National College of Ireland

Exploration of Advanced Machine Learning Algorithms for Enhanced Fraud Detection in Financial Transactions

MSc Research Project
Data Analytics

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Exploration of Advanced Machine Learning Algorithms for Enhanced Fraud Detection in Financial Transactions

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Abstract

Financial institutions has been facing a growing threat of fraud in their complex transactions across the globe. This study analyzes various machine learning methods which strengthen the financial security by detecting the fraud related to the financial transactions. Where the study investigates the applications of the machine learning methods like k-Nearest Neighbors (KNN), Decision Trees, Random Forest, and Logistic Regression can identify and prevent the financial transaction fraud. These multiple algorithms have been evaluated for identifying various types of complicated patterns and abnormalities in large amount data sets to improve financial system adaptability to recognize it all. Our Research evaluates the people's ability to recognize and prevent from the fraudulent transactions. The findings in this study which contribute's to financial security machine learning understanding and the use of it. This results where the Financial institutions and organizations can greatly enhance their financial fraud prevention measures by utilizing the insights generated by machine learning techniques such as k-Nearest Neighbors, Decision Trees, Random Forest, and Logistic Regression.

Keywords: Advance Machine Learning Algorithms, Financial Fraudulents, Fraudulent Detection

1 Introduction

In the field of financial sector where the institutions are struggling to prevent the issues of fraud within the ever-changing patterns of their transactions. Where as the traditional fraud detection techniques have proven that are inadequate in effectively addressing this challenge, especially in the digitization of financial systems (El Hajj and Hammoud; 2023). With these developments to digital transactions, there has been a surge in both the volume and intricacy of financial transactions,where this making it increasingly challenging to identify and prevent from fraudulent activity. In response to this evolving patterns, the implementation of advanced machine learning algorithms has emerged as the one of the promising solution which helps to strengthen financial security by accurately detecting and preventing the fraudulent transactions (Hilal et al.; 2022).

The significance of this research is becomes important when we consider the need to safeguard the financial systems against an evolving of these fraudulent activities. According to the 2021 report by the Association of Certified Fraud Examiners (ACFE), which tells that global financial losses due to fraud have surpassed to $3.5 trillion USD in

the same year Dull and Rice (2023). This statistic amount underscores that there is the importance of preventing fraud in the financial sector (Bao et al.; 2022). Fraud in the financial institutions has been a longstanding issue, with individuals and the organizations are exploiting there vulnerabilities for personal gain throughout the history. However, in recent times, the techniques of doing any fraud has drastically changed, thanks primarily to various development of technological advancements. The days of identity theft through the stolen documents or physical acts like building signatures is passed in the field of fraud. Now there is a new generation of scammers have appeared in the age of technology, utilizing advanced techniques to take the advantage of vulnerabilities in online and digital transactions.The scope of the issue becomes very clear in the ACFE report regarding the Financial Fraud. In addition to becoming financially difficult, globally it losses due to fraud above $3.5 trillion in just one year which represents the threat to the sustainability of the financial sector as a whole (Mangathayaru et al.; 2023). It serves as a serious reminder that the clever and technologically skilled scammers of today's generation can no longer be defeated by rule based traditional techniques for fraud prevention and detection El Hajj and Hammoud (2023); Hilal et al. (2022).

Traditional Technologies which are the rule-based systems have been the backbone for the fraud detection which for a considerable passed time. Where the transaction can be tracked and gets the additional investigation if it deviates from any established regulations and setup limitations that these systems operate under. Although this method has been demonstrated some success in identifying various fundamental types of fraud, after the time passed it is inappropriate to handle the constantly evolving and constantly changes the structure of financial fraudulent activity (Wang et al.; 2023). One of the key issues with the rule-based systems is their failure to keep updating with evolving fraud patterns and tactics. As fraudsters they develops the new approaches and methodologies, where these systems become outdated and ineffective. They are defined by rigid fixed rules and often fail to detect violations that were not clearly outlined in the financial security system. Additionally, these systems struggle's to adapt and learn from current data and patterns of fraud activities and violations. The research by (Aburbeian and Ashqar; 2023) as well as (Wang et al.; 2023) have highlighted that the flaws of rule-based systems, where as the including of their tendency to produce the inaccurate results by mistakenly labeling the legitimate transactions as fraudulent due to small minor discrepancies. It is clear that the rule-based systems are not capable enough to effectively combat fraud in today's ever-changing techniques.

The Primary objective of this study's is to find out the efficacy of various machine learning methods— which includes k-Nearest Neighbors (KNN), Decision Trees, Random Forest, and Logistic Regression— those are at increasing financial security. The capacity of these algorithms can analyze huge amounts of data and can recognize the complex trends and problems that can help to detect fraudulent transactions has evaluated a lot of concernGan et al. (2022)

1.1 Research Question and Objectives

The research questions are:

- Can advanced machine learning algorithms enhance the financial security by detecting and preventing from any kind of fraudulent transactions?

- How do the advance machine learning model's adapt it to the diverse fraud tactics?

The specific research objectives which include:

- Obtaining the effectiveness of the advanced machine learning algorithms in recognizing and preventing financial transaction fraud.
- The research will explore the adaptability of various algorithms in identifying different types of fraud techniques and their effectiveness in detecting and adapting to new fraud patterns. patterns.

The primary goal is to enhance performance, specifically by determining whether advanced machine learning algorithms can better detect and prevent fraud in comparison to rule-based systems. Given that the overall objective is to improve the security of financial institutions, this aspect is critical. The secondary objective examines the effectiveness of these algorithms in adapting to the ever-changing field of fraud. It results in the importance for a fraud detection system should be flexible enough to evolve and learn alongside fraudsters. In order to assess their practicality of these machine learning algorithms, it is crucial to analyse how well they are adapting and responding to the various fraudulent activities. Furthermore, these algorithms are expected to represents it adaptability by rapidly detecting and preventing fraudulent activities and patterns in the ever-evolving nature of the global financial sector.

In order to develop the more robust financial system, where the research looks into the practical applications for these machine learning algorithms and how they could impact financial fraud detection. The objective of this study is to offer the various important insights that can assist financial in situations for preventing their operations against fraudulent activities by performing an in-depth investigation into the efficacy and adaptability of advanced machine learning algorithms in it. This research has the greater implications than just the financial services sector.

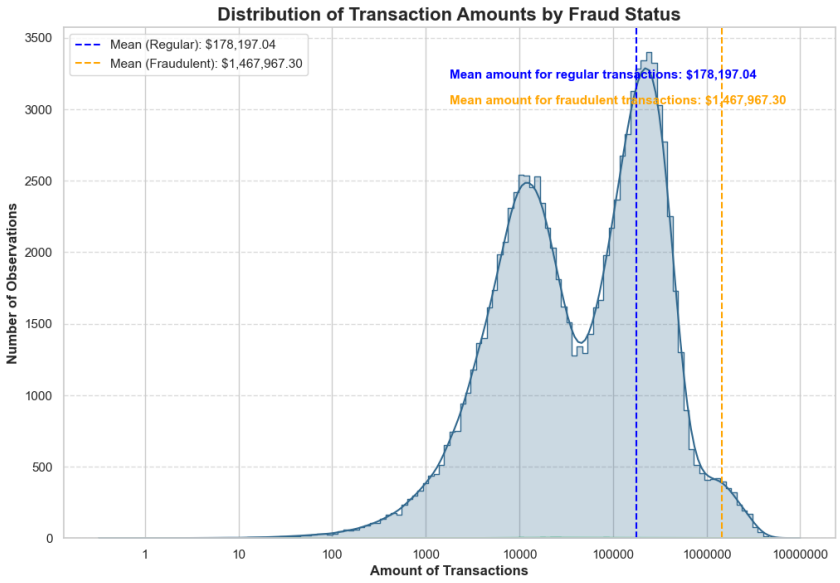

Figure 1: Distribution of Transaction Amounts by Fraud Status (Chaquet-Ulldemolins et al.; 2022)

Since digitalization continues to impact numerous areas of society, the approaches and instruments created to combat financial fraud can be adapted and used to address equivalent issues in other fields.

The financial fraud is an important and most-concerning issue in the modern world which requires the various types of innovative approaches. To handle these problems, the application of several advanced machine learning techniques seems feasible. By evaluating their effectiveness and adaptability of various types of machine learning algorithms, this study seeks to the body of knowledge with the ultimate goal of enhancing the financial stability in an environment where traditional approaches are no longer sufficient to prevent from the modern day financial fraud activities. It aims to accomplish this by establishing the framework for a more secure and robust financial environment, which is important for both the stability and the development of economies throughout the world.

2 Related Work

In the field of recognizing fraudulent activities in financial transactions, numerous approaches and kinds of technology have been researched over a recent period of time (Xu et al.; 2023). we delve into the current landscape of research in the field of fraud detection, considering both traditional rule-based methodologies and the ever-increasing influence of machine learning techniques. We cite recent research papers that provide valuable insights into various aspects of fraud detection, emphasizing advanced approaches that leverage machine learning to elevate security. In addition to this, we explore the potential of employing machine learning algorithms as enhanced algorithm techniques for the detection and prevention of fraudulent activities (Hilal et al.; 2022; Pazho et al.; 2022).

2.1 Rule-Based Systems in Fraud Detection

Standard fraud detection systems commonly rely on rule-based approaches. These rule-based approach systems operate by comparing transactions with a predetermined set of rules that are specifically formulated to detect instances of fraudulent behavior (Xu et al.; 2023; Zhu et al.; 2021). As an illustration, a rule-based system has the capability to identify a transaction as potentially fraudulent under two conditions: if the transaction amount exceeds a certain threshold, or if the transaction originates from a previously unrecorded location (Aburbeian and Ashqar; 2023).Rule-based systems have demonstrated considerable effectiveness in the field of fraud detection over a period of time. However, there are certain restrictions associated with them. Initially, it might be challenging to sustain and update rule-based systems. As offenders of fraudulent activities keep developing, it becomes necessary to introduce more rules into the current framework. The process that has been described can be both labor-intensive and costly (Wang et al.; 2023). Furthermore, rule-based systems frequently show weaknesses in their ability to identify new and evolving fraudulent activities. The reason for this is that the rules are based on existing research, and those performing fraudulent activities are consistently inventing new methods to avoid detection (Xu et al.; 2023).

2.2 Challenges in Traditional Fraud Detection

The challenges related to traditional fraud detection methods have become more obvious due to the continuous evolution and increased complexity of fraudulent activities committed by people trying to take advantage of systems. Some of the key challenges include:

- Day by day the increasing amount and complexity of financial transactions . Where this makes it more difficult for rule-based systems to detect and prevent fraudulent activity.
- Growing use of various digital platforms for financial transactions. This also made it easier for the fraudsters to operate without being detected.
- Evolving nature of fraud activities . Fraudsters are constantly evolving their methods and use the modern technology tools to avoid from being detected and to caught.

2.3 Machine Learning in Fraud Detection

Fraud detection has attested that the increasing in popularity with the rise of machine learning approaches. Unlike the traditional rule-based systems which may have their own limitations, where the machine learning algorithms have the potential to surpass these boundaries to learn and evolve according to the situations. By being trained using historical data, these algorithms can effectively detect and learn the patterns associated with various types of fraudulent behavior. This allows them to rapidly identify any fraudulent transactions in real-time (Li and Jung; 2023).

By using the various advanced machine learning algorithms for fraud detection provides the several amount of benefits then the rule-based systems. One of the major advantage is the ability to train these algorithms on large amount of dataset, where enhancing their capability to recognize new and evolving types of fraudulent activities (El Hajj and Hammoud; 2023; Hilal et al.; 2022). In Addition, these types of algorithms can be regularly updated, where providing the more efficient approach compared to fixed defined rule-based systems (Mangathayaru et al.; 2023).

2.4 Contribution of Our Research to the Industry

Our research aim is to overcome from the weakness of the traditional rule-based systems and delve into the possibilities of advanced machine learning algorithms in bolstering financial security. Through an evaluation of these algorithms' effectiveness in detecting and deterring fraudulent financial transactions, our study aims to offer valuable results to the area of financial fraud detection. In addition, we explore the flexibility of these machine learning algorithms in combating various types of fraud schemes while remaining adaptable to address with fraud trends. These objectives provides the results of our investigation and hold the effective potential in enhancing the safety and reliability of financial institutions.

- **Enhancement in Financial Security:** Our study cooperate itself into the capabilities of advanced machine learning algorithms in identifying and neutralizing

the financial transaction fraud, potentially it can equipped by financial institutions with mighty preventions against misleading practices, thus enhancing their financial security.

- **Adaptability to Evolving the Fraud Patterns:** Our research derives into the adaptability of algorithms models to various fraudulent strategies and their ability to beat with evolving fraud patterns over a time period. This allows us to handle the continuously changing the nature of financial fraud, providing a careful approach to fraud detection.

- **Applicability Beyond the Finance:** Our research has discovered important insights that can be applied just beyond the financial sector services. In today's increasingly digitalized world, these adaptable techniques and tools for detecting financial fraud can be easily customized to tackle similar security challenges in other industries, such as cybersecurity, healthcare, and e-commerce.

3 Research Methodology

The objective of this phase is that the all inclusive approach utilized in conducting a thorough evaluation of high-level machine learning techniques in order to improve and classify the fraud detection in financial transactions. This approach completes with a series of key steps such as data collection, data preprocessing for analysis, meticulously selection of appropriate machine learning algorithms, model training, model performance evaluation analysis.

3.1 Data Collection

Our research begins from collecting the vast range of data, which is important for accurately address the task and the efficiency of machine learning algorithms. The dataset overall a vast array of financial transactions, board varying types, values, timestamps, and destinations. Finding the right balance between authentic and the fraudulent transactions is important for developing any kind models that can accurately differentiate between them.

3.1.1 Characteristics of Dataset

The dataset which is utilized in this study it was acquired via Kaggle, a well-established site where its role in facilitating the sharing and accessibility of datasets. The dataset can be accessed through the following unique source link: `https://www.kaggle.com/datasets/ealaxi/paysim1/data`

Dataset Attributes

The dataset encompasses a range of attributes relevant to historical financial transactions data. The dataset attributes include in Table 1:

Table 1: Description of Features Lopez-Rojas (2017)

Name of Features	Description	Data Type
step	Maps a unit of time in the real world. In this case, 1 step is 1 hour of time. Total steps 744 (30 days simulation).	Int64
type	Types of Transactions: CASH-IN, CASH-OUT, DEBIT, PAYMENT, and TRANSFER	Object
amount	Amount of the transaction in local currency.	Float64
nameOrig	Customer who started the transaction.	Object
oldbalanceOrg	Initial balance before the transaction.	Float64
newbalanceOrig	New balance after the transaction.	Float64
nameDest	Customer who is the recipient of the transaction.	Object
oldbalanceDest	Initial balance recipient before the transaction. Note that there is no information for customers that start with M (Merchants).	Float64
newbalanceDest	New balance recipient after the transaction. Note that there is no information for customers that start with M (Merchants).	Float64
isFraud	This is the transactions made by the fraudulent agents inside the simulation. In this specific dataset, the fraudulent behavior of the agents aims to profit by taking control of customers' accounts and try to empty the funds by transferring to another account and then cashing out of the system.	Int64
isFlaggedFraud	The business model aims to control massive transfers from one account to another and flags illegal attempts. An illegal attempt in this dataset is an attempt to transfer more than 200,000 in a single transaction.	Int64

For this research, the 'isFraud' attribute has been selected as the target variable for Fraudulent Transaction using advance machine learning models where we had total price of fraudulent transactions made is represented in Figure 1. Other attributes may also be explored for additional analyses and research objectives. The dataset, as obtained from Kaggle, is subjected to preprocessing and exploratory data analysis (EDA) to ensure data quality and relevance for the research.

3.2 Data Preprocessing

To ensure the quality, consistency, and integrity of the dataset, a rigorous data preprocessing phase was undertaken. During this stage which involves the various key steps to make the dataset more reliable and suitable for the machine learning models:

3.2.1 Handling Missing Data

In real-world datasets, missing data is a frequent concern because they are raw where there may be that dataset is not cross checked, what is the quality of dataset can greatly affect the performance of our models. To overcome from this challenge, we uses a various of imputation methods- from simple methods like mean imputation to more advanced approaches like k-nearest neighbors imputation to fill the missing values. This careful approach allowed us to create the comprehensive and dependable dataset for our further analyses.

3.2.2 Normalization of Transaction Amounts

Transaction amounts that can vary greatly in value, which can have an minor impact on the effectiveness of certain machine learning algorithms. To address this issue, transaction amounts were standardized using methods like Min-Max scaling or standardized normalization. By standardizing transaction amounts, it creates consistency in the feature space and equalize the features, preventing algorithms from being biased towards variables with larger scales.

3.2.3 Handling Outliers

During the preprocessing phase, any outliers - which could be signs of irregular or even deceptive behaviors were detected and dealt with accordingly to their . We employed reliable statistical techniques, such as the IQR method and advanced outlier detection algorithms Seo (2006), to ensure the dataset remained sound and the impact of outliers on model training was minimized.

By carefulling handling the missing values which are associated with in the dataset, normalizing the transaction amounts, and elimination of any anomalies, the development of a cleaned and uniform dataset is achieved, setting the phase for successful training of machine learning models.

3.3 Exploratory Data Analysis (EDA)

The important aspect of the analytical process is understanding what is the data is. Through Exploratory Data Analysis (EDA), we can comprehensively summarize the key features related to the dataset using statistical techniques and visualization representations in Financial Fraud Detection. The objective of EDA is to understand the data's structure and patterns, and then discover any relationships between variables, and detect any interesting trends or irregularities.

3.4 Model Selection

Throughout the Research when it comes to the selection of machine learning algorithms is of most importance. The main objective is to evaluate the effectiveness of various approaches through several machine learning models in detecting and preventing financial transaction fraud. After the careful consideration, we chosen the four algorithms which are strategically chosen to handle the complexities of fraud detection:

3.4.1 K-Nearest Neighbors (KNN)

The K-Nearest Neighbors (KNN) (Odhiambo; 2022) algorithm is a algorithms which is much adaptable and intimate approach widely used in classification tasks. This involves classifying a data point by taking into account the majority class of its nearest neighbors, with the number of neighbors, 'k' being a user-defined parameter. This machine learning algorithm is particularly advantageous in detecting fraud activities, as it excels for situations where the local relationships and the patterns within the dataset which are important. Its straightforward and open model which make it a desirable option, especially when dealing with datasets of varying different different complexities. KNN can adept at identifying various types of patterns that may indicate to the fraudulent activity.

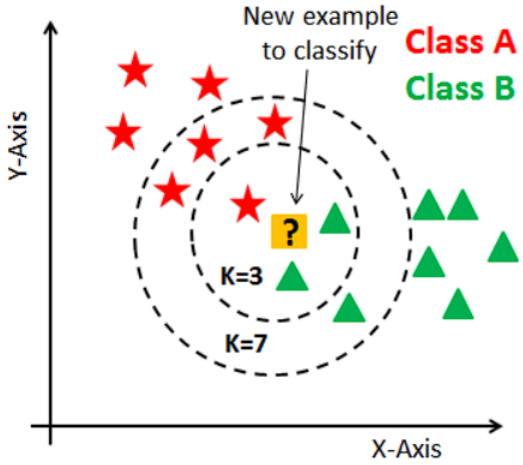

Figure 2: K-Nearest Neighbors Classification(KNN) (Odhiambo; 2022)

3.4.2 Decision Tree

Decision Trees (El Hajj and Hammoud; 2023) is a admirable when it comes in the task for classifications. This is a impressive model which create the structured tree to map out decision paths by utilizing feature splits, as demonstrated in Figure 3.When it comes in the task for detecting fraud, Decision Trees glows in capturing the intricate relationships within the data points. One of the key advantages of this algorithm is its transparency and interpretability which is easy, allowing for a deeper understanding of factors situated for recognizing the fraudulent activities.

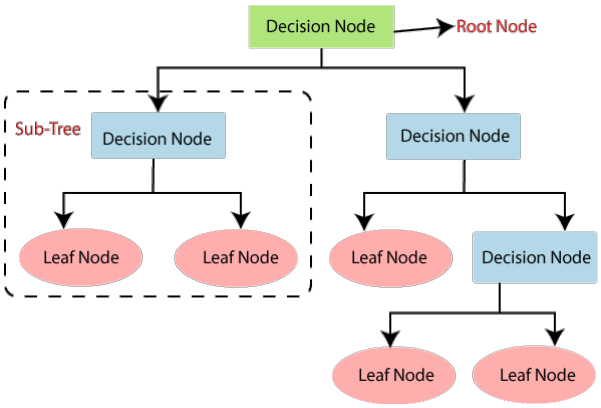

Figure 3: Decision Tree Architecture (El Hajj and Hammoud; 2023)

3.4.3 Random Forest

Random Forest (Gan et al.; 2022) is a powerful ensemble learning technique that surpass the power of Decision Trees. Where the combining the outputs of multiple trees, it not only increases the accuracy of projections, but also helps in prevent the overfitting, as seen in Figure 4. This method makes it an ideal choice for detecting fraud attributes and feature variables, which often requires the comprehensive method, particularly when facing with the complex datasets and their patterns associated with in. It has the ability to encapsulate results from various trees, Random Forest creates a more flexible model, which is capable for detecting the divergences in the data that may indicate the pattern in any fraudulent activity.

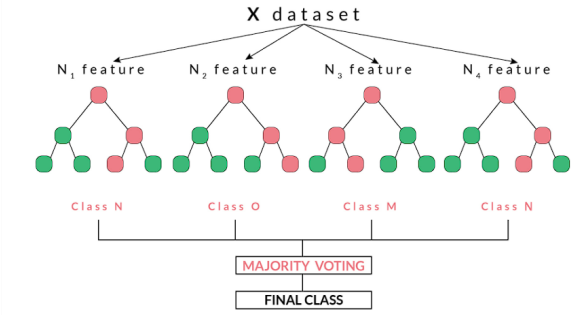

Figure 4: Random Forest Architecture (Gan et al.; 2022)

3.4.4 Logistic Regression

Logistic Regression (Umar et al.; 2022), it is actually a derived as a linear model which specifically developed for binary classification type of tasks. In the area of fraud detection, this model provides as a highly valuable benchmark due to its simplicity, interpretability, and ability to provide insights into the importance of unique certain features. While it may not be as adapt at capturing complex non-linear relationships as other algorithms do, Logistic Regression still offers a foundation for comparison between them all as a baseline model. By understanding the importance of each features in the fraud classification

context, it becomes easier to identify the most critical feature attributes associated with fraudulent transactions.

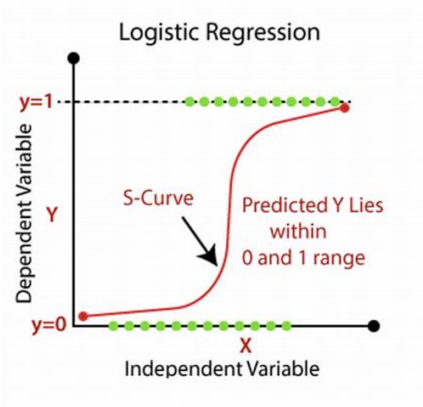

Figure 5: Logistic Regression Architecture (Umar et al.; 2022)

The selection of four machine learning algorithms was carefully chosen by examination of existing literature, the evidence which representing their effectiveness in fraud detection, and meaningly consideration of their suitability for the task at hand. The study's primary goal is to gain a comprehensive understanding of financial transaction fraud by integrating diverse models. Each algorithm will be utilized for its unique strengths in order to effectively handle the multifaceted nature of the detection task. This strategy aligns perfectly with the aim of the study to evaluate the effectiveness of different methods and ultimately contribute to the improvement of highly reliable fraud detection systems.

3.5 Model Training

Once the dataset had been preprocessed and the most promising algorithms had been selected, now the process shifted to training the machine learning models. The training process is pivotal in enabling algorithms to learn patterns associated with both genuine and fraudulent transactions. The following steps outline the model training process:

3.5.1 Feature Engineering

Feature engineering involves selecting and transforming relevant features from the dataset to improve the model's discriminatory power. Domain knowledge, coupled with exploratory data analysis, guided the identification of features critical for fraud detection. Additionally, new features, such as transaction velocity or frequency, were engineered to capture nuanced aspects of transaction behavior.

3.5.2 Training Dataset Split

To assess the performance of the trained models accurately, the dataset was split into training and validation sets. The training set, comprising the majority of the data, facilitated the actual training of the models, while the validation set, kept separate and unseen during training, allowed for unbiased evaluation of model generalization.

3.5.3 Ensemble Methods

For algorithms like Random Forest, which inherently employ an ensemble of decision trees, optimizing the ensemble's parameters was an additional consideration. Balancing the number of trees, depth of trees, and other ensemble-specific parameters contributed to the overall effectiveness of the Random Forest algorithm.

3.6 Model Evaluation

The evaluation of machine learning models is a multi-faceted process that involves obtaining their performance on a separate set of data not used during the training phase. The metrics which are chosen for evaluation provide the comprehensive analysis of how well the trained machine learning models performed to distinguish between genuine and fraudulent transactions. The primary evaluation metrics which includes:

3.6.1 Accuracy

Accuracy represents the overall correctness of the model in classifying projected transactions. Where the calculation involves in determining the ratio of accurately Baldi et al. (2000) classified projected transactions to the overall number of transactions.

$$Accuracy = \frac{TruePositives + TrueNegatives}{TotalTransactions}$$

3.6.2 Precision

Precision is a crucial metric that represents the accuracy of identifying Baldi et al. (2000) fraudulent transactions within all those classified as such. It is particularly relevant in scenarios where minimizing false positives is crucial.

$$Precision = \frac{TruePositives}{TruePositives+FalsePositives}$$

3.6.3 Recall

Recall, calculates the ability of the model to correctly identify all the actual predicted fraudulent transactions. It is instrumental in scenarios where the cost of false negatives is high.

$$Recall = \frac{TruePositives}{TruePositives+FalseNegatives}$$

3.6.4 F1 Score

The F1 score metrics which combines the precision and recall into a single metric, which providing in balanced assessment of a model's performance.

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision+Recall}$$

4 Design Specification

The design specification for the fraud detection system which includes the various process in the methodological structure that commences with data preprocessing. The preprocessing stage encompasses the handling of missing values, remove any duplicates values if situated, and the transformation of categorical variables to numerical values. The initial phase of Exploratory Data Analysis (EDA) which is the foundation for selecting the relevant features, which subsequently facilitates the training of the machine learning models including K-Nearest Neighbors, Decision Tree, Logistic Regression, and Random Forest. The evaluation of model performance encompasses many metrics including as accuracy, precision, recall, and Area Under the Curve (AUC), which are supplemented by a thorough examination of confusion matrices. The primary objective of the design is to prioritize the achievement of precise and dependable results in the realm of fraud detection. Potential areas for future research encompass the investigation of advanced techniques for model interpretability, the integration of real-time monitoring capabilities, and the resolution of scalability and security concerns to establish a resilient and efficient system. The incorporation of feedback methods and interaction with emerging technologies is an integral component of the design process, facilitating continuous improvement where this process is represents in Figure. 6.

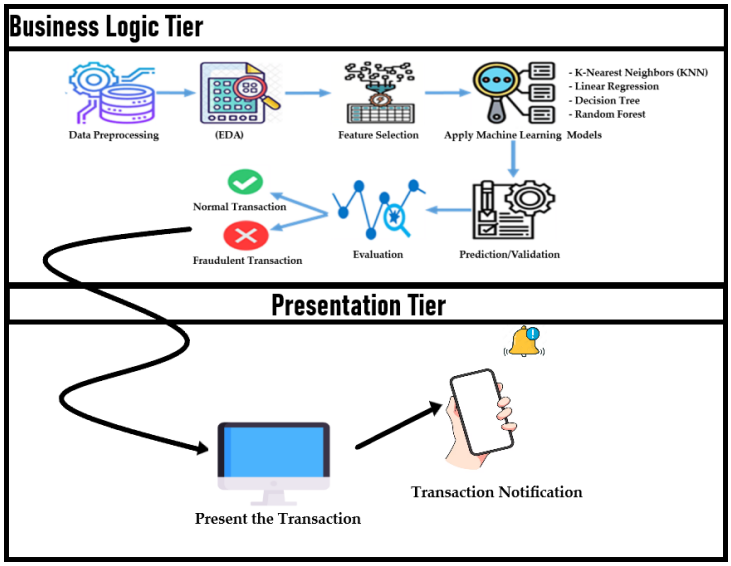

Figure 6: Design Specification for Fraud Detection

5 Implementation of the Fraud Detection in Financial Transactions

During the concluding phase of the implementation process, the proposed solution was performed, resulting in the generation of outputs that successfully fulfilled the objectives of fraud detection. This stage encompassed the subsequent essential steps:

5.1 Data Exploration Understanding:

The dataset encompasses a range of features that provide valuable information for analysis. These features include transaction type, amount, origin and destination account details, and flags that indicate instances of fraud which are represents in Figure 7.

```
# View the dataset information
dataFrame.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6362620 entries, 0 to 6362619
Data columns (total 11 columns):
 #   Column          Dtype
---  ------          -----
 0   step            int64
 1   type            object
 2   amount          float64
 3   nameOrig        object
 4   oldbalanceOrg   float64
 5   newbalanceOrig  float64
 6   nameDest        object
 7   oldbalanceDest  float64
 8   newbalanceDest  float64
 9   isFraud         int64
 10  isFlaggedFraud  int64
dtypes: float64(5), int64(3), object(3)
memory usage: 534.0+ MB
```

Figure 7: Basic Information about Fraud Dataset

To gain additional insight into the dataset as entirety, an exploratory data analysis (EDA) was performed. The purpose of this investigation was to count the number of fraudulent transactions, find relationships between various variables, and examine the distribution of transaction types all are represents in Figure 8, Figure 9. By taking an exploratory approach, we were able to get insight into the dataset with regards to the above factors.

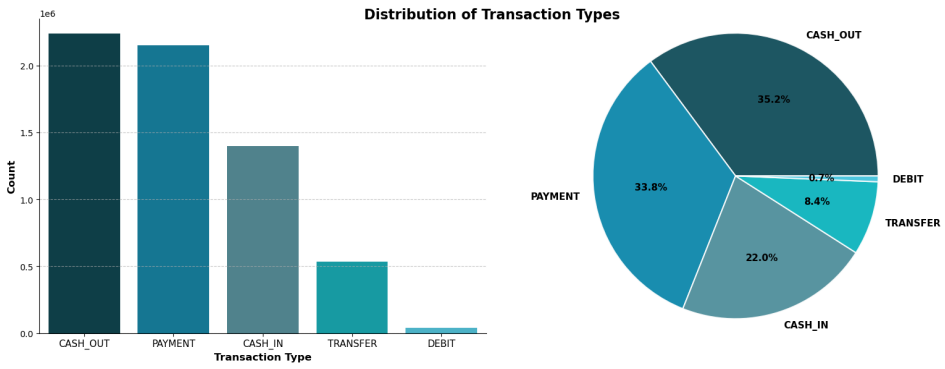

Figure 8: Distribution of Transaction Types

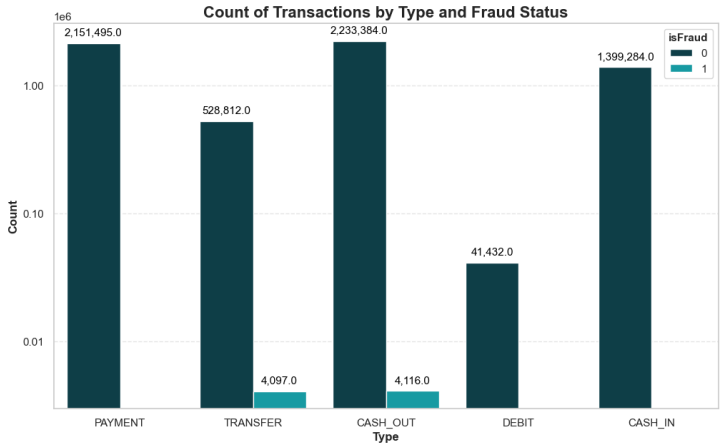

Figure 9: Count of Transactions by Type and Fraud Status

5.2 Data Cleaning & Preprocessing:

In the initial dataset, the categorical features had a process known as label encoding, which involved transforming them into numerical values. The numerical characteristics were scaled using Min-Max scaling to obtain uniform limits for efficient model training. This method of scaling ensures that all features have values between 0 and 1. This helps ensure that any separated, large-scale characteristic affects the model's development more than it needs to. When working with features that encompass many scales or units of measurement, this method excels. When it comes to training a reliable and precise model, Min-Max scaling plays an important part by normalizing the numerical features. Data set transformed by encoding categorical features which and scaling numerical features represents in 10.The dataset was modified so that machine learning models could make use of it.

- No missing values were found in the dataset, and there were no duplicates.
- Categorical variables were encoded using Label Encoding.
- Feature scaling was applied using Min-Max Scaling to bring all features to a similar scale.

```
#datatypes of the dataset attributes
dataFrame.dtypes
```

Python

```
step              int64
type             object
amount          float64
nameOrig         object
oldbalanceOrg   float64
newbalanceOrig  float64
nameDest         object
oldbalanceDest  float64
newbalanceDest  float64
isFraud           int64
isFlaggedFraud    int64
dtype: object
```

```
#encode the string objects to the categorical values to numerical values
encoder = {}
for i in dataFrame.select_dtypes('object').columns:
    encoder[i] = LabelEncoder()
    dataFrame[i] = encoder[i].fit_transform(dataFrame[i])
```

Python

Figure 10: Convert categorical values to numerical values

5.3 Model Development:

A selection of machine learning models were selected and afterwards trained using the transformed dataset. In this step, various algorithms from the scikit-learn library were utilized. These algorithms include KNeighborsClassifier, DecisionTreeClassifier, LogisticRegression, and RandomForestClassifier. During the training process, the models underwent fine-tuning and optimization specifically for the purpose of fraud detection.

All models demonstrated a significant level of accuracy, with both the Decision Tree and Random Forest models obtaining accuracy rates that were nearly perfect, approaching 100

6 Evaluation of Results

6.1 Evaluation Metrics:

To evaluate the performance of each training model, we utilized commonly used classification metrics. Our primary goal was to assess the effectiveness of these models in accurately differentiating between fraudulent and non-fraudulent transactions. By analyzing these metrics, we gained valuable insights into the strengths and weaknesses of each model, allowing us to form informed opinions on its suitability for the task at hand. These evaluation measures provided impartial criteria, facilitating a methodical analysis of the models and aiding in determining their unique capabilities.

The performance of various models was assessed by generating ROC AUC curves. The primary objective of these curves is to visually depict the discriminatory capacity of each model in distinguishing between positive and negative cases. Out all the several models that were assessed, the Random Forest model exhibited outstanding performance, attaining a flawless AUC score of 1.00 which is indicated in Figure 11. This finding suggests that the Random Forest model demonstrated a high level of accuracy in classifying cases with a significant level of certainty.

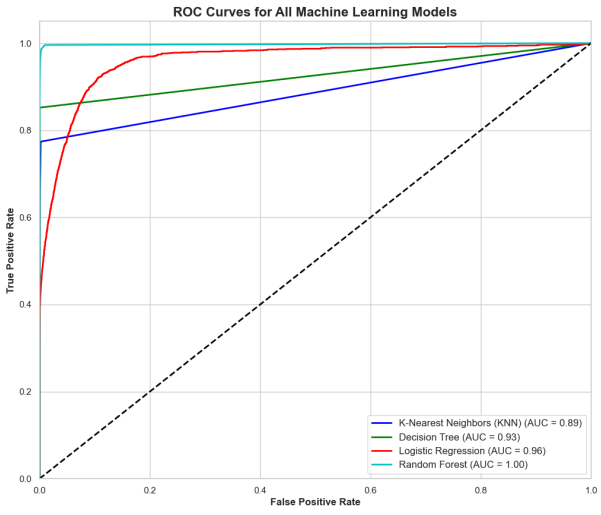

Figure 11: ROC Curve b/w All Machine Learning Models

AUC is a common metric used to evaluate the performance of binary classification models, which are used to predict one of two possible outcomes.Lets evaluate the AUC results of each model in detailed.

- **K-Nearest Neighbors (KNN) (AUC = 0.89):** An AUC score of 0.89 suggests that this KNN model achieved a good level of discrimination, though not perfect, in distinguishing between the two classes it's predicting. The closer the AUC score is to 1.0, the better the model's performance.
- **Decision Tree (AUC = 0.93):** An AUC score of 0.93 indicates that the Decision Tree model has a strong ability to differentiate between the classes it's predicting. It's performing quite well in this context.
- **Logistic Regression (AUC = 0.96)** n AUC score of 0.96 is quite high, indicating that the Logistic Regression model is very effective at classifying data. It is excellent at distinguishing between the two classes.
- **Random Forest (AUC = 1.00):** An AUC score of 1.00 means that the Random Forest model has achieved perfect discrimination. It can perfectly distinguish between the two classes in the dataset, indicating extremely strong performance.

6.2 Model Comparison:

A comprehensive review was conducted to compare different machine learning models, with a specific emphasis on the assessment criteria. The aim of this phase was to ascertain the model or models that exhibited the utmost level of effectiveness in identifying cases of fraudulent operations which is represents in a form of confusion matrix in Figure 12.

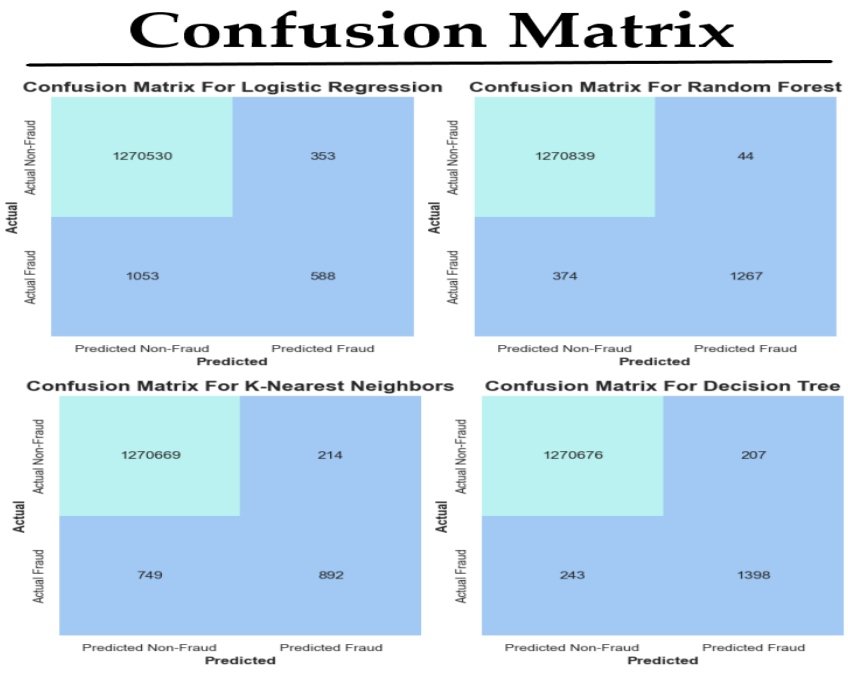

Figure 12: Confusion Matrices b/w All Machine Learning Models

In general, we can see that the Random Forest is perform well across these confusion metrics is depicted Figure. 12. However, the choice of the best model might depend on the specific goals of your financial fraud detection application system. If minimizing the false positives (precision) is important, then the Random Forest best to be the good fit choice.

Table 2: Classification Reports for Different Models

Model	Precision	Recall	F1-Score	Support
Random Forest	1.00	1.00	1.00	1270883
	0.97	0.77	0.86	1641
	1.00	1.00	1.00	1272524
Decision Tree	1.00	1.00	1.00	1270883
	0.87	0.86	0.87	1641
	1.00	1.00	1.00	1272524
KNN	1.00	1.00	1.00	1270883
	0.81	0.54	0.65	1641
	1.00	1.00	1.00	1272524
Logistic Regression	1.00	1.00	1.00	1270883
	0.62	0.36	0.46	1641
	1.00	1.00	1.00	1272524

- **Accuracy:** All models exhibit high accuracy, suggesting overall good performance in predicting both classes.
- **AUC:** Random Forest stands out with a perfect AUC (1.00), indicating flawless discrimination.
- **Class 1 Performance:** Decision Tree performs well in achieving a balance between precision and recall for Class 1.
- **F1-Score:** Random Forest and Decision Tree have higher F1-scores for Class 1, suggesting better balance between precision and recall compared to KNN and Logistic Regression.

In summary, the AUC scores reflect the classification performance of these models. A higher AUC score generally implies better model performance in terms of distinguishing between the two classes, and Random Forest, with an AUC of 1.00, stands out as having achieved perfect discrimination in this context.

7 Conclusion and Discussion

The results obtained from our research on fraud detection models highlights the highly efficient configuration and the evaluation process, leading to the influential advancements in distinguishing and mitigating the fraudulent transactions. Our investigation involved the utilization of the various machine learning algorithms, encompassing the K-Nearest Neighbors (KNN), Decision Tree, Logistic Regression, and Random Forest, all of which showed the admirable degrees of the accuracy, precision, and recall in handling the challenge of fraud detection.

Table 3: Comparative Different Accuracies

Models	Accuracies
K-Nearest Neighbors (KNN)	99.92%
Decision Tree	99.96%
Logistic Regression	99.89%
Random Forest	99.97%

Especially, the Random Forest model appeared as a prominent performer, demonstrating the perfect and outstanding results with an accuracy of around 99% and a flawless the Area Under the Curve (AUC) value. The ensemble nature of combining the multiple decision trees of the Random Forest, proved to be a compelling factor in acquiring the superior preferential capabilities. This line up with the exploration findings of Li and Jung (2023), where the ensembling of multiple trees in the Random Forest model consistently showed the robust outcomes in making final decisions.

Examining the individual model performances provides further insights into their specific potential strengths:

- **K-Nearest Neighbors (KNN) Model**
  - Achieved an accuracy of 99.92%.
  - Demonstrated the vigorous discriminatory capabilities with notable precision and recall for both fraudulent and non-fraudulent transactions.
- **Decision Tree Model**
  - Attained an accuracy of 99.96%.
  - Exhibited high precision, recall, and F1-score, particularly excelling in identifying fraudulent transactions.
- **Logistic Regression Model**
  - Recorded an accuracy of 99.89%.
  - Demonstrated the strong precision for non-fraudulent transactions, though with a relatively lower precision for fraudulent transactions.
  - Moderate recall indicates reasonable preferential abilities.
- **Random Forest Model**
  - Outperformed other models with an accuracy of 99.97%.
  - Showcased the exceptional precision, recall, and F1-score for non-fraudulent transactions.
  - Retrieved the high precision and good recall for fraudulent transactions.

In conclusion, the Random Forest model consistently delivered outstanding performance in distinguishing fraudulent activities across the extensive scenarios. The ensemble approach, combining the multiple decision trees, proved to be a vigorous strategy for enhancing accuracy and effectiveness in fraud detection. These findings highlights the practical viability and reliability of machine learning models, especially the Random Forest, in handling the complex challenges presented by fraudulent transactional activities.

7.1 Future Work:

- **Developments of Fairness Evaluations:** Keep in mind for fairness in all the dimensions, where it is advised to conduct thorough and comprehensive evaluations that consider realtionships and correlations of the different types of demographic factors. This includes the analyzing an impact of model predictions on various subgroups, with the goal of maintaining the fairness across all dimensions.

- **Code of Ethics:** Here the goal is to establish a code of ethics that would be adaptable to keep evolving types of fraud patterns and including the ethical issues. Regular updates to ethical principles are crucial in effectively addressing new challenges and ensuring that the model remains aligned with ethical standards in a constantly evolving environment.

- **Real Time Monitoring:** Where here the process will integrate ethical considerations and real-time model performance monitoring. Create methods that allow for rapid identification and settlement of biases, abnormalities, or ethical issues in real-world situations.

- **Collaboration and Stakeholder Involvement:** Support collaborative efforts with other organizations, including regulatory agencies and industry experts, to together address moral challenges related to fraud detection. The involvement of stakeholders in continuous addresses is essential for the integration of multiple viewpoints into the management of models.

By focusing awareness towards these prospective areas, the fraud detection system has the potential to develop into a more resilient, fair, and ethically responsible resolution that corresponds with the constantly evolving domain of financial transactions and the developing environment of technology and ethics.

References

Aburbeian, A. M. and Ashqar, H. I. (2023). Credit card fraud detection using enhanced random forest classifier for imbalanced data, *International Conference on Advances in Computing Research*, Springer, pp. 605–616.

Alarfaj, F. K., Malik, I., Khan, H. U., Almusallam, N., Ramzan, M. and Ahmed, M. (2022). Credit card fraud detection using state-of-the-art machine learning and deep learning algorithms, *IEEE Access* **10**: 39700–39715.

Baldi, P., Brunak, S., Chauvin, Y., Andersen, C. A. and Nielsen, H. (2000). Assessing the accuracy of prediction algorithms for classification: an overview, *Bioinformatics* **16**(5): 412–424.

Bao, Y., Hilary, G. and Ke, B. (2022). Artificial intelligence and fraud detection, *Innovative Technology at the Interface of Finance and Operations: Volume I* pp. 223–247.

Chaquet-Ulldemolins, J., Gimeno-Blanes, F.-J., Moral-Rubio, S., Muñoz-Romero, S. and Rojo-Álvarez, J.-L. (2022). On the black-box challenge for fraud detection using machine learning (i): Linear models and informative feature selection, *Applied Sciences* **12**(7): 3328.

Dull, R. B. and Rice, M. M. (2023). An examination of occupational fraud committed by information technology professionals, *Journal of Forensic Accounting Research* pp. 1–21.

El Hajj, M. and Hammoud, J. (2023). Unveiling the influence of artificial intelligence and machine learning on financial markets: A comprehensive analysis of ai applications in trading, risk management, and financial operations, *Journal of Risk and Financial Management* **16**(10): 434.

Gan, Y., Han, Q. and Gao, Y. (2022). Combining traditional machine learning and anomaly detection for several imbalanced android malware dataset's classification, *2022 7th International Conference on Machine Learning Technologies (ICMLT)*, pp. 74–80.

Hilal, W., Gadsden, S. A. and Yawney, J. (2022). Financial fraud: a review of anomaly detection techniques and recent advances, *Expert systems With applications* **193**: 116429.

Hisham, S., Makhtar, M. and Aziz, A. A. (2022). A comprehensive review of significant learning for anomalous transaction detection using a machine learning method in a decentralized blockchain network, *International Journal of Advanced Technology and Engineering Exploration* **9**(95): 1366.

Jha, R. K. (2023). Strengthening smart grid cybersecurity: An in-depth investigation into the fusion of machine learning and natural language processing, *Journal of Trends in Computer Science and Smart Technology* **5**(3): 284–301.

Josyula, H. P. (2023). Fraud detection in fintech leveraging machine learning and behavioral analytics.

Kumar, S., Ahmed, R., Bharany, S., Shuaib, M., Ahmad, T., Tag Eldin, E., Rehman, A. U. and Shafiq, M. (2022). Exploitation of machine learning algorithms for detecting financial crimes based on customers' behavior, *Sustainability* **14**(21): 13875.

Li, G. and Jung, J. J. (2023). Deep learning for anomaly detection in multivariate time series: Approaches, applications, and challenges, *Information Fusion* **91**: 93–102.

Lim, K. S., Lee, L. H. and Sim, Y.-W. (2021). A review of machine learning algorithms for fraud detection in credit card transaction, *International Journal of Computer Science & Network Security* **21**(9): 31–40.

Liu, J., Gu, X. and Shang, C. (2020). Quantitative detection of financial fraud based on deep learning with combination of e-commerce big data, *Complexity* **2020**: 1–11.

Lopez-Rojas, E. (2017). Synthetic financial datasets for fraud detection.
URL: *https://www.kaggle.com/datasets/ealaxi/paysim1/data*

Mangathayaru, N., Kumar, N. R., Kumar, G. R. et al. (2023). Fraudulent transaction detection by machine and deep learning algorithms, *Journal of Population Therapeutics and Clinical Pharmacology* **30**(14): 446–453.

Nguyen, T. T., Tahir, H., Abdelrazek, M. and Babar, A. (2020). Deep learning methods for credit card fraud detection, *arXiv preprint arXiv:2012.03754* .

Odhiambo, O. (2022). *Exploring the Machine Learning and Artificial Intelligence Algorithm Needed to Detect Healthcare Financial Statement Anomalies*, PhD thesis, Colorado Technical University.

Pazho, A. D., Noghre, G. A., Purkayastha, A. A., Vempati, J., Martin, O. and Tabkhi, H. (2022). A survey of graph-based deep learning for anomaly detection in distributed systems, *arXiv preprint arXiv:2206.04149* .

Sánchez-Aguayo, M., Urquiza-Aguiar, L. and Estrada-Jiménez, J. (2021). Fraud detection using the fraud triangle theory and data mining techniques: A literature review, *Computers* **10**(10): 121.

Seo, S. (2006). *A review and comparison of methods for detecting outliers in univariate data sets*, PhD thesis, University of Pittsburgh.

Torres, R. A. L. and Ladeira, M. (2020). A proposal for online analysis and identification of fraudulent financial transactions, *2020 19th IEEE International Conference on Machine Learning and Applications (ICMLA)*, IEEE, pp. 240–245.

Umar, I., Samsudin, R. S. and Mohamed, M. (2022). The types, costs, prevention and detection of occupational fraud: The acfe perspective.

Verma, J. (2022). Application of machine learning for fraud detection–a decision support system in the insurance sector, *Big Data Analytics in the Insurance Market*, Emerald Publishing Limited, pp. 251–262.

Wang, H., Zheng, J., Carvajal-Roca, I. E., Chen, L. and Bai, M. (2023). Financial fraud detection based on deep learning: Towards large-scale pre-training transformer models, *China Conference on Knowledge Graph and Semantic Computing*, Springer, pp. 163–177.

Xu, M., Fu, Y. and Tian, B. (2023). An ensemble fraud detection approach for online loans based on application usage patterns, *Journal of Intelligent & Fuzzy Systems* (Preprint): 1–14.

Zhu, X., Ao, X., Qin, Z., Chang, Y., Liu, Y., He, Q. and Li, J. (2021). Intelligent financial fraud detection practices in post-pandemic era, *The Innovation* **2**(4).