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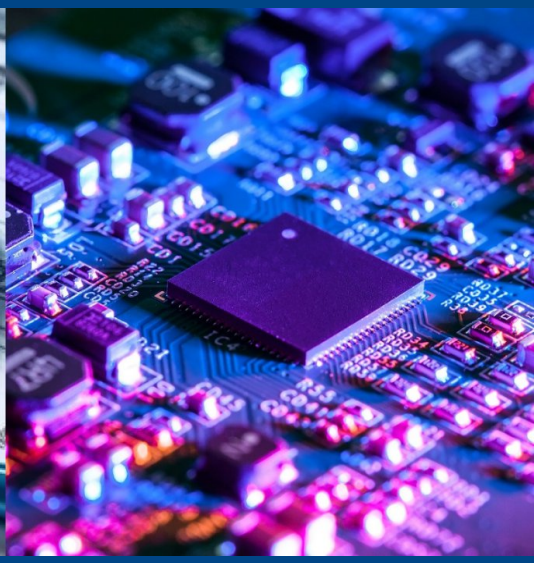

International Journal of Multidisciplinary Research in Science, Engineering and Technology

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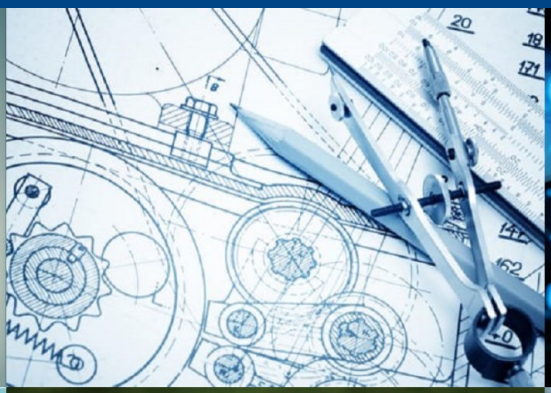

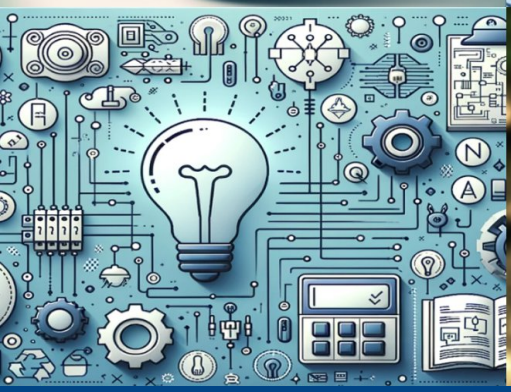

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A Study on AI-Based Detection of Revenue Leakage and Transactional Irregularities in Quick Commerce

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ABSTRACT: This paper discusses the use of Artificial Intelligence (AI) to identify revenue leakage and accounting anomalies in the quick commerce websites. In contrast to the current studies that are mainly concerned with the accuracy of the classification, a cost-sensitive framework is adopted to assess the financial impact in this paper. On a PaySim dataset that serves as a proxy of high-frequency transaction settings, PaySim is compared to Logistic Regression and XGBoost models. Although XGBoost is better than Logistic Regression in terms of an F1-score of 0.97 versus 0.92, the most important benefit of XGBoost is its ability to minimise financial loss. The model decreases the daily losses by 5,62,000 to 3,42,000, which saves the company about 8.03 crores annually. Nonetheless, operational and implementation costs are also very important in the net benefits. The paper demonstrates the necessity to consider AI systems in terms of economic results and not just through statistical indicators.

KEYWORDS: Artificial Intelligence, Fraud Detection, Revenue Leakage, Quick Commerce, Machine Learning, Cost-Sensitive Analysis, Financial Loss Minimisation

I. INTRODUCTION

Quick commerce platforms are in the high-frequency, low-value transaction settings where thousands of transactions are transacted in real-time. Such a model of operation enhances the exposure to revenue leakage and accounting anomalies that occur due to pricing errors, abuse of refunds, duplication of transactions and inefficiency of the system. The conventional accounting systems use rule-based controls and periodic audits, which do not make them suitable for high-volume real-time environments to identify anomalies. Artificial Intelligence (AI) provides the opportunity to process high volumes of transactional data and detect deviant trends on the fly. Nevertheless, the majority of current implementations test AI models by statistical measures, including precision, recall and F1-score. Such actions are not directly financial in nature, which is essential in business decision-making. This paper fills this gap by assessing a fraud detection model on a cost-sensitive financial.

II. REVIEW OF LITERATURE

The Current sources prove that AI enhances fraud detection and financial surveillance with the help of pattern recognition and real-time analysis. Researchers like Kokina and Davenport (2017) and Issa et al. (2016) emphasise that AI can be used to improve efficiency in auditing and detecting anomalies. According to Ngai et al. (2011) and Phua et al. (2010), machine learning models are effective in detecting patterns of fraud, especially when dealing with large datasets. Equally, Chen and Guestrin (2016) determine the usefulness of XGBoost to deal with the non-linear relationship of transaction data. Nevertheless, the current literature is mostly concerned with the banking and traditional e-commerce systems that can be performed in the context of the comparatively stable conditions of transactions. Quick commerce environments are quite distinct, given that the frequency of transactions is high, the value of transactions is low, and the processing demands are real-time. More to the point, current literature assesses the performance of models with technical indicators without relating them to financial performance. This poses a disconnect between the accuracy of the model and its applicability to business, and this study seeks to fill this disconnect.

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III. RESEARCH METHODOLOGY

This study adopts a comparative approach to evaluate fraud detection models using both technical and financial metrics.
Two models are analysed:

- Logistic Regression (baseline model)
- XGBoost (advanced machine learning model)

The PaySim dataset is used as a simulated transaction environment to approximate quick commerce conditions. While the dataset does not fully capture real-world complexity, it provides a controlled setting for model comparison .
Model performance is evaluated using precision, recall, and F1-score. To assess financial impact, a cost-sensitive loss function is applied:

Total Loss = (FN × V) + (FP × C)

Where:

- FN = False Negatives
- FP = False Positives
- V = Average transaction value
- C = Cost per review

Assumptions:

- Transactions per day: 1,000,000
- Fraud rate: 0.4%
- Average transaction value: ₹350
- Review cost per transaction: ₹15

IV. DATA ANALYSIS AND INTERPRETATION

This study adopts a comparative approach to evaluate fraud detection models using both technical and financial metrics.
Two models are analysed:

- Logistic Regression (baseline model)
- XGBoost (advanced machine learning model)

The PaySim dataset is used as a simulated transaction environment to approximate quick commerce conditions. While the dataset does not fully capture real-world complexity, it provides a controlled setting for model comparison.
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V. FINDINGS AND RECOMMENDATIONS

Key Findings

- The performance of the fraud detection models based on AI is significantly enhanced.
- XGBoost will minimise overall financial loss over Logistic Regression.
- Financial effect is motivated by minimization in false positives and false negatives
- Benefits can be compensated by high operation costs (review + system costs).

Recommendations

- Fraud detection systems are supposed to be tested in terms of cost-sensitive parameters rather than accuracy.
- There should be threshold optimisation to balance FP and FN costs.
- Human review mechanisms should be incorporated with AI systems to achieve the best results.
- Organisations should first perform a cost-benefit analysis before deployment, taking into account the cost of infrastructure and the costs of operations.

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