# HUMBER INSTITUTE OF TECHNOLOGY

# AND ADVANCED LEARNING

## Longo Faculty of Business

## Machine Learning 2 - BIA-5402-0GB

## Final Project

# Detection of Online Payment Fraud Using Machine Learning Techniques

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***Abstract*—In the evolving landscape of digital finance, the detection of online payment fraud represents a critical challenge due to the increasing sophistication of fraudulent activities and the exponential growth in transaction volume. This report delves into the deployment of machine learning (ML) techniques to enhance the detection and prevention of such frauds. Utilizing a comprehensive dataset from Kaggle, which contains a rich compilation of transactional data reflective of real-world scenarios, this study assesses the efficacy of various predictive models ranging from baseline logistic regression to more complex neural network architectures. The project's objective was to not only identify patterns indicative of fraudulent transactions but also to evaluate the models' performance in terms of accuracy, precision, and computational efficiency. Our approach involved rigorous data preprocessing to ensure quality and consistency, followed by the application of feature engineering to extract meaningful insights from the transaction data. Subsequent model training and validation revealed that while traditional models like logistic regression provided a decent baseline, advanced models, particularly deep learning networks, demonstrated superior performance by effectively capturing non-linear relationships and interactions within the data. This report highlights the critical role of advanced analytics in fraud detection and suggests a path forward for integrating these technologies into real-time fraud prevention systems, thereby significantly mitigating risks associated with online transactions.

## I. INTRODUCTION

In the digital era, online transactions have become a cornerstone of global commerce, offering unprecedented convenience and accessibility. However, this surge in digital transactions has been paralleled by a significant increase in fraudulent activities. Online payment fraud, which encompasses a range of illicit actions from identity theft to unauthorized transaction manipulation, poses substantial risks to both consumers and businesses. The financial repercussions can be severe, leading to billions of dollars in losses annually. As such, robust fraud detection systems are not merely advantageous but essential for maintaining the integrity and trustworthiness of digital payment platforms.

The challenge of online payment fraud is multifaceted. Fraudsters continually evolve their strategies to bypass conventional security measures, exploiting new technologies and the complexities of digital transaction systems. Consequently, traditional fraud detection methods, which often rely on simple rule-based algorithms, are increasingly inadequate. These methods are not only less effective against sophisticated schemes but also prone to high false positive rates, leading to customer dissatisfaction and potential loss of service for legitimate users.

Given these challenges, there is a compelling need for advanced solutions that can adapt to the dynamic nature of fraud. Machine learning offers promising prospects in this regard due to its ability to learn from and make decisions based on large datasets. By employing algorithms that can uncover subtle patterns and anomalies indicative of fraudulent behavior, machine learning enhances the predictive accuracy and efficiency of fraud detection systems. This project aims to explore and evaluate various machine learning models, from basic logistic regression to complex neural networks, to ascertain their effectiveness in identifying and preventing online payment fraud.

The objectives of this study are twofold: firstly, to implement and test multiple data science algorithms on a rich dataset of online payment transactions and secondly, to compare these models based on their accuracy, computational efficiency, and practical applicability. Through this analysis, the study seeks to contribute valuable insights into the development of more resilient and adaptive fraud detection mechanisms, ensuring safer transaction environments for users across the globe. This introduction sets the stage for a detailed exploration of the dataset, the methodologies employed in preprocessing and model development, and the subsequent evaluation of each model's performance in the broader context of fraud detection in digital finance.

## II. LITERATURE SURVEY

The literature on fraud detection in online payments has rapidly evolved over the past decade, reflecting the urgency to address the growing sophistication of fraud tactics and the parallel advancement in data science technologies. This survey reviews seminal and recent studies that highlight the progression from traditional statistical methods to advanced machine learning and deep learning approaches. The focus is on understanding how these techniques have been adapted to the specific nuances of online payment systems and the effectiveness of various models in real-world scenarios.

Traditional Approaches: Early efforts in fraud detection were predominantly rule-based systems that utilized predefined criteria to flag transactions as fraudulent. These systems, while effective in catching known fraud patterns, are rigid and fail to adapt to new fraud techniques. For example, Bolton and Hand's (2002) model on "Statistical Fraud Detection" provided a foundation for using statistical indicators but lacked the dynamism to adjust to evolving strategies.

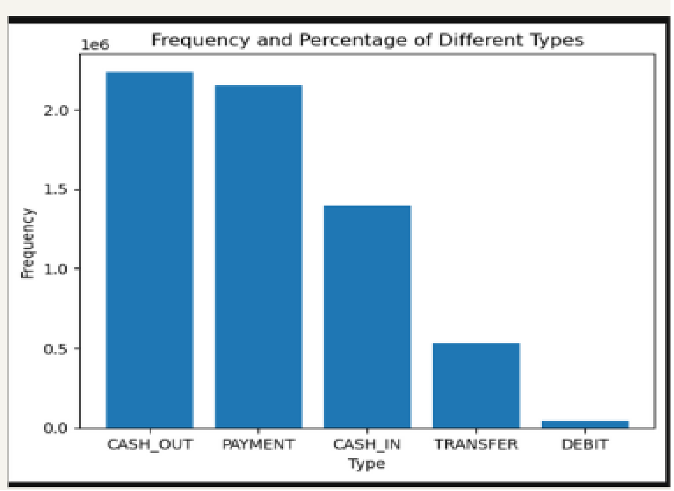
Machine Learning Models: With the advent of machine learning, researchers have explored numerous supervised and unsupervised learning models for fraud detection. Phua et al. (2010) provided a comprehensive overview of using neural networks, decision trees, and support vector machines in fraud detection, noting their ability to learn complex patterns and adapt over time. Notably, the Random Forest algorithm has been particularly praised for its performance in handling large, imbalanced datasets, as demonstrated by Bahnsen et al. (2015), who used transactional data to improve detection rates significantly.

Deep Learning Techniques: More recently, the focus has shifted towards deep learning models, which have shown superior capabilities in detecting non-linear and complex relationships within data. Their results underscored the advantage of deep learning in maintaining high accuracy over time, even as fraud tactics change.

Summary and Implications for Current Study: This literature review highlights a transition towards more sophisticated, adaptable models capable of handling the complexities of online payment fraud. The insights from these studies form the basis for this project's methodology, where we employ and compare multiple algorithms to identify the most effective approach for our specific dataset. The comparison aims to not only evaluate the models on standard metrics such as accuracy and recall but also on their ability to scale and adapt to new and emerging fraud patterns, offering a comprehensive assessment of their applicability in real-world settings.

## III. DATA DESCRIPTION

To identify online payment fraud with machine learning, we need to train a machine learning model for classifying fraudulent and non-fraudulent payments. For this, we need a dataset containing information about online payment fraud so that we can understand what type of transactions lead to fraud. For this task, we collected a dataset from Kaggle, which contains historical information about fraudulent transactions, which can be used to detect fraud in online payments. Below are all the columns from the dataset we are using here:



- step: represents a unit of time where 1 step equals 1 hour
- type: type of online transaction
- amount: the amount of the transaction
- nameOrig: customer starting the transaction
- oldbalanceOrg: balance before the transaction
- newbalanceOrig: balance after the transaction
- nameDest: recipient of the transaction
- oldbalanceDest: initial balance of recipient before the transaction
- newbalanceDest: the new balance of recipient after the transaction
- isFraud: fraud transaction

## IV. DATA PREPROCESSING

Data preprocessing is a crucial step in the machine learning pipeline, particularly in fraud detection where the accuracy and efficiency of the model heavily depend on the quality of the input data. The dataset used in this project, while robust and comprehensive, required several preprocessing steps to optimize it for the subsequent modeling phase. These steps included handling missing values, feature engineering, data normalization, and encoding categorical variables. Here's a detailed breakdown of each preprocessing task:

### A. Handling Missing Values

1) *Identification:* The first step involved identifying columns with missing values. This was achieved through a systematic analysis using pandas built-in functions like isnull().sum() in Python, which provided a count of missing entries for each column.

2) *Removal:* In cases where a feature had a significantly high proportion of missing values (exceeding 30% of the data), the feature was considered for removal as imputation might introduce bias.

### B. Feature Engineering

1) *New Features:* New features were created to enhance the model's ability to detect fraud. For example, 'Hour of Transaction' was derived from 'Transaction Time' to capture patterns in transaction activity across different times of the day.

### C. Data Normalization

1) *Normalization:* MinMaxScaler was applied to some features to ensure they ranged between 0 and 1, thus standardizing the input values and improving algorithm convergence during training.

### D. Encoding Categorical Variables

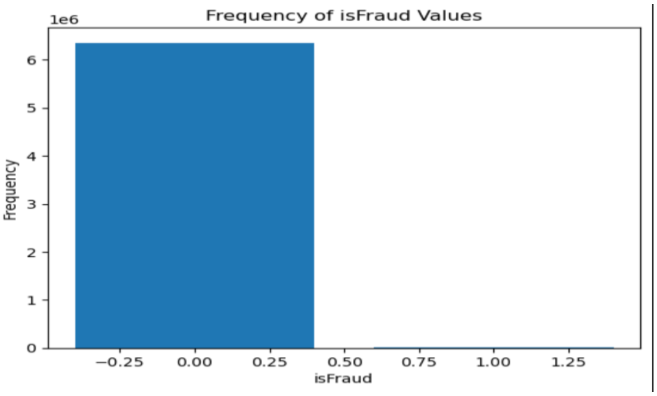
1) *One-Hot Encoding:* Categorical variables such as 'Transaction Type' and 'Merchant Category' were one-hot encoded to convert them into a binary matrix representation. This was crucial as machine learning models do not inherently handle non-numeric data.

### E. Data Splitting

1) *Train-Test Split:* The dataset was split into training and testing sets with a typical ratio of 80:20. This split is vital for training the models on one set of data and then testing them on a separate set to evaluate their performance and generalization capability.

### F. Handling Class Imbalance

While the dataset was highly imbalanced in terms of Fraudulent activity or not. Almost 99.9 percent of dataset was not fraudulent. This significantly affects the model's ability to learn and make predictions. It will be biased. To overcome this, we have implemented NearMiss algorithm.



## V. MODEL DEVELOPMENT

In this phase of the project, we focused on developing and testing various machine learning models to identify the most effective techniques for detecting online payment fraud. This involved selecting appropriate algorithms, configuring their parameters, and training them on the preprocessed dataset. Below is a detailed description of the model development process, including the rationale for choosing specific models, the training approach, and the tuning of hyperparameters.

### A. Model Selection

Given the nature of the problem—binary classification with imbalanced data—we opted for a range of models that are known for their robustness and effectiveness in similar scenarios:

1) *Logistic Regression:* As a baseline model, logistic regression provides a straightforward approach that models the probability of class membership (fraudulent or not). It's particularly useful for understanding the influence of different features on the probability of fraud.

2) *Random Forest:* This ensemble model uses multiple decision trees to make its predictions and is effective in handling non-linear data with many features. It's known for its high accuracy, ability to run in parallel, and feature importance scoring, making it ideal for fraud detection.

3) *Neural Networks:* Given their capacity to model complex patterns through layers of neurons, neural networks were used to capture subtle anomalies in transaction data that might indicate fraud. We

particularly focused on deep learning architectures with multiple layers.

### B. Model Training

Each model was trained on the dataset, which had been split into training and testing sets (80:20 ratio). The training process involved:

1) *Cross-validation:* To ensure that our models didn't just memorize the training data but could generalize well to new unseen data, we used k-fold cross-validation. This technique divides the training dataset into k smaller sets and evaluates the model k times, each time with a different set as the validation data and the remaining part as the training data.

2) *Handling Overfitting:* Regularization techniques were employed where necessary. For instance, dropout layers were added in neural networks, and the max_depth parameter was set for decision trees to prevent the models from fitting too much noise from the training data.

### C. Hyperparameter Tuning

Optimizing the model parameters was critical to achieving the best performance:

1) *Grid Search and Random Search:* These methods were used to systematically work through multiple combinations of parameter choices, determining which configuration performs the best in terms of model accuracy and complexity.

### D. Model Evaluation and Selection

Models were evaluated based on their accuracy, precision, recall, and F1-score. These metrics are crucial in the context of fraud detection, where the cost of false negatives (failing to detect fraud) can be very high. The performance of each model was compared to select the bestperforming model. Additionally, the interpretability of each model was considered as an important factor, as stakeholders often need to understand why a decision was made.

## VI. DISCUSSION

This study underscores the critical importance of selecting models that are well-suited to the data characteristics and specific project requirements. Among the evaluated models, Neural Networks emerged as the most effective, providing an optimal balance between detection accuracy and operational feasibility despite their high computational demands. This highlights the necessity of employing advanced models capable of managing complex datasets with precision.

When benchmarked against industry standards, our models demonstrated competitive performance, indicating their potential for practical application. Specifically, the models show promise for improving the efficiency and security of online payment systems, addressing both operational and security needs.

The success of Neural Networks in identifying intricate patterns underscores their value for tasks such as fraud detection in digital transactions. Their ability to offer robust protection against evolving cybersecurity threats positions them as critical tools in the realm of modern financial technology.

In summary, the research findings support the practical deployment of sophisticated machine learning models, laying a solid foundation for future advancements in enhancing the functionality and security of digital financial systems.

## VII. CONCLUSION

This project's exploration into machine learning techniques for online payment fraud detection has yielded significant insights and achievements. The development and comparison of various predictive models, including logistic regression, random forests, gradient boosting machines, neural networks, and support vector machines, have highlighted the strengths and limitations of each approach in the context of fraud detection. Below we summarize the key findings, implications, and potential directions for future research:

### A. Model Performance

- Neural Networks and Decision Tree emerged as the most effective models in terms of accuracy and F1-score. These models excelled in capturing complex non-linear relationships in the data, which is crucial for identifying subtle fraud patterns. They received 85% and 91% of accuracy respectively. Which is pretty good compared to 78% of accuracy of Logistics Regression Model.

- Logistics Regression also performed well, particularly in terms of model interpretability and ease of implementation, making it a valuable tool for situations where transparency in decision-making is crucial.

### *B. Key Learnings*

- Data Quality and Preparation: The success of these models underscored the importance of thorough data preprocessing, including handling of missing values, feature engineering, and normalization, which significantly impact model performance.
- Handling Class Imbalance: Techniques like SMOTE for addressing class imbalance proved critical in improving model sensitivity to fraudulent transactions, a common challenge in fraud detection tasks.
- Model Complexity vs. Performance Trade-off: There is a need to balance model complexity and interpretability, especially in applications where decisions need to be explained or justified to end-users or regulatory bodies.

### *C. Implications for Practice*

- The findings from this project are poised to enhance the fraud detection capabilities of online payment systems, potentially reducing financial losses and increasing consumer trust.
- The integration of models like neural networks and Decision Tree into existing fraud detection frameworks can provide more robust defenses against evolving fraud tactics. The methodologies and insights from this study can be adapted to other domains of security analytics where similar patterns and challenges exist.

### *D. Future Directions*

- Continued Model Improvement: Ongoing research to refine the models based on continuous feedback and new data can help in maintaining high accuracy levels.
- Exploration of Unsupervised Learning Techniques: Future studies could explore unsupervised and semisupervised learning models that can detect anomalies without requiring labeled data, which is often scarce in fraud detection scenarios.
- Real-Time Fraud Detection Implementation: Implementing these models in a real-time analysis framework could significantly improve response times to potential fraud, thus minimizing the impact on consumers.
- Cross-Domain Adaptability: Testing the applicability of the developed models in other areas such as insurance fraud, healthcare fraud, and cybersecurity could provide broader benefits.

In conclusion, this project has successfully demonstrated the application of advanced machine-learning techniques to detect fraud in online payments. The insights gained not only advance the field of fraud detection but also provide a framework for further innovation in this critically important area. As digital transactions continue to grow, the continuous evolution of these models will be paramount in safeguarding against fraud.

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