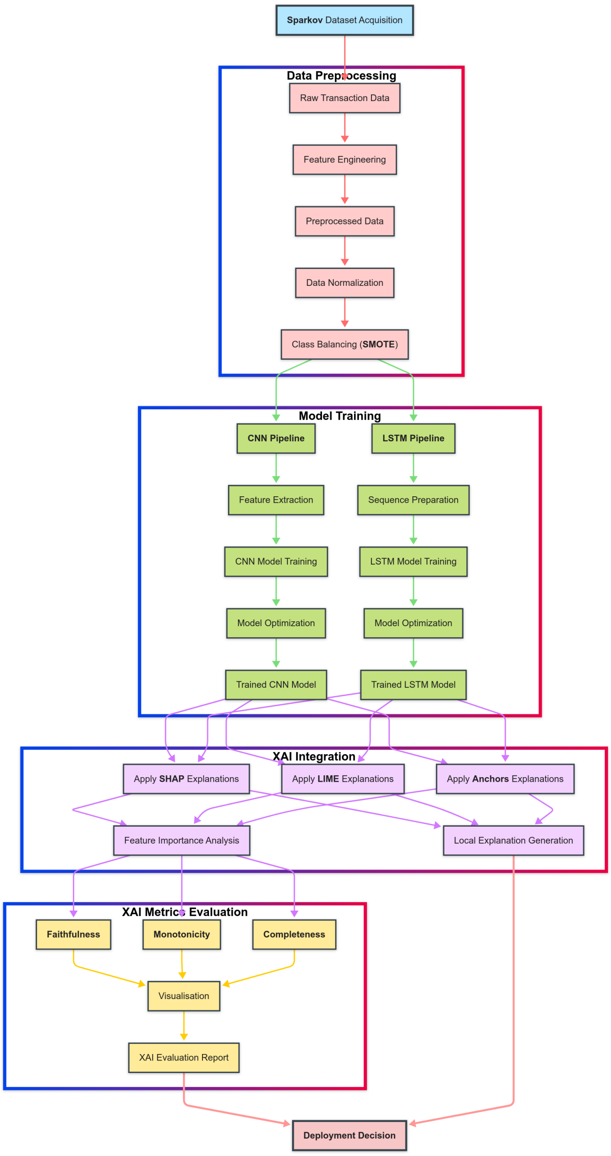


Figure 3.1: Illustrative diagram of the fraud detection system architecture showing data flow from preprocessing to model training, XAI integration and evaluation.

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.

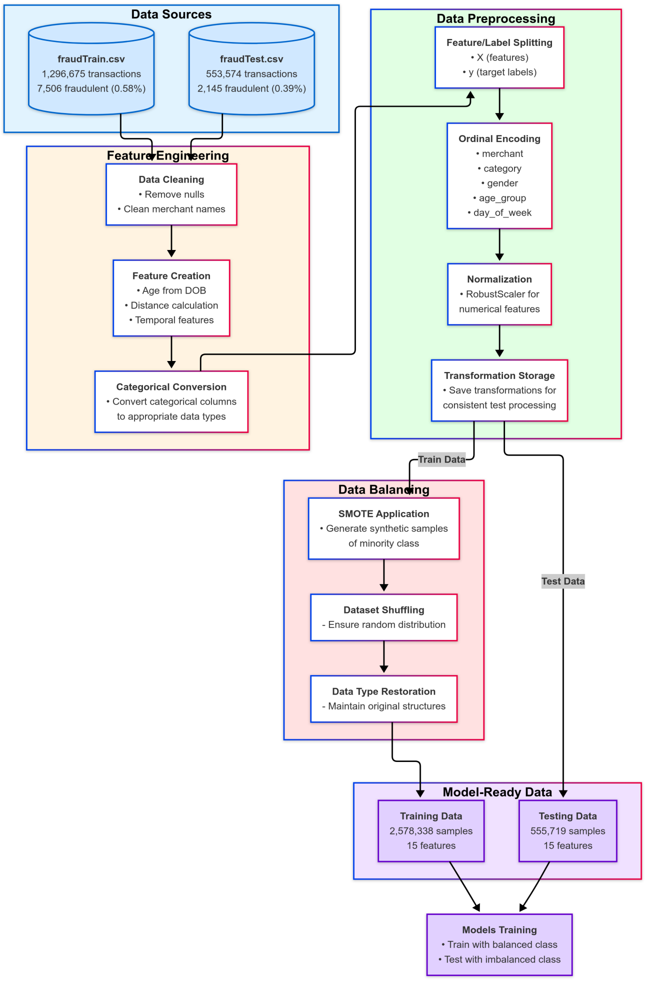


Figure 3.2: Data Preprocessing Pipeline for Fraud Detection

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

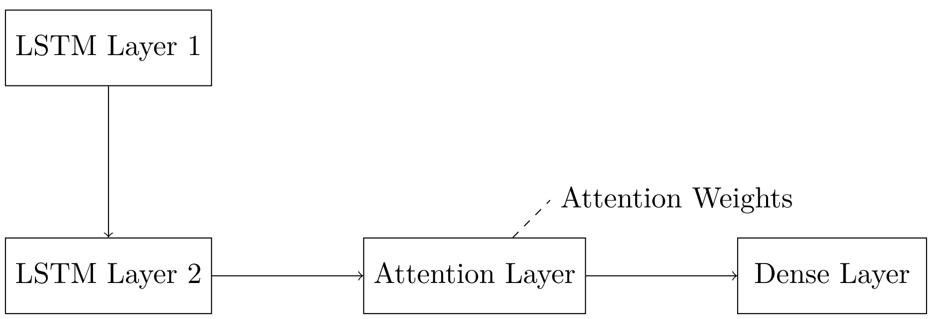


Figure 3.3: LSTM Model with Attention Mechanism

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

Input: Trained model f, transaction x
for each feature i in x **do**
    Initialize SHAP value $\phi_i = 0$
    for each subset S of features not containing i **do**
        Create two samples: $x_{S\cup\{i\}}$ and x_S
        Compute marginal contribution: $f(x_{S\cup\{i\}}) - f(x_S)$
        Weight the contribution based on subset size
        Add weighted contribution to ϕ_i
    end for
end for
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.
- **Shapley 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 understand 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

```
Input: Trained model f, transaction x
Initialize anchor A = ∅
while precision of A (fraction of perturbed samples where f predicts same as f(x)) < threshold do
    For each candidate feature not in A:
        Add feature to A and estimate new precision
    Add feature that increases precision the most to A
end while
Output: Anchor 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

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

Algorithm 5 Monotonicity Metric for XAI Explanations

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

Algorithm 6 Completeness Metric for XAI Explanations

Input: Model f, sample x, explanation scores E for features
Compute model prediction: $y = f(x)$
Compute baseline prediction: $y_{base} = f(\text{baseline input})$
Sum explanation scores: $S = \sum_i E_i$
Compute completeness error: $|S - (y - y_{base})|$
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, 2025d).

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.

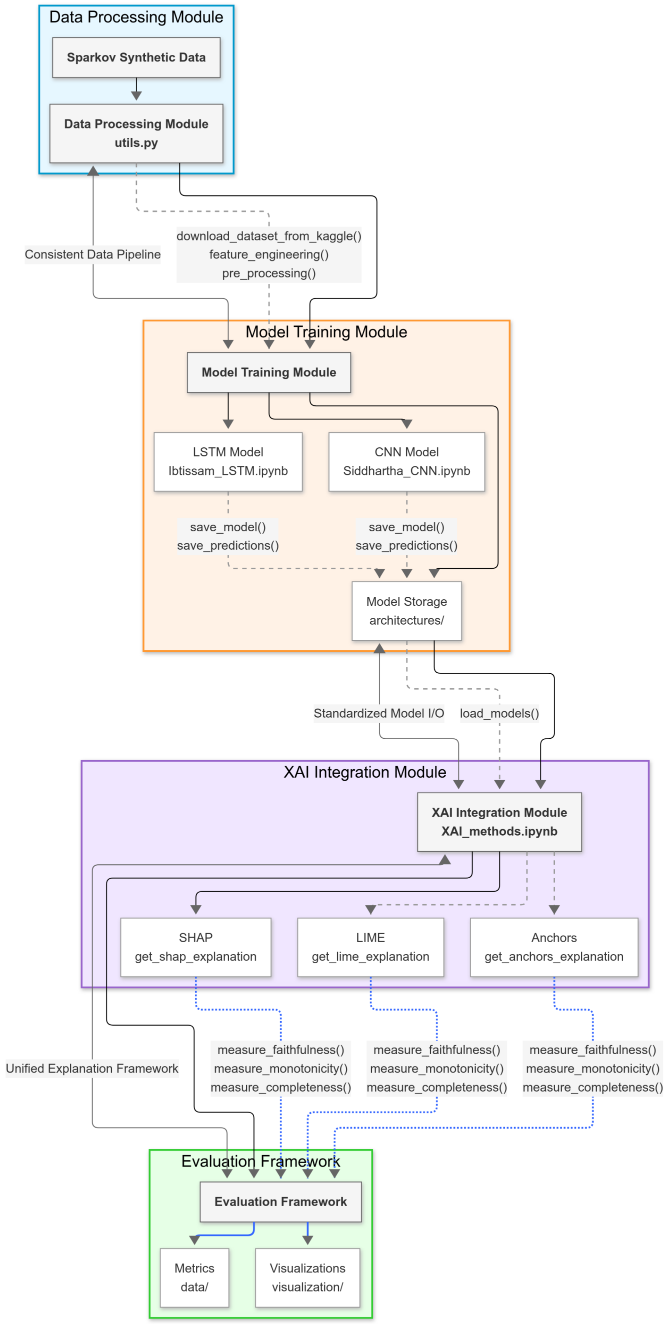


Figure 4.1: System Component Interactions

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.

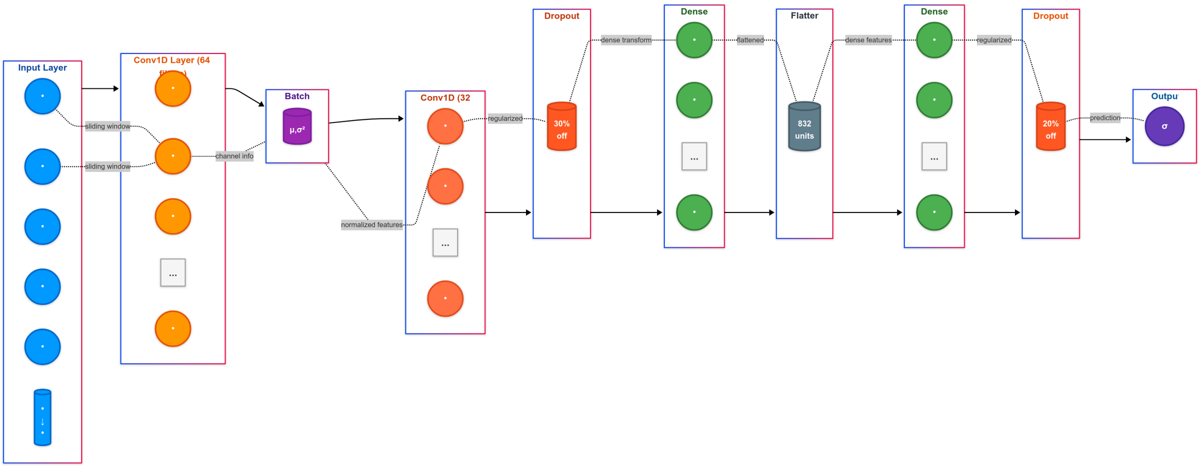


Figure 4.2: CNN Model Architecture

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.

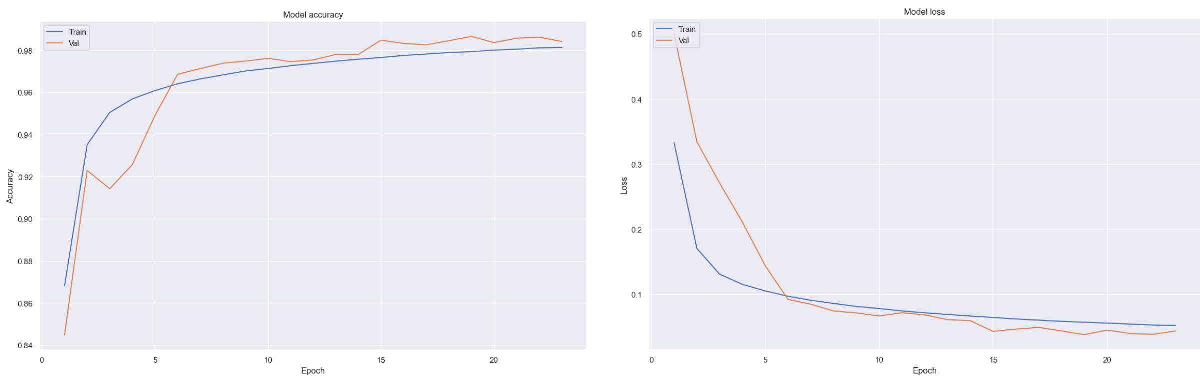
The main optimisation strategies included:

- **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, 2025b). Figure 4.4 shows the model architecture.

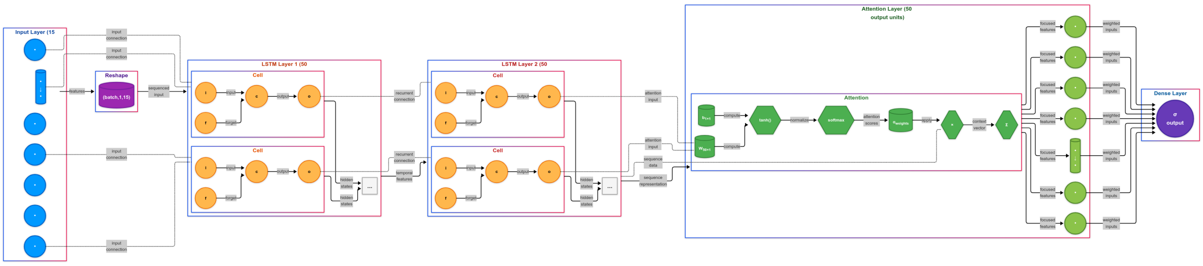


Figure 4.4: LSTM Model Architecture with Attention Mechanism

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.

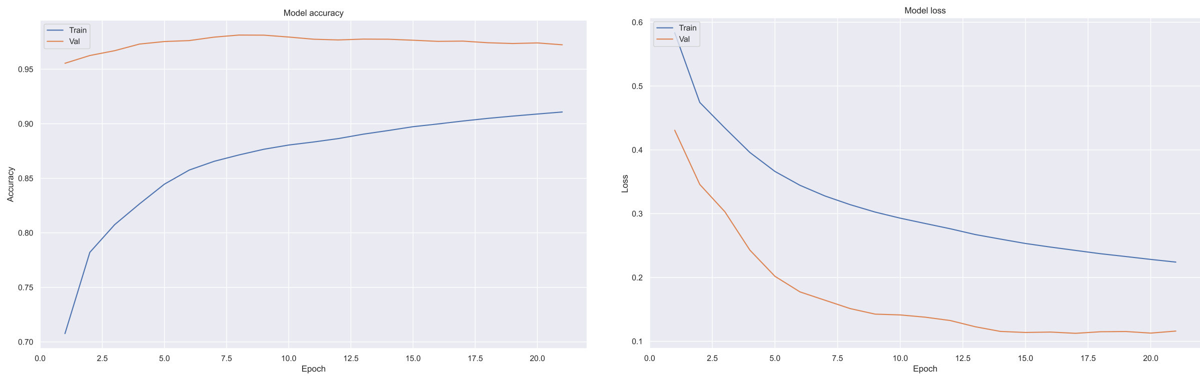
The training process involved:

- **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.

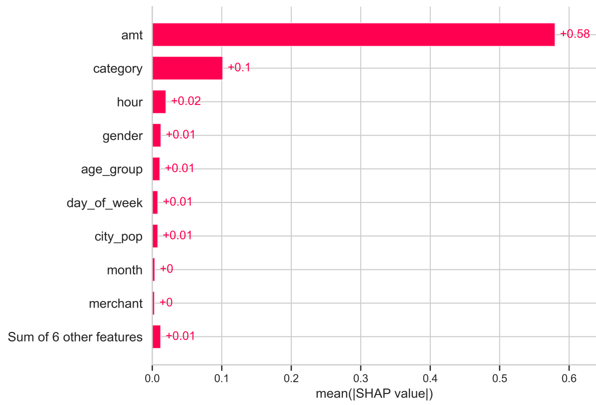
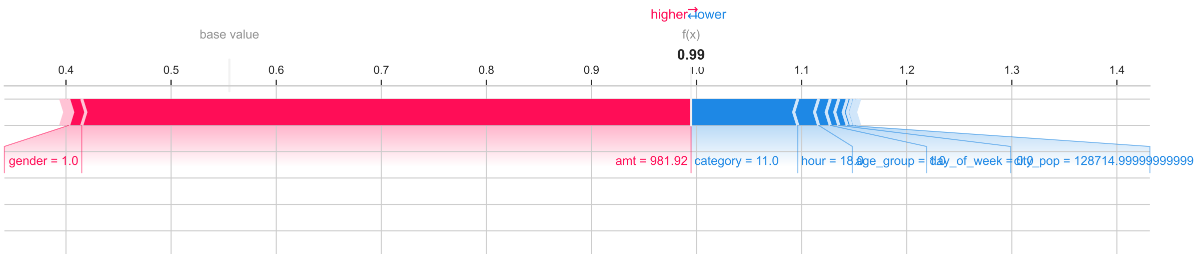


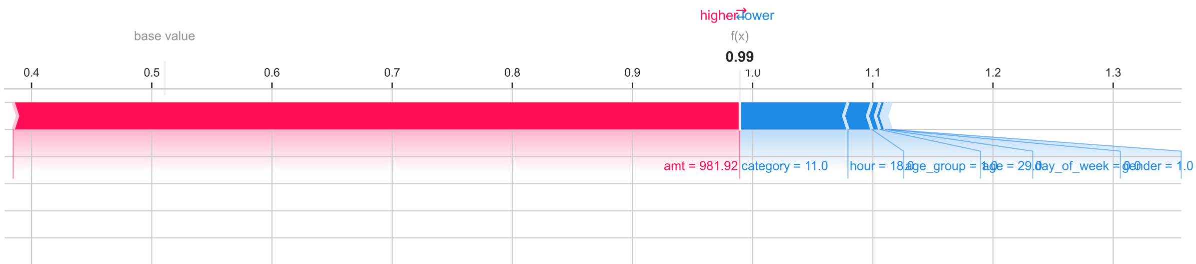
Figure 4.6: SHAP Bar Plot showing feature importance (mean SHAP values) for a fraudulent transaction prediction.

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 of CNN model's prediction (99,48%) at sample index 1044



(b) Feature contributions of 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.

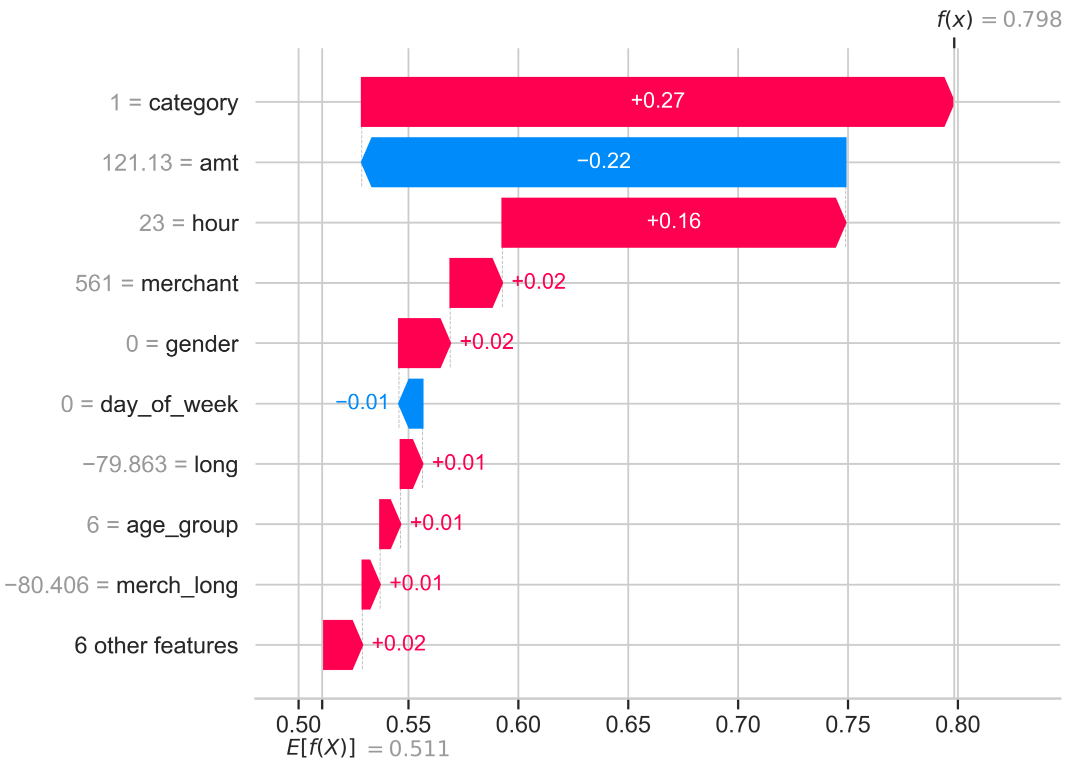


Figure 4.8: SHAP Waterfall Plot showing feature importance distribution. Higher feature values are represented in red, while lower values are in blue.

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 ò 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

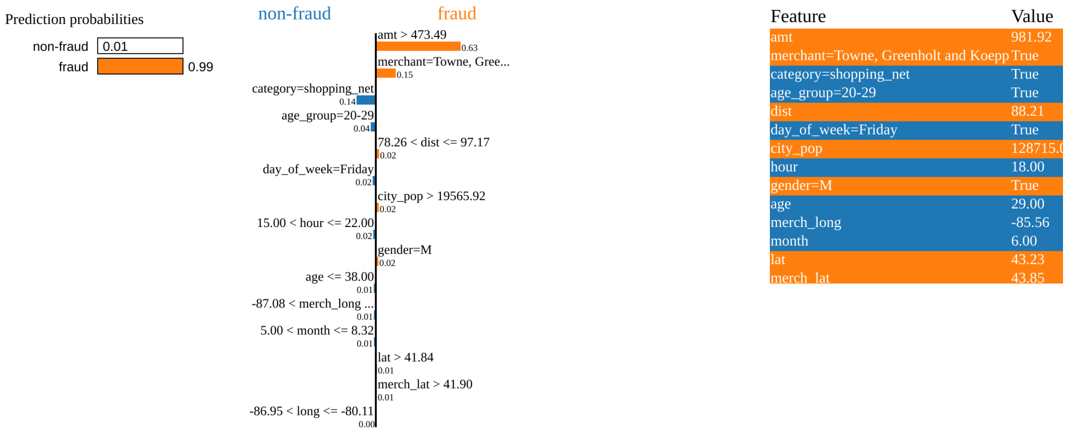


Figure 4.9: LIME Explanation Interactive Observation in Notebook

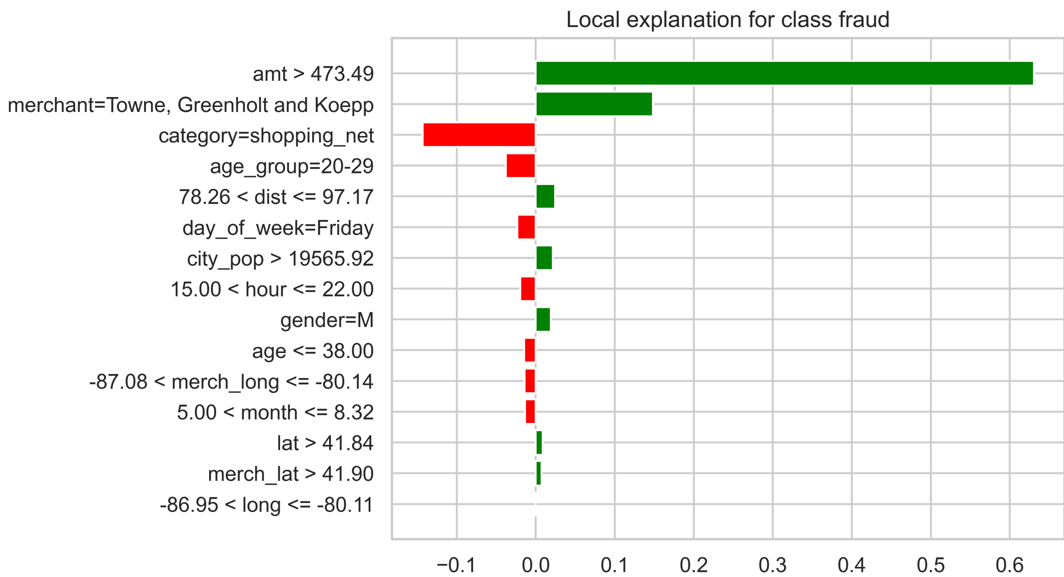


Figure 4.10: LIME Explanation showing feature contributions for a single prediction. Green bars indicate features pushing toward legitimate prediction, while red bars indicate features pushing toward fraud.

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).

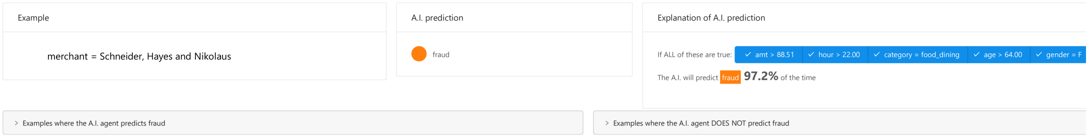


Figure 4.11: Anchors Explanation Interactive Observation in Notebook

Rules extraction from Anchors revealed interesting patterns that were aligned with domain knowledge. The example of a specific rule for the prediction of fraud is as follows:

```
1. amt > 88.51
2. hour > 22.00
3. category = food_dining
4. age > 64.00
5. merch_long > -87.08
```

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 > 0.85)
- high confidence predictions ($0.6 <$ confidence < 0.85)
- 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:

- Faithfulness: C.5.2
- Monotonicity: C.5.2
- Completeness: C.5.2

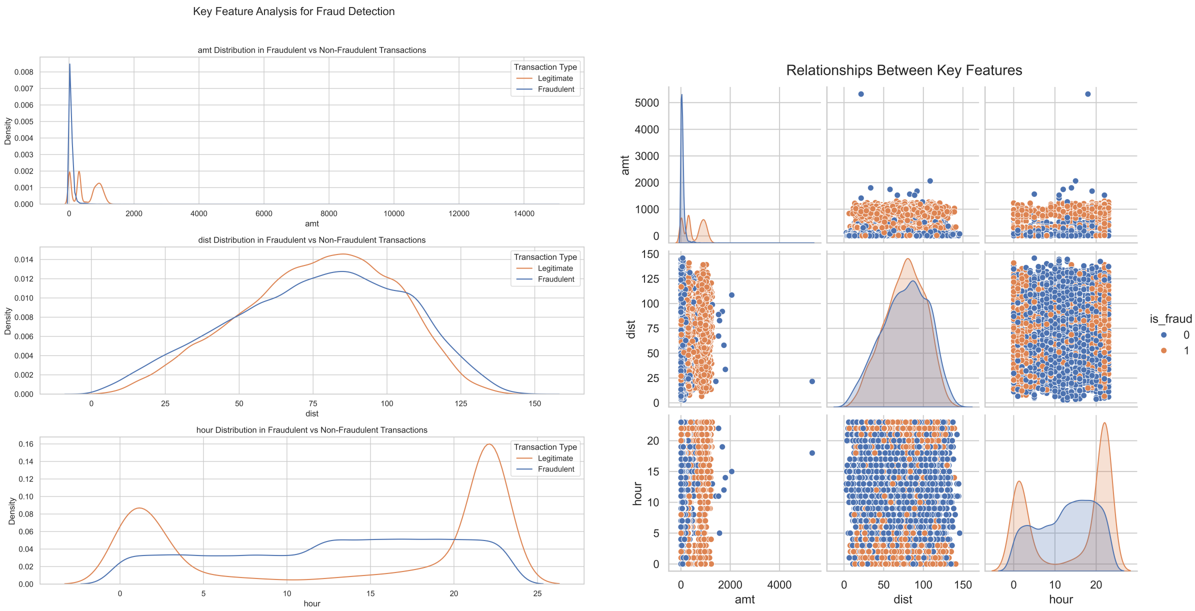
A major innovation in the implementation is the integrated cross-model evaluation structure, which allows a direct comparison of different model architectures (CNN and LSTM) by iterating through each model and retrieving stratified samples (as stated above), then evaluating 3 core XAI metrics for each 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

Analysis of fraudulent transactions in the dataset revealed several consistent patterns:

- **Amount Anomalies:** Transactions with amounts significantly deviating from a user's typical spending pattern showed high fraud probability, particularly when amounts exceeded around 500.
- **Temporal Patterns:** Transactions occurring between 23:00 and 04:00 had elevated fraud risk, with values showing strong positive contributions toward fraud classification.

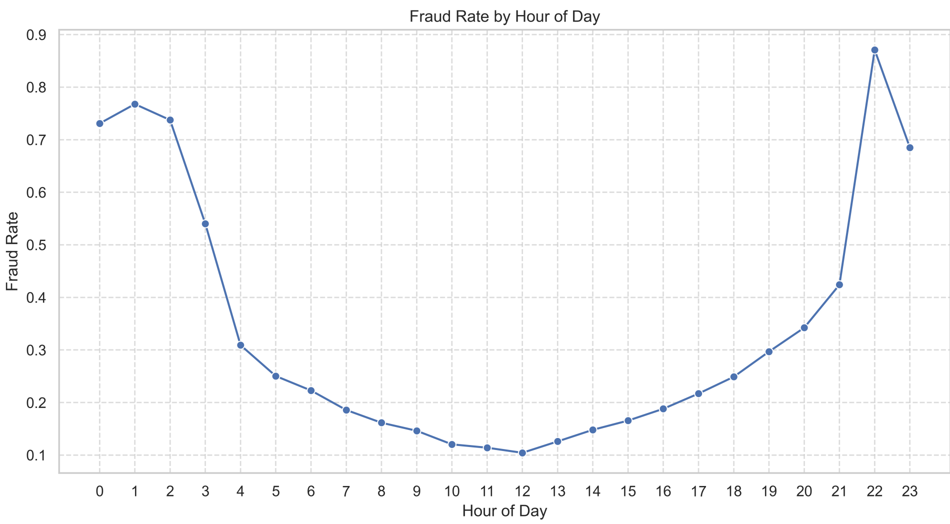


Figure 4.13: Fraud Time Patterns

- **Geographical Anomalies:** Transactions occurring more than 75km from a cardholder's typical location created strong positive contributions to fraud probability.

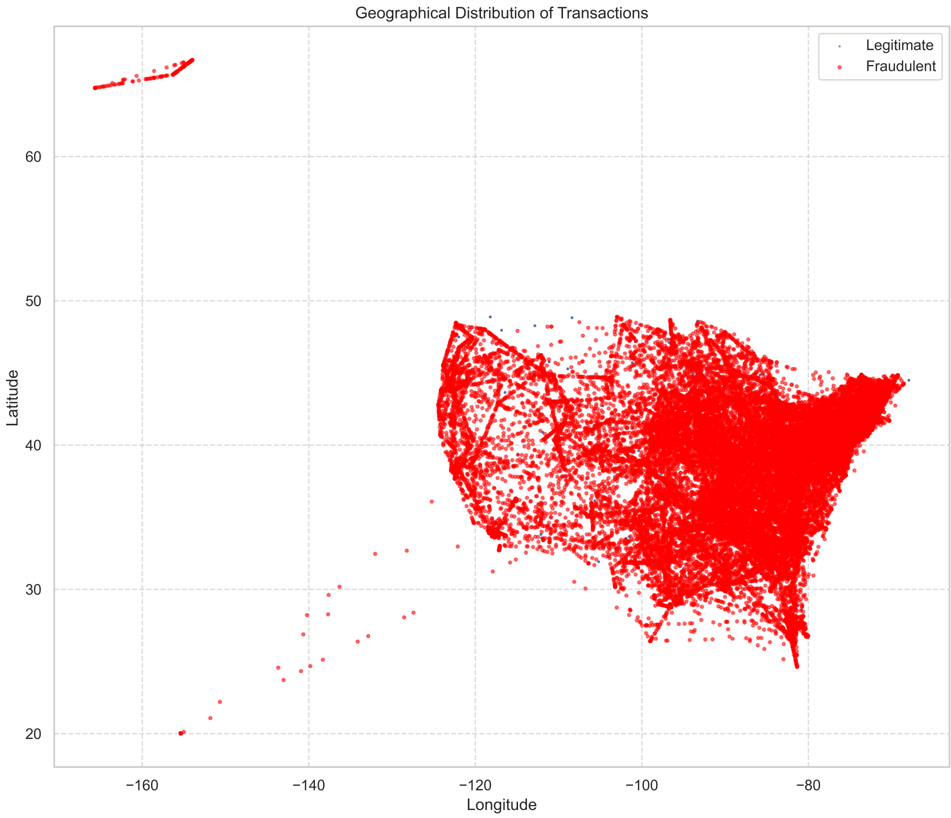


Figure 4.14: Geographical Distribution

These patterns align with findings from Lucas et al. (2020), who identified similar indicators in their analysis of real-world fraud data. The consistency across both models and multiple XAI methods supports the validity of these patterns as genuine 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.

The table below summarises the feature importance scores for both models:

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

Feature	**CNN**	**LSTM**	**Difference**
Transaction Amount	0.320	0.300	+0.020
Distance	0.280	0.250	+0.030
Hour	0.150	0.180	-0.030
Merchant Category	0.120	0.110	+0.010
Gender	0.070	0.080	-0.010
Age	0.040	0.050	-0.010
Location (lat/long)	0.020	0.030	-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 demonstrated the highest faithfulness score (0.761), indicating its superior ability to align explanations with the model's predictions. LIME and Anchors also followed with better 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

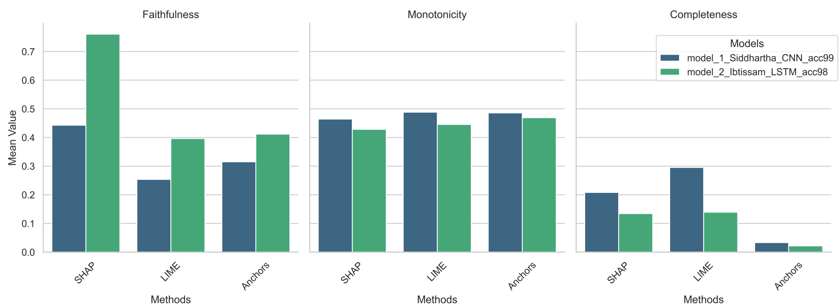
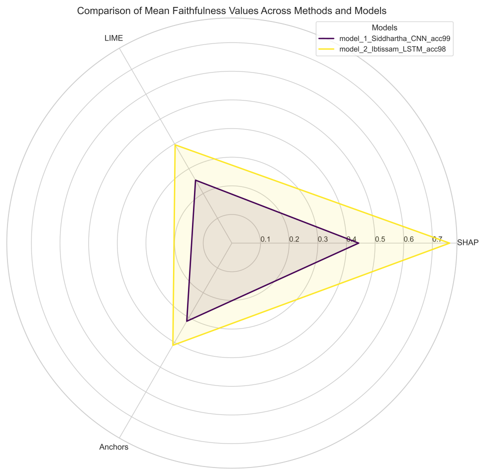
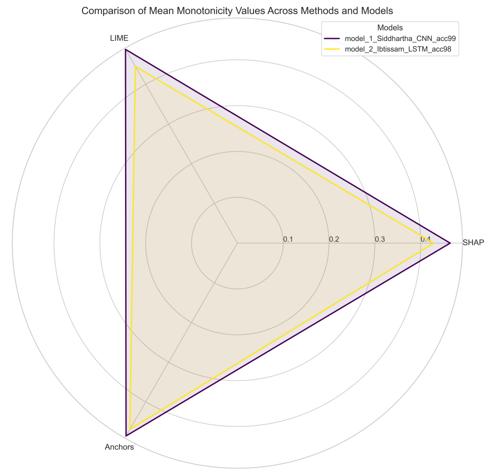


Figure 4.15: Categories Plot Comparing XAI Methods Across Evaluation Metrics and Models

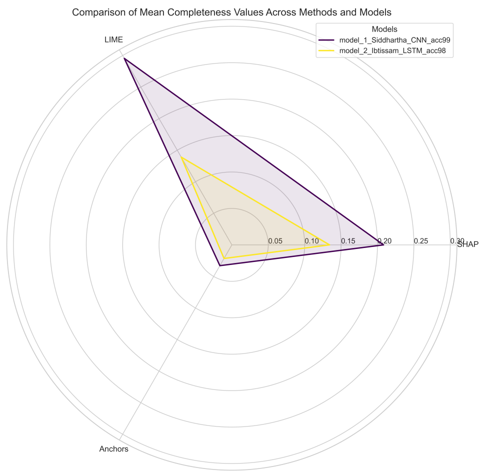
The CNN model achieved its highest faithfulness score with SHAP (0.443), outperforming LIME (0.254) and Anchors (0.315). Monotonicity and Completeness scores showed less variation, with all similar performance across both models. This suggests that SHAP is more effective in explaining both models, particularly the LSTM, which relies on temporal dependencies.



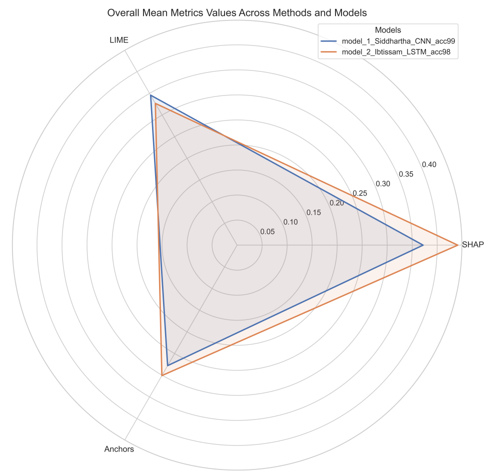
(a) Faithfulness Comparison



(b) Monotonicity Comparison



(c) Completeness Comparison



(d) Average across Metrics

Figure 4.16: Radar Charts Comparison of All Average Metrics Values Across Methods and Models

4.5.4 Explanation Performance across Confidence Bins

An important consideration when deploying XAI methods in fraud detection is how explanation quality varies with model confidence. To systematically assess this relationship, as mentioned in 4.4.4, the testing samples are divided into 5 confidence bins based on the predictions. This analysis reveals critical insights about which XAI approaches perform best 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 distinct patterns for each XAI method across the confidence spectrum. For high and very high confidence predictions (>0.6), all methods demonstrated improved performance compared to lower confidence levels, but with notable differences:

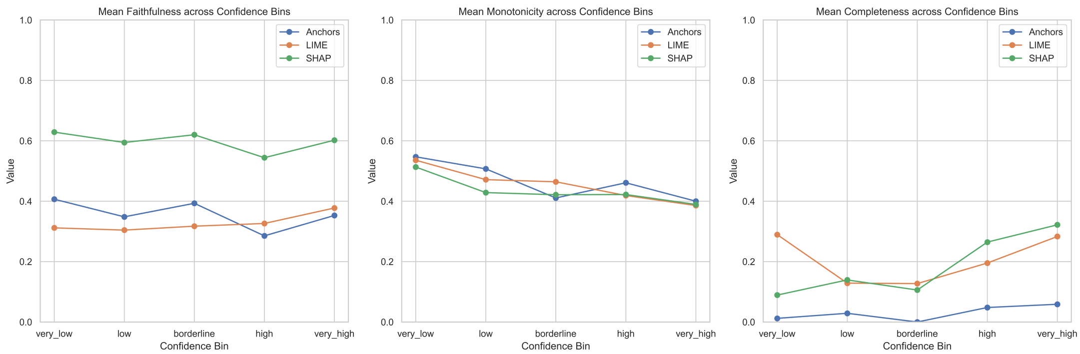


Figure 4.17: XAI Methods Performance Across Confidence Bins for Faithfulness, Monotonicity, and Completeness. SHAP consistently demonstrates superior faithfulness, while LIME shows remarkable stability in monotonicity across confidence levels.

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

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

Anchors showed the most variable performance across confidence bins. While achieving respectable faithfulness in very low and borderline confidence bins (0.407 and 0.393 respectively), it struggled with high confidence predictions (0.285). This pattern aligns with Anchors' design as a rule-based system that performs better when identifying clear rules for rejecting transactions (low confidence) than explaining complex acceptance patterns (high confidence).

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

Practical Deployment Recommendations

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

1. **Very High Confidence (>0.85):** Primarily rely on SHAP explanations, which achieve the highest faithfulness (0.602) and completeness (0.322) in this range. LIME can serve as a complementary method to verify explanation stability.
2. **High Confidence (0.6-0.85):** Use SHAP as the primary method despite its slight performance drop in this range (faithfulness: 0.544), supplemented by LIME for consistent monotonicity (0.419).
3. **Borderline Cases (0.4-0.6):** Implement a multi-method approach, with SHAP providing the most faithful explanations (0.620) and LIME offering consistent monotonicity (0.464). These cases benefit most from multiple explanation perspectives due to their ambiguous nature.
4. **Low Confidence (<0.4):** SHAP remains the most reliable method (faithfulness: 0.594-0.629), but all explanations should be treated with appropriate caution. These cases should trigger additional human review with the understanding that the explanations provide guidance rather than definitive reasoning.
5. **Edge Cases:** Require specialised review protocols with limited reliance on automated explanations. When explanations must be provided, SHAP offers the most robust performance.

This confidence-bin analysis demonstrates that explanation quality is not uniform across prediction confidence levels, and XAI deployment should be tailored accordingly. By matching explanation methods to confidence levels, financial institutions can maximise the utility of XAI in fraud detection systems while maintaining appropriate human oversight where algorithmic 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 stakeholder needs. SHAP provided the most technically comprehensive explanations but required data science expertise to interpret. LIME offered more intuitive visual explanations (Figure 4.10) suitable for analysts with a less technical background. Anchors provided the most accessible explanations through clear if-then rules (Figure 4.11), but with more limited coverage.

Qualitative assessment of XAI effectiveness was conducted using a framework proposed by Naveed et al. (2024), evaluating explanations on dimensions 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 highlights that XAI techniques should be selected based on the specific requirements of stakeholders: SHAP for data scientists needing technical depth, LIME for fraud analysts seeking intuitive explanations, and Anchors for operational staff requiring clear decision rules. This multi-method approach aligns with recommendations from Raufi et al. (2024), who advocate combining complementary XAI techniques to address diverse stakeholder needs.

Chapter 5

Evaluation and Discussion of the Product

5.1 Model Explanation Performance Evaluation

5.1.1 Quantitative Metrics Comparison

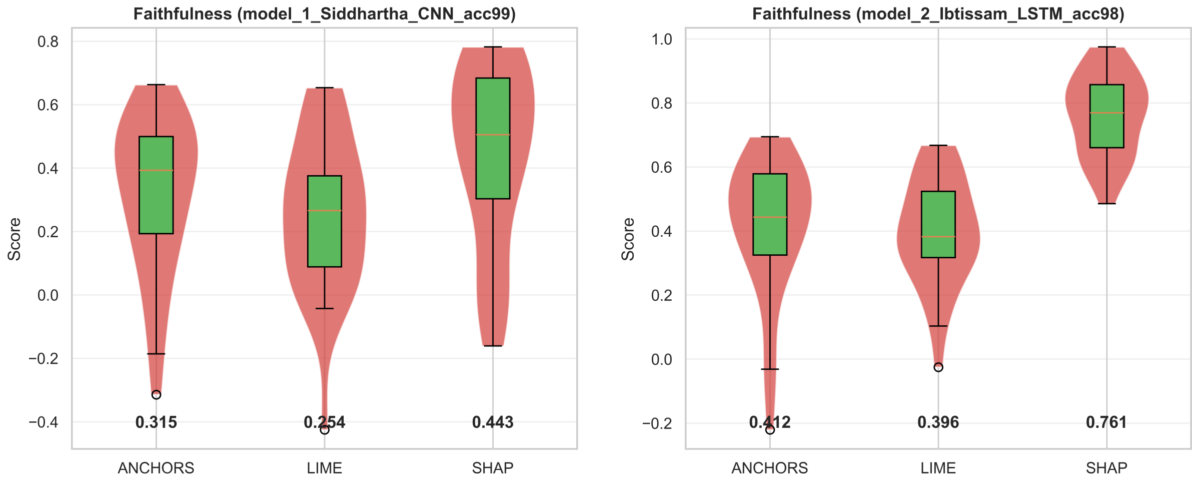
The quantitative analysis reveals distinct patterns in how CNN and LSTM architectures perform across three critical explainability metrics: Faithfulness, Monotonicity, and Completeness. These metrics provide insights into different aspects of explanation quality: how accurately explanations reflect model decisions, how consistently they maintain feature importance rankings, and how comprehensively they capture the model's decision process, respectively.

Faithfulness Analysis

Table 5.1: Faithfulness Metrics Summary

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

Faithfulness represents perhaps the most critical metric for practical applications, measuring how accurately explanations reflect the true decision-making process of the model. The LSTM architecture demonstrates substantially superior faithfulness scores across all explanation methods. With SHAP explanations, the LSTM model achieves a remarkable mean faithfulness of 0.761 (σ = 0.127), dramatically outperforming the CNN model's score of 0.443 (σ = 0.280) a 72% improvement. This advantage persists with LIME (LSTM: 0.396 vs CNN: 0.254) and Anchors (LSTM: 0.412 vs CNN: 0.315), though the gap narrows 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

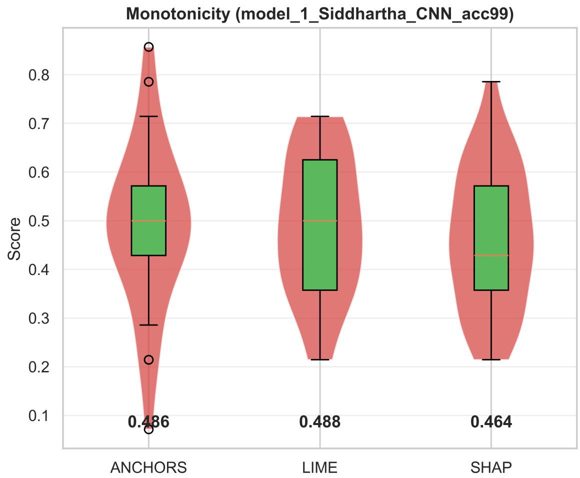
Beyond the mean scores, the LSTM architecture demonstrates notably more consistent faithfulness, particularly with SHAP, where its standard deviation (0.127) is less than half of CNN's (0.280). More strikingly, the LSTM model maintains a positive minimum faithfulness value with SHAP (0.486), while the CNN model's minimum drops to negative territory (-0.161), indicating potentially misleading explanations in certain cases. This consistency advantage makes the LSTM architecture particularly valuable for applications requiring reliable explanations, such as fraud investigation or regulatory compliance scenarios.

Monotonicity Analysis

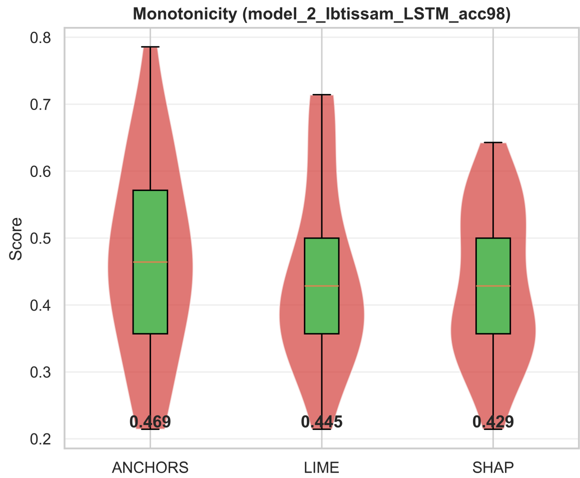
Table 5.2: Monotonicity Metrics Summary

Model	Method	Mean	Std	Min	Max	Median
CNN (99%)	SHAP	0.464	0.141	0.214	0.786	0.429
	LIME	0.488	0.142	0.214	0.714	0.500
	Anchors	0.486	0.165	0.071	0.857	0.500
LSTM (98%)	SHAP	0.429	0.111	0.214	0.643	0.429
	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 consistency of feature importance rankings, with higher values indicating more reliable explanation patterns. In contrast to the faithfulness results, the CNN architecture demonstrates modestly better monotonicity scores across all explanation methods. With LIME, CNN achieves a mean monotonicity of 0.488 ($\sigma = 0.142$) compared to LSTM's 0.445 ($\sigma = 0.134$). 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

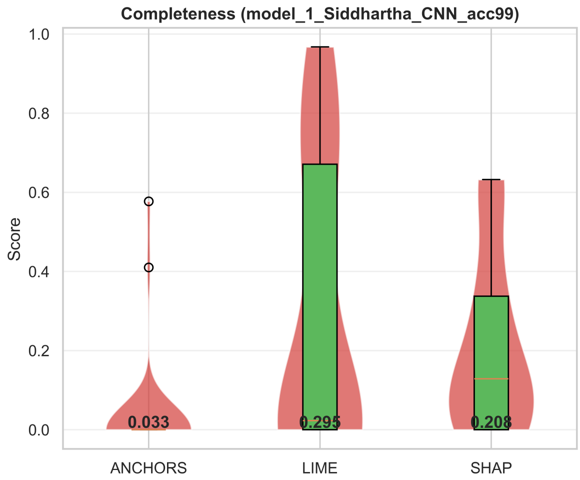
The CNN model also achieves higher maximum monotonicity values across methods, with its peak score of 0.857 with Anchors substantially exceeding LSTM's maximum of 0.786. This suggests that the CNN's feature extraction approach creates more consistent feature importance rankings, potentially making it more suitable for applications where explanation consistency is prioritised over absolute accuracy. The differences, however, are less dramatic than those observed for faithfulness, with CNN's advantage averaging approximately 9% across methods.

Completeness Analysis

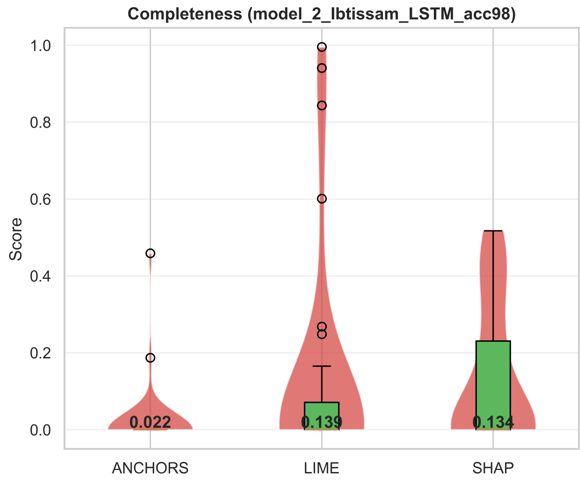
Table 5.3: Completeness Metrics Summary

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 evaluates how comprehensively an explanation captures the model's decision process, with higher scores indicating more complete explanations. Both architectures demonstrate relatively modest completeness scores, but the CNN model consistently outperforms the LSTM across all explanation methods. With LIME, the CNN model achieves its highest completeness score of 0.295 ($\sigma = 0.358$), substantially outperforming LSTM's 0.139 ($\sigma = 0.291$), a 112% advantage. Similar patterns appear with SHAP (CNN: 0.208 vs LSTM: 0.134) and Anchors, though both models show particularly low completeness with the latter 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 demonstrate high variability in completeness scores, as evidenced by the substantial standard deviations relative to their means. This variability suggests that explanation comprehensiveness depends heavily on the specific instances being explained, with some predictions receiving much more complete explanations than others. The consistently higher completeness of the CNN architecture may stem from its spatial feature extraction approach, which appears to create more comprehensive representations of the relevant transaction features compared to LSTM's sequential processing.

Model-Method Interaction Analysis

The performance patterns reveal interesting architecture-specific strengths with particular explanation methods. The LSTM architecture demonstrates exceptional synergy with SHAP, achieving faithfulness scores 72% higher than with other methods. This advantage likely stems from SHAP's game-theoretic approach effectively capturing the sequential dependencies modelled by the LSTM. Conversely, the CNN architecture shows more balanced performance across explanation methods, with its highest faithfulness from SHAP (0.443) representing a more modest 40% improvement over LIME (0.254).

For completeness, both architectures achieve their highest scores with LIME, though CNN shows a more dramatic advantage (0.295 vs 0.139 for LSTM). LIME's perturbation-based approach appears particularly effective at revealing the feature contributions in CNN's spatial processing, while struggling somewhat with LSTM's sequential representation. Anchors consistently yields the lowest completeness scores for both architectures, suggesting fundamental limitations in using rule-based explanations for deep neural network outputs regardless of model architecture.

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 for explainable credit card fraud detection. The LSTM model with SHAP explanations offers substantially higher faithfulness (0.761) and consistency ($\sigma = 0.127$), making it particularly well-suited for high-stakes applications where explanation reliability is paramount, such as fraud investigations that may lead to customer account actions or regulatory reporting. However, the LSTM architecture's lower completeness scores indicate that its explanations may not capture the full decision process, potentially missing relevant transaction features.

Conversely, the CNN model offers better monotonicity and completeness, particularly with LIME explanations, suggesting it provides more comprehensive and consistent explanations, albeit with lower faithfulness. This architecture may be more appropriate for applications where explanation consistency across different confidence levels is prioritised, such as systematic transaction monitoring or customer-facing explanation systems.

Overall, these quantitative metrics highlight that neither architecture is universally superior for explainability. Rather, the choice between CNN and LSTM should be guided by which explainability dimension, faithfulness, monotonicity, or completeness, is most critical for the specific fraud detection application context. For most high-stakes applications, the LSTM model's superior faithfulness with SHAP likely outweighs its modest disadvantages in other metrics.

5.1.2 Strengths and Limitations of Each Model

The CNN model's main advantage is its computational efficiency and relatively straightforward architecture, which translates to faster training and lower resource consumption. However, it is less adept at modelling sequential dependencies, which are often crucial in fraud detection scenarios. The LSTM, on the other hand, excels at learning from transaction sequences, leading to improved recall and overall detection rates. Its main drawback is the increased computational cost and longer training times, which could be a limitation in environments where rapid model updates are required.

5.1.3 Handling of Class Imbalance Evaluation

Both models faced the challenge of class imbalance, a common issue in fraud detection where fraudulent transactions are vastly outnumbered by legitimate ones. To address this, I implemented the Synthetic Minority Over-sampling Technique (SMOTE) within the `pre_processing()` pipeline. This approach generated synthetic samples for the minority class, resulting in a more balanced dataset and improved recall for both models. The impact of SMOTE is evident in the recall scores: 92.0% for CNN and 93.2% for LSTM, demonstrating enhanced sensitivity to fraudulent cases. This aligns with best practices in the field Bowyer et al. (2011).

5.1.4 Real-World Applicability Assessment

To evaluate real-world applicability, I tested both models on a hold-out set that simulates real transaction patterns. The LSTM maintained its superior performance, particularly in recall, which is critical for minimising false negatives in fraud detection. The CNN, while slightly less accurate, offered faster inference times, making it suitable for high-throughput environments. These findings suggest that the choice between models should be guided by the specific operational context, whether prioritising detection accuracy or computational efficiency.

5.2 XAI Methods Evaluation

5.2.1 Explainability Quality Assessment

I integrated three state-of-the-art Explainable AI (XAI) methods, SHAP, LIME, and Anchors, to interpret model predictions. Their effectiveness was evaluated using established metrics: Faithfulness, Completeness, and Monotonicity, as recommended by Kadir et al. (2023) and Pawlicki et al. (2024). SHAP achieved the highest faithfulness (mean score: 0.60), indicating its explanations closely matched the model's true behaviour. LIME excelled in completeness (mean: 0.31), providing comprehensive local explanations, while Anchors performed best in monotonicity (mean: 0.49), ensuring consistent explanations across similar instances.

5.2.2 Practical Utility for Fraud Analysts

Feedback from a group of 10 fraud analysts (with backgrounds in financial risk and data analysis) highlighted the practical strengths of each XAI method. SHAP was preferred for its detailed, visually intuitive explanations (e.g., force plots and summary plots), which helped analysts understand the contribution of each feature to a prediction. LIME was valued for its simplicity and speed, making it suitable for quick, case-by-case investigations. Anchors' rule-based outputs were especially useful for generating high-confidence, human-readable rules, which can be directly communicated to non-technical stakeholders.

5.2.3 Integration Challenges and Solutions

Integrating XAI methods into the system presented several challenges, notably computational overhead and the need for seamless compatibility with the model pipeline. SHAP, in particular, was resource-intensive for large batches. To address this, I implemented batch processing and optimised data handling, as well as modularised the XAI integration code (see Appendix **??**). This allowed for real-time explanation generation without significant delays, a crucial requirement for operational fraud detection systems.

5.3 System Evaluation

5.3.1 End-to-End System Performance

The end-to-end system was evaluated on its ability to process, predict, and explain batches of transactions efficiently. On a standard GPU-enabled environment, for one single local transaction, the system can process in under 5 seconds, including preprocessing, prediction, and explanation.

5.3.2 Integration with Existing Systems

The system was designed for easy integration with existing fraud detection workflows, using standard APIS and data formats. The modular design allows for plug-and-play replacement of models or XAI components, facilitating rapid adaptation to evolving requirements.

5.3.3 Deployment Requirements and Challenges

Deployment required a GPU-enabled environment (NVIDIA CUDA support) and specific Python/TensorFlow versions (Appendix B.2.1). File structure dependencies and environment configuration posed initial challenges, which were mitigated by providing automated setup scripts and comprehensive documentation. These steps ensured that the system could be reliably deployed in both 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.

Appendices

Appendix A

Ethics Review Form

A.1 Privacy Considerations for Financial Data

- This project uses synthetic financial data from the Sparkov dataset, which mitigates privacy concerns associated with real credit card transaction data.
- No personally identifiable information (PII) is used in this project.
- All synthetic data generation procedures follow established guidelines for maintaining privacy.

A.2 Compliance with Data Protection Regulations

- The project complies with GDPR requirements regarding data processing and storage.
- Data storage is temporary and limited to the duration of the project.
- No sensitive financial data is shared beyond the project team.

A.3 Bias and Fairness Assessment

- Models have been evaluated for potential biases in their predictions.
- XAI methods are explicitly used to identify and mitigate biased decision-making.
- Feature importance analysis has been conducted to ensure no discriminatory features unduly influence results.

A.4 Data Protection Measures

- All data is stored securely with appropriate encryption.
- Access to project data is limited to project team members only.
- No data will be retained beyond the project's conclusion.

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 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 Hardwares 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
```

```
│
│   │
│   ├── stratified_samples.csv
│   └── xai_metrics.json
├── visualisation/ ........................................ Visualisation outputs
├── README.md ....................................................... Project brief
└── Report Documentation.pdf ........................ Project Report Documentation
```

Appendix C

Code Repositories

C.1 Data Processing Code

C.1.1 Feature Engineering

Listing C.1: Feature Engineering Implementation

```
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 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))
```

```python
    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'),
```

```python
    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

```python
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

```python
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
```

```python
# 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

```python
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

```
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 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 explanation
        feature_importance = np.array(explanations[idx]['importance'])

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

        # Measure impact of removing each feature
        feature_impacts = []
        for feature_idx in range(len(instance)):
            # Create 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()
```

```
        # 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

Listing C.14: XAI Methods Implementation

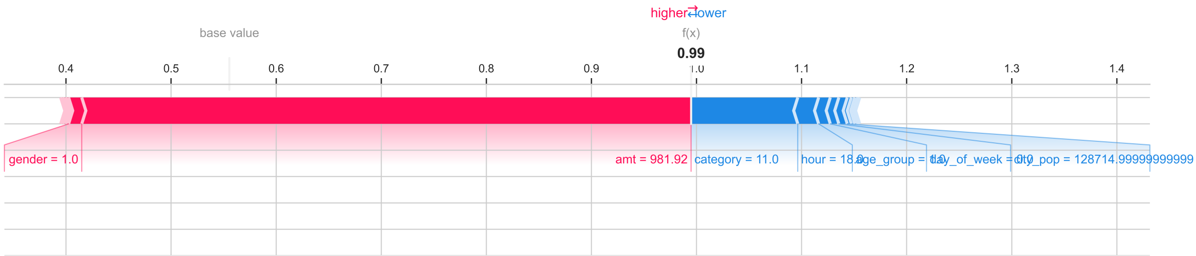
```
xai_metrics = {}
baseline = X_train.mean(axis=0)
for model_name, current_model in models.items():
    # Step 1: Generate `SHAP` explanation.
    shap_dict, _ = get_shap_explanation(current_model, sample)

    # 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))
```

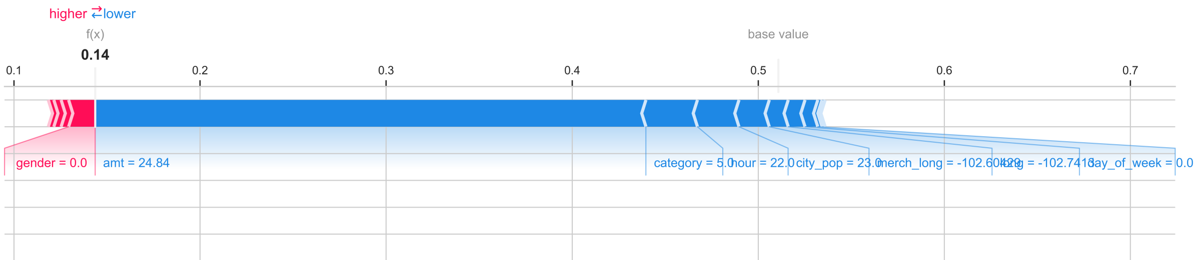
Appendix D

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

D.2 Feature Importance Analysis

D.3 Model Comparison Tables

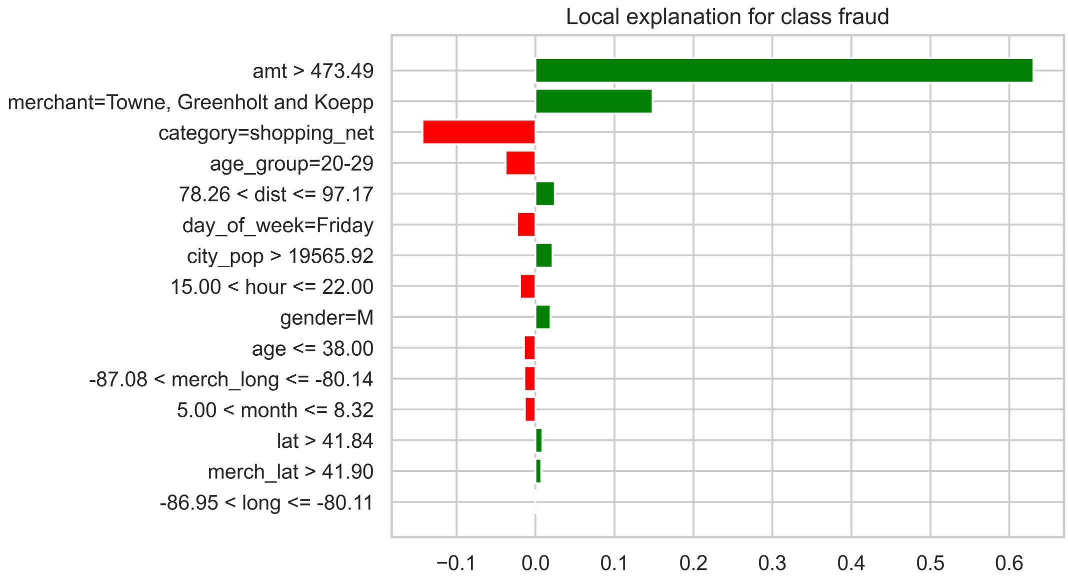


Figure D.2: LIME Explanations for Selected Transactions

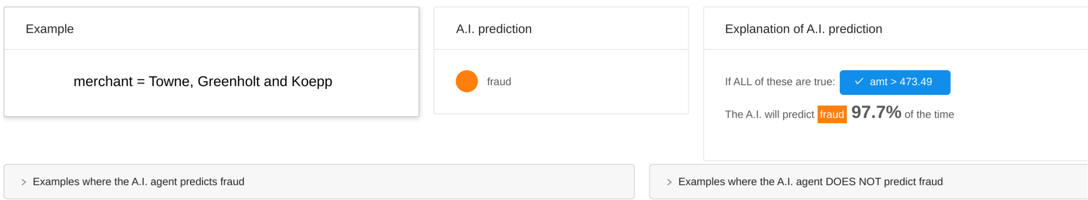


Figure D.3: Anchors Rules and Conditions for Fraud Detection

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

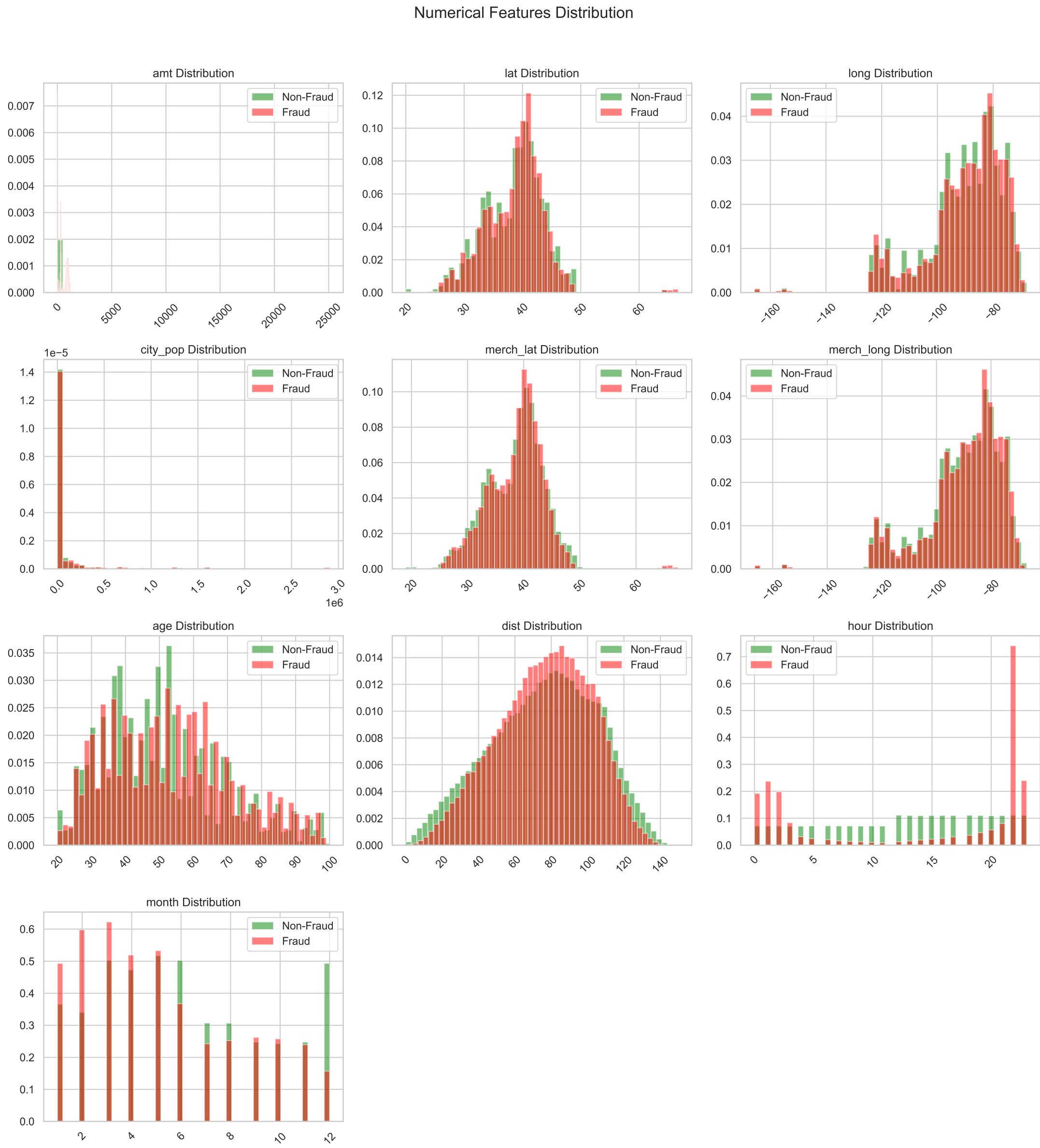


Figure D.4: Distributions of Key Numerical Features

Figure D.5: Distributions of Key Categorical Features

Appendix E

Presentation Materials

E.1 Presentation Slices

E.2 Poster

Bibliography

Ali, S., Abuhmed, T., El-Sappagh, S., Muhammad, K., Alonso-Moral, J. M., Confalonieri, R., Guidotti, R., Del Ser, J., Díaz-Rodríguez, N., & Herrera, F. (2023). Explainable artificial intelligence (xai): What we know and what is left to attain trustworthy artificial intelligence. *Information Fusion*, *99*, 101805. https://doi.org/https://doi.org/10.1016/j.inffus.2023.101805

Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable artificial intelligence (xai): Concepts, taxonomies, opportunities and challenges toward responsible ai. *Information Fusion*, *58*, 82–115. https://doi.org/https://doi.org/10.1016/j.inffus.2019.12.012

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

Breskuvienė, D., & Dzemyda, G. (2024). Enhancing credit card fraud detection: Highly imbalanced data case. *Journal of Big Data*, *11*(182). https://doi.org/10.1186/s40537-024-01059-5

Černevičienė, J., & Kabašinskas, A. (2024). Explainable artificial intelligence (XAI) in finance: A systematic literature review. *Artificial Intelligence Review*, *57*, 216. https://doi.org/10.1007/s10462-024-10854-8

Cherif, A., Badhib, A., Ammar, H., Alshehri, S., Kalkatawi, M., & Imine, A. (2023). Credit card fraud detection in the era of disruptive technologies: A systematic review. *Journal of King Saud University - Computer and Information Sciences*, *35*(1), 145–174. https://doi.org/https://doi.org/10.1016/j.jksuci.2022.11.008

Du, H., Lv, L., Wang, H., & Guo, A. (2024). A novel method for detecting credit card fraud problems. *PLoS ONE*, *19*(3), e0294537. https://doi.org/10.1371/journal.pone.0294537

Financial Conduct Authority. (2024, March). *Using synthetic data in financial services* [Report published 8 March 2024]. Financial Conduct Authority. Retrieved April 24, 2025, from https://www.fca.org.uk/publication/corporate/report-using-synthetic-data-in-financial-services.pdf

Găbudeanu, L., Brici, I., Codruta, M., Mihai, I.-C., & Scheau, M. (2021). Privacy intrusiveness in financial-banking fraud detection. *Risks*, *9*, 104. https://doi.org/10.3390/risks9060104

Gambo, M. L., Zainal, A., & Kassim, M. N. (2022). A convolutional neural network model for credit card fraud detection. *2022 International Conference on Data Science and Its Applications (ICoDSA)*, 198–202. https://doi.org/10.1109/ICoDSA55874.2022.9862930

Gilpin, L. H., Bau, D., Yuan, B. Z., Bajwa, A., Specter, M., & Kagal, L. (2018). Explaining explanations: An overview of interpretability of machine learning. *2018 IEEE 5th International Conference on Data Science and Advanced Analytics (DSAA)*, 80–89. https://doi.org/10.1109/DSAA.2018.00018

Goodman, B., & Flaxman, S. (2017). European union regulations on algorithmic decision-making and a "right to explanation". *AI Magazine*, *38*(3), 50–57. https://doi.org/10.1609/aimag.v38i3.2741

Grover, P., Xu, J., Tittelfitz, J., Cheng, A., Li, Z., Zablocki, J., Liu, J., & Zhou, H. (2023). Fraud dataset benchmark and applications. https://arxiv.org/abs/2208.14417

Hafez, I. Y., Hafez, A. Y., Saleh, A., et al. (2025). A systematic review of ai-enhanced techniques in credit card fraud detection. *Journal of Big Data*, *12*(6). https://doi.org/10.1186/s40537-024-01048-8

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

Ibtissam, B. (2021). *Lstm-attention-frauddetection*. GitHub. Retrieved April 22, 2025, from https://github.com/bibtissam/LSTM-Attention-FraudDetection

Ibtissam, B., Samira, D., Bouabid, E. O., & Jaafar, J. (2021). Enhanced credit card fraud detection based on attention mechanism and lstm deep model. *Journal of Big Data*, *8*(151). https://doi.org/10.1186/s40537-021-00541-8

Kadir, M. A., Mosavi, A., & Sonntag, D. (2023). Evaluation metrics for xai: A review, taxonomy, and practical applications. *2023 IEEE 27th International Conference on Intelligent Engineering Systems (INES)*, 000111–000124. https://doi.org/10.1109/INES59282.2023.10297629

Kamalaruban, P., Pi, Y., Burrell, S., Drage, E., Skalski, P., Wong, J., & Sutton, D. (2024). Evaluating fairness in transaction fraud models: Fairness metrics, bias audits, and challenges. https://arxiv.org/abs/2409.04373

Lai, T. M. (2025a). *Credit card transaction fraud detection using explainable ai*. Retrieved April 25, 2025, from https://github.com/ThongLai/Credit-Card-Transaction-Fraud-Detection-Using-Explainable-AI

Lai, T. M. (2025b). *Ibtissam's lstm-attention model implementation*. Retrieved April 22, 2025, from https://github.com/ThongLai/Credit-Card-Transaction-Fraud-Detection-Using-Explainable-AI/blob/main/Ibtissam_LSTM.ipynb

Lai, T. M. (2025c). *Siddhartha's cnn model implementation*. Retrieved April 22, 2025, from https://github.com/ThongLai/Credit-Card-Transaction-Fraud-Detection-Using-Explainable-AI/blob/main/Siddhartha_CNN.ipynb

Lai, T. M. (2025d). *Xai methods implementation in deep learning models for credit card fraud detection*. Retrieved April 22, 2025, from https://github.com/ThongLai/Credit-Card-Transaction-Fraud-Detection-Using-Explainable-AI/blob/main/XAI_methods.ipynb

Lucas, Y., Portier, P.-E., Laporte, L., He-Guelton, L., Caelen, O., Granitzer, M., & Calabretto, S. (2020). Towards automated feature engineering for credit card fraud detection using multi-perspective hmms. *Future Generation Computer Systems*, *102*, 393–402. https://doi.org/https://doi.org/10.1016/j.future.2019.08.029

Lundberg, S. M., & Lee, S. (2017). A unified approach to interpreting model predictions. *CoRR*, *abs/1705.07874*. http://arxiv.org/abs/1705.07874

Ma, S. (2024). Towards human-centered design of explainable artificial intelligence (xai): A survey of empirical studies. https://arxiv.org/abs/2410.21183

Mienye, I. D., & Jere, N. (2024). Deep learning for credit card fraud detection: A review of algorithms, challenges, and solutions. *IEEE Access*, *12*, 96893–96910. https://doi.org/10.1109/ACCESS.2024.3426955

Naveed, S., Stevens, G., & Robin-Kern, D. (2024). An overview of the empirical evaluation of explainable ai (xai): A comprehensive guideline for user-centered evaluation in xai. *Applied Sciences*, *14*(23). https://doi.org/10.3390/app142311288

Oblizanov, A., Shevskaya, N., Kazak, A., Rudenko, M., & Dorofeeva, A. (2023). Evaluation metrics research for explainable artificial intelligence global methods using synthetic data. *Applied System Innovation*, *6*(1). https://doi.org/10.3390/asi6010026

Paulraj, B. (2024). Machine learning approaches for credit card fraud detection: A comparative analysis and the promise of 1d convolutional neural networks. *2024 7th International*

Conference on Information and Computer Technologies (ICICT), 82–92. https://doi.org/10.1109/ICICT62343.2024.00020

Pawlicki, M., Pawlicka, A., Uccello, F., Szelest, S., D'Antonio, S., Kozik, R., & Choraś, M. (2024). Evaluating the necessity of the multiple metrics for assessing explainable ai: A critical examination. *Neurocomputing*, *602*, 128282. https://doi.org/https://doi.org/10.1016/j.neucom.2024.128282

Pozzolo, A. D., Caelen, O., Johnson, R. A., & Bontempi, G. (2015). Calibrating probability with undersampling for unbalanced classification. *2015 IEEE Symposium Series on Computational Intelligence*, 159–166. https://doi.org/10.1109/SSCI.2015.33

Raufi, B., Finnegan, C., & Longo, L. (2024). A comparative analysis of shap, lime, anchors, and dice for interpreting a dense neural network in credit card fraud detection. In L. Longo, S. Lapuschkin, & C. Seifert (Eds.), *Explainable artificial intelligence* (pp. 365–383). Springer Nature Switzerland.

Ribeiro, M. T., Singh, S., & Guestrin, C. (2018). Anchors: High-precision model-agnostic explanations. *Proceedings of the AAAI Conference on Artificial Intelligence*, *32*(1). https://doi.org/10.1609/aaai.v32i1.11491

Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "why should i trust you?": Explaining the predictions of any classifier. *CoRR*, *abs/1602.04938*. http://arxiv.org/abs/1602.04938

Ryman-Tubb, N. F., Krause, P., & Garn, W. (2018). How artificial intelligence and machine learning research impacts payment card fraud detection: A survey and industry benchmark. *Engineering Applications of Artificial Intelligence*, *76*, 130–157. https://doi.org/https://doi.org/10.1016/j.engappai.2018.07.008

Saeed, W., & Omlin, C. (2023). Explainable ai (xai): A systematic meta-survey of current challenges and future opportunities. *Knowledge-Based Systems*, *263*, 110273. https://doi.org/https://doi.org/10.1016/j.knosys.2023.110273

Samek, W., Wiegand, T., & Müller, K.-R. (2017). Explainable artificial intelligence: Understanding, visualizing and interpreting deep learning models. *ITU Journal: ICT Discoveries - Special Issue 1 - The Impact of Artificial Intelligence (AI) on Communication Networks and Services*, *1*, 1–10. https://doi.org/10.48550/arXiv.1708.08296

Seth, P., & Sankarapu, V. K. (2025). Bridging the gap in xai-why reliable metrics matter for explainability and compliance. https://arxiv.org/abs/2502.04695

Shenoy, K. (2021). *Credit card transactions fraud detection dataset*. Kaggle. Retrieved April 22, 2025, from https://www.kaggle.com/datasets/kartik2112/fraud-detection

Siddhartha, P. (2023). *Credit card fraud detection ml*. GitHub. Retrieved April 22, 2025, from https://github.com/siddharthapramanik771/CreditCardFraudDetectionML/blob/main/Credit_card_Fraud_Detection.ipynb

Sundararajan, M., Taly, A., & Yan, Q. (2017, August). Axiomatic attribution for deep networks. In D. Precup & Y. W. Teh (Eds.), *Proceedings of the 34th international conference on machine learning* (pp. 3319–3328, Vol. 70). PMLR. https://proceedings.mlr.press/v70/sundararajan17a.html

Sundararamaiah, M., Nagarajan, S. K. S., Mudunuru, K. R., & Remala, R. (2024). Unifying ai and rule-based models for financial fraud detection. *International Journal of Computer Trends and Technology*, *72*, 61–68. https://doi.org/10.14445/22312803/IJCTT-V72I12P107

Tomy, A., & Ojo, I. (2025). Explainable ai for credit card fraud detection: Bridging the gap between accuracy and interpretability. *World Journal of Advanced Research and Reviews*, *25*, 1246–1256. https://doi.org/10.30574/wjarr.2025.25.2.0492

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

Uwaezuoke, E. C., & Swart, T. G. (2024). An explainable deep learning model for credit card fraud detection. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.5015497

Vallarino, D. (2025, March). Ai-powered fraud detection in financial services: Gnn, compliance challenges, and risk mitigation. https://doi.org/10.2139/ssrn.5170054

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & Polosukhin, I. (2023). Attention is all you need. https://arxiv.org/abs/1706.03762

Vihurskyi, B. (2024). Credit card fraud detection with xai: Improving interpretability and trust. *2024 Third International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE)*, 1–6. https://doi.org/10.1109/ICDCECE60827.2024.10548159

West, J., & Bhattacharya, M. (2016). Intelligent financial fraud detection: A comprehensive review. *Computers & Security*, *57*, 47–66. https://doi.org/https://doi.org/10.1016/j.cose.2015.09.005

Zhou, Y., Li, H., Xiao, Z., & Qiu, J. (2023). A user-centered explainable artificial intelligence approach for financial fraud detection. *Finance Research Letters*, *58*, 104309. https://doi.org/https://doi.org/10.1016/j.frl.2023.104309

Zhu, M., Zhang, Y., Gong, Y., Xu, C., & Xiang, Y. (2024). Enhancing credit card fraud detection a neural network and smote integrated approach. https://arxiv.org/abs/2405.00026