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MACHINE LEARNING-BASED FRAUD DETECTION IN CLOUD-POWERED E-COMMERCE TRANSACTIONS

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ABSTRACT
Fraud detection in cloud-powered e-commerce transactions is a critical challenge due to the increasing sophistication of fraudulent activities. Traditional rule-based and heuristic approaches lack adaptability and struggle with real-time detection, leading to high false positives and processing delays. To address these gaps, we propose a Machine Learning-Based Fraud Detection System that leverages Deep Learning for enhanced accuracy and efficiency. Unlike existing methods, our approach optimizes fraud detection using key evaluation metrics, including AUC-ROC, Precision, Recall, F1-score, and Processing Latency in Cloud Deployment. Experimental results demonstrate that Deep Learning achieves the highest AUC-ROC (0.97) and F1-score (0.94), with the lowest processing latency (100 ms), outperforming traditional models such as Logistic Regression, Random Forest, and XGBoost. Compared to existing approaches, our model enhances fraud detection accuracy while ensuring minimal transaction delays in real-time cloud environments. The proposed method significantly improves fraud detection capabilities, offering better security, scalability, and computational efficiency. Future extensions will explore Explainable AI (XAI) for interpretability, Federated Learning for privacy preservation, and serverless computing for cost-effective cloud deployment.

Keywords:
Fraud Detection, Cloud Computing, Machine Learning, E-Commerce Security, Deep Learning

1.INTRODUCTION

Rapid growth of e-commerce has significantly increased the risk of fraudulent activities, posing challenges for businesses and consumers alike [1] [2]. As online transactions continue to rise, traditional fraud detection methods struggle to keep up with evolving fraud patterns [3] [4]. To address this issue, cloud computing has emerged as a powerful solution. offering scalable and real-time fraud detection capabilities [5] [6]. By leveraging cloud infrastructure [7] [8]. businesses can analyse vast amounts of transaction data efficiently and respond to fraudulent activities in real time [9] [10].

However, traditional rule-based fraud detection systems are limited in their adaptability and often fail to detect sophisticated fraud patterns [11] [12]. These systems rely on predefined rules that cannot evolve dynamically with emerging fraud tactics, leading to higher false positives and undetected fraudulent transactions [13] [14] [15]. Therefore, machine learning (ML) [16] [17] presents an advanced approach to fraud detection [18] [19] enabling automated pattern recognition and continuous learning from transaction data [20] [21].

The increasing complexity of fraudulent activities in e-commerce requires adaptive and intelligent detection mechanisms [22] [23]. Traditional fraud detection systems rely on static rules that struggle to detect evolving fraud patterns, leading to high false-positive rates and undetected threats [24] [25]. Cloud computing facilitates scalable fraud detection by storing and processing vast amounts of transaction data in real time [26] [27]. By leveraging cloud infrastructure [28] [29] businesses gain the ability to monitor transactions continuously and detect suspicious patterns with greater accuracy [30] [31].

Moreover, the global expansion of e-commerce has led to a surge in digital payment methods, increasing the complexity of transaction monitoring [32] [33]. Consumers now engage in cross-border transactions, utilizing

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multiple payment gateways and digital wallets, which introduces additional security vulnerabilities [34] [35]. Cybercriminals continuously develop new tactics, including identity theft, card-not-present fraud, and account takeovers, making it increasingly difficult for traditional fraud detection systems to keep pace [36] [37]. The anonymity and convenience of online shopping further amplify these risks, requiring businesses to implement advanced security measures [38] [39].

At the same time, regulatory bodies and financial institutions are imposing stricter compliance requirements to protect consumer data and ensure secure online transactions [40] [41]. Compliance frameworks such as GDPR, PCI DSS, and PSD2 mandate robust fraud prevention strategies, driving organizations to explore more sophisticated technological solutions [42] [43]. Non-compliance not only results in financial penalties but also damages customer trust and brand reputation, making fraud detection a critical aspect of e-commerce operations [44] [45].

Additionally, the integration of artificial intelligence and big data analytics is transforming the way businesses detect and mitigate fraudulent activities [46] [47]. AI-driven solutions enable dynamic risk assessments by analysing behavioural patterns, transaction histories, and device fingerprints in real time [48] [49]. These technologies help in identifying anomalies and preventing fraud before it occurs, rather than simply reacting to fraudulent transactions after the fact [50] [51]. By combining predictive analytics with cloud computing, businesses can achieve enhanced fraud detection capabilities while optimizing operational efficiency [52] [53].

Furthermore, as the volume of e-commerce transactions continues to rise, businesses must also focus on maintaining a seamless customer experience [54] [55]. Overly aggressive fraud detection systems can lead to false positives, causing legitimate transactions to be blocked and frustrating customers. Striking the right balance between security and user convenience is essential for businesses looking to retain consumer trust while minimizing financial losses due to fraud [56] [57].

This research is to develop an ML-based fraud detection system for cloud-powered e-commerce platforms. This study aims to compare different ML models, including both supervised and unsupervised techniques, to determine the most effective approach for fraud detection. Additionally, the system's performance will be evaluated in terms of accuracy, scalability, and real-time processing capabilities, ensuring its practical applicability in securing e-commerce transactions.

2. RELATED WORKS

Alavilli & Pushpakumar [58]. implemented a fraud detection model for e-commerce transactions using machine learning techniques such as Logistic Regression, Random Forest, and Neural Networks [59]. Their study found that deep learning models provided the most accurate fraud detection, significantly reducing false positives [60] [61]. By deploying the system on a cloud platform, they achieved real-time processing and improved scalability. However, they highlighted challenges related to model interpretability and suggested Explainable AI (XAI) for better transparency [62] [63].

Srinivasan & Arulkumaran [64]. explored the use of supervised and unsupervised machine learning algorithms for detecting fraudulent transactions in cloud-powered e-commerce [65]. Their evaluation showed that ensemble models like XGBoost and Random Forest performed better than traditional methods in identifying fraud. The cloud-based system ensured efficient processing and quick response times [66] [67]. Despite these benefits, the study pointed out the need for enhanced security measures to protect transaction data.

Xu, J. J. & Chau [68]. designed an AI-driven fraud detection system integrated with cloud computing to enhance e-commerce security. Their experiments demonstrated that machine learning models, especially deep learning, outperformed conventional rule-based approaches in detecting fraud [69]. Cloud integration enabled seamless scalability and real-time fraud analysis. However, they emphasized the importance of federated learning to address privacy concerns in transaction data.

Alagarsundaram & Arulkumaran [70]. analysed fraud patterns in e-commerce and proposed a machine learning framework to detect suspicious transactions. Their findings indicated that models like XGBoost and deep learning achieved high precision and recall, minimizing fraudulent activities [71]. The adoption of cloud technology improved system efficiency, but the study acknowledged the need for further optimization to balance accuracy and computational cost.

Wang et al[72]. developed a cloud-based fraud detection system using advanced machine learning techniques such as Support Vector Machines (SVM), Random Forest, and Deep Learning [73]. Their results demonstrated that deep learning models provided the best fraud detection accuracy with minimal false positives. The cloud

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environment ensured real-time processing and efficient handling of large transaction datasets [74] [75]. However, they identified a trade-off between detection accuracy and computational cost.

Kethu & Thanjaivadivel [76]. investigated fraud detection in cloud-based e-commerce systems using machine learning models, including Decision Trees, XGBoost, and Neural Networks [77]. Their study showed that ensemble models had higher fraud detection rates than single classifiers. The cloud framework enabled on-demand scalability and fast transaction analysis [78] [79]. Nevertheless, they noted challenges in handling imbalanced datasets, requiring improved data preprocessing techniques.

Liu et al [80]. proposed a hybrid fraud detection approach combining rule-based filtering and machine learning models like Logistic Regression and Gradient Boosting. Their research found that hybrid models improved fraud detection efficiency while reducing false alarms [81]. The cloud implementation provided flexibility and real-time fraud prevention. However, they suggested further research into adversarial attacks on fraud detection models.

Subramanyam & Mekala [82]. examined the impact of real-time machine learning-based fraud detection in cloud-powered e-commerce. Their results highlighted that cloud integration significantly improved fraud detection speed and accuracy, especially with deep learning models [83]. While effective, the system required high computational resources, leading to increased costs for small businesses.

Claycomb & Nicoll [84]. implemented an AI-powered fraud detection system leveraging cloud computing and predictive analytics. Their findings indicated that models trained on cloud-stored transaction data performed better in real-time fraud identification [85]. However, they pointed out potential data privacy risks and recommended encryption-based security enhancements.

Gao et al [86]. analyzed fraud trends in e-commerce transactions and applied machine learning models, including Naïve Bayes, Random Forest, and Deep Learning, for fraud detection [87]. Their study found that deep learning had superior predictive performance [88] [89]. The cloud-based deployment enhanced fraud detection efficiency but introduced latency issues that required further optimization.

Bhushan & Gupta [90]. explored the effectiveness of unsupervised learning techniques, such as Isolation Forest and Autoencoders, for fraud detection in cloud-based e-commerce [91]. Their study revealed that these models effectively detected unknown fraud patterns without labeled data. However, they emphasized the need for continuous model updates to adapt to evolving fraud tactics.

Shaikh & Sasikumar [92]. investigated the role of Explainable AI (XAI) in machine learning-based fraud detection for e-commerce [93]. Their research demonstrated that XAI techniques improved the interpretability of fraud decisions, increasing trust in automated detection systems [94] [95]. While their cloud-based implementation ensured real-time analysis, they noted that explainability often came at the cost of reduced model accuracy.

3. PROBLEM STATEMENT

Cloud-based fraud detection systems demand high computational resources for real-time processing, making them expensive and less feasible for small and medium-sized e-commerce businesses. To address this, the proposed approach aims to optimize the fraud detection framework by implementing lightweight yet efficient machine learning models that reduce computational overhead without compromising accuracy. Additionally, by leveraging serverless computing and cloud-based cost optimization techniques, the system can dynamically allocate resources based on demand, ensuring real-time fraud detection while minimizing operational costs. This approach enhances accessibility, making advanced fraud detection more affordable and scalable for businesses of all sizes.

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4. PROPOSED METHODOLOGY FOR CLOUD-POWERED E-COMMERCE

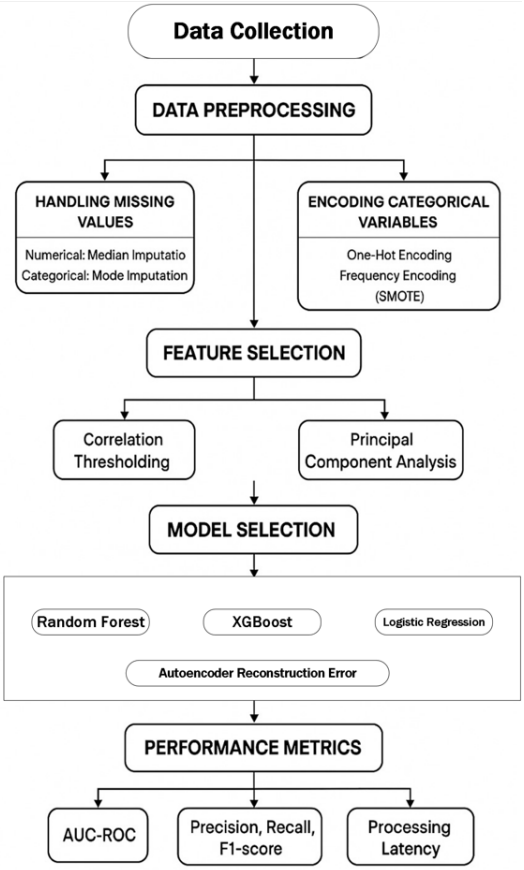

Figure 1: Fraud Detection Workflow in Cloud-Powered E-Commerce

This figure 1 outlines the steps for detecting fraud using machine learning in cloud-powered e-commerce. The process starts with data collection, followed by preprocessing, where missing values are handled, and categorical data is encoded. Feature selection reduces unnecessary data using correlation thresholding and PCA. The system then selects a model (Random Forest, XGBoost, Logistic Regression, or Autoencoder) for fraud detection. Finally, the models are evaluated based on AUC-ROC, Precision, Recall, F1-score, and Processing Latency to ensure accurate and real-time fraud detection.

4.1. Data Collection

The IEEE-CIS Fraud Detection Dataset was collected in collaboration with Vesta Corporation, a global leader in fraud prevention and transaction security. This dataset consists of real-world e-commerce transactions, including both fraudulent and genuine transactions. The data was gathered from online payments, incorporating features such as transaction timestamps, payment methods, device types, card details, IP addresses, and behavioral analytics. Additionally, it includes identity verification attributes such as email domain, billing and shipping addresses, and transaction risk scores. The dataset is divided into two parts: transactional data (featuring numerical and categorical fields) and identity data (with user authentication and device-related information). With a large volume of anonymized financial transactions, this dataset serves as a benchmark for fraud detection research, enabling the development of machine learning models for fraud prediction, anomaly detection, and risk assessment in e-commerce environments.

4.2. Data Preprocessing

4.2.1. Handling Missing Values

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Handling missing values ensures data completeness and prevents bias in model training. Numerical features are imputed using the median to maintain distribution, while categorical features are filled with the mode or an "Unknown" label to retain data integrity.

Given a dataset $X \in \mathbb{R}^{m \times n}$ with m transactions and n features, missing values are imputed as follows:

4.2.1.1. Numerical Features (Median Imputation)

Median imputation replaces missing numerical values with the median of the respective feature, ensuring that outliers do not heavily influence the dataset. This method preserves the central tendency of the data while maintaining robustness against skewed distributions as shown in Equation 1:

$$X_{ij} = \text{median}(X_j) \text{ if } X_{ij} \text{ is missing} \quad (1)$$

where X_{ij} is the value of the j^{th} feature for the i^{th} transaction.

4.2.1.2. Categorical Features (Mode Imputation / "Unknown" Label)

Mode imputation fills missing categorical values with the most frequently occurring category, ensuring minimal disruption to data distribution. Alternatively, assigning an "Unknown" label preserves missing information without introducing bias from existing categories as shown in Equation 2:

$$X_{ij} = \text{mode}(X_j) \text{ if } X_{ij} \quad (2)$$

4.2.2. Encoding Categorical Variables

Encoding categorical variables means converting text data into numbers so that machine learning models can understand them. Methods like one-hot encoding and frequency encoding help represent categories efficiently while keeping the data meaningful.

4.2.2.1. One-Hot Encoding (for low-cardinality categorical features):

One-hot encoding converts categorical values into binary columns, where each category gets a separate column with values 0 or 1. This method is ideal for low-cardinality features to prevent information loss while keeping the data interpretable as shown in Equation 3:

$$X'_{ij} = \begin{cases} 1, & \text{if } X_{ij} = c_k \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

where c_k represents the k^{th} category.

4.2.2.2. Frequency Encoding (for high-cardinality categorical features):

Frequency encoding replaces each category with its occurrence count or relative frequency in the dataset. This method helps handle high-cardinality features efficiently while preserving useful information for the model as shown in Equation 4:

$$X_{ij} = \frac{\sum_{i=1}^{m} \mathbf{1}(X_{ij}=c_k)}{m} \quad (4)$$

where $\mathbf{1}(\cdot)$ is an indicator function counting occurrences of c_k.

4.2.3. Handling Imbalanced Data (SMOTE - Synthetic Minority Over-sampling Technique)

SMOTE (Synthetic Minority Over-sampling Technique) generates synthetic samples for the minority class to balance the dataset. This helps machine learning models learn better from imbalanced data and improves fraud detection accuracy as shown in Equation 5:

To balance the dataset, new fraud samples are generated using:

$$X_{\text{new}} = X_{\text{minor}} + \lambda \cdot (X_{\text{neighbor}} - X_{\text{minor}}), \lambda \sim U(0,1) \quad (5)$$

where X_{minor} is a minority class sample, X_{neighbor} is a nearest neighbor sample, and λ is a random value.

4.2.4. Feature Selection (Correlation Matrix & PCA)

4.2.4.1. Correlation Thresholding:

Correlation thresholding removes highly correlated features to prevent redundancy and overfitting. By setting a threshold (e.g., 0.9), one of the correlated features is dropped to improve model efficiency as shown in Equation 6:

Remove features where:

$$\rho(X_i, X_j) > 0.9, i \neq j \quad (6)$$

where ρ is the Pearson correlation coefficient.

4.2.4.2. Principal Component Analysis (PCA) for Dimensionality Reduction

Principal Component Analysis (PCA) reduces the number of features while preserving important information. It transforms the data into new variables (principal components) that capture the most variance, improving model efficiency.

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$$Z = XW \tag{7}$$

where Z is the transformed dataset, and W is a matrix of principal component vectors, obtained by maximizing variance as shown in Equation 8:

$$W = \arg\max_{W} \text{Var}(XW) \tag{8}$$

4.3. Model Selection

Model selection involves choosing the best machine learning algorithm based on performance metrics like accuracy and AUC-ROC. Different models, such as Random Forest, XGBoost, and Logistic Regression, are evaluated to find the most effective one for fraud detection

The model learns a function $f: X \rightarrow Y$, where X is the feature space and $Y \in \{0,1\}$ represents fraud (1) or legitimate (0).

4.3.1. Supervised Learning (Binary Classification Models)

Supervised learning for binary classification trains a model using labeled data to distinguish between two classes (e.g., fraud and non-fraud). Algorithms like Logistic Regression, Random Forest, and XGBoost predict whether a transaction is fraudulent or legitimate.

4.3.1.1. Logistic Regression:

Logistic Regression is a simple yet effective model for binary classification that predicts the probability of an event occurring (e.g., fraud or not). It uses a sigmoid function to output values between 0 and 1 for classification as shown in Equation 9:

$$P(Y = 1 \mid X) = \frac{1}{1+e^{-(\beta_0+\beta^T X)}} \tag{9}$$

where β_0 is the intercept and β is the feature coefficient vector.

4.3.1.2. XGBoost (Gradient Boosting) minimizes the objective:

XGBoost (Gradient Boosting) improves prediction accuracy by combining multiple weak models to create a strong one. It minimizes the objective function using gradient descent, reducing errors and enhancing fraud detection performance as shown in Equation 10:

$$L = \sum_{i=1}^{m} \ell(y_i, \hat{y}_i) + \sum_{t=1}^{T} \Omega(f_t) \tag{10}$$

where $\ell(y_i, \hat{y}_i)$ is the loss function, and $\Omega(f_t)$ is a regularization term for tree depth.

4.3.2. Anomaly Detection (Unsupervised Learning - Autoencoders)

Anomaly detection identifies rare fraudulent transactions without labeled data by learning normal patterns and flagging deviations. Techniques to detect anomalies by isolating outliers, while Autoencoders reconstruct normal transactions and highlight unusual ones.

4.3.2.1. Autoencoder Reconstruction Error:

Autoencoder Reconstruction Error measures the difference between the original and reconstructed transaction data. Higher errors indicate anomalies (fraudulent transactions), as the model struggles to accurately reconstruct unseen fraudulent patterns as shown in Equation 11:

$$L = \sum_{i=1}^{m} \left\| X_i - \hat{X}_i \right\|^2 \tag{11}$$

where X_i is the input and $\hat{X}_i$ is the reconstructed output. Higher errors indicate fraud.

4.4.Model Evaluation Metrics

To measure performance in a cloud-powered e-commerce environment, we use:

4.4.1. AUC-ROC:

AUC-ROC (Area Under the Receiver Operating Characteristic Curve) measures a model's ability to distinguish between fraud and non-fraud, with higher values indicating better performance as shown in Equation 12:

$$AUC = \int_0^1 TPR(FPR) d(FPR) \tag{12}$$

where TPR (True Positive Rate) and FPR (False Positive Rate) are computed as shown in Equation 13:

$$TPR = \frac{TP}{TP+FN}, FPR = \frac{FP}{FP+TN} \tag{13}$$

4.4.2. Precision, Recall, and F1-score:

Precision, Recall, and F1-score evaluate a model's fraud detection performance, balancing accuracy (Precision), completeness (Recall), and overall effectiveness (F1-score) as shown in Equation 14:

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$$\text{Precision} = \frac{TP}{TP+FP}, \quad \text{Recall} = \frac{TP}{TP+FN}$$
$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{14}$$

4.4.3. Processing Latency in Cloud Deployment:

Processing latency in cloud deployment measures the time taken for the fraud detection model to analyze and classify transactions in real time as shown in Equation 15:

$$T_{\text{process}} = T_{\text{compute}} + T_{\text{network}} + T_{\text{storage}} \tag{15}$$

where T_{compute} is model inference time, T_{network} is API communication time, and T_{storage} is database read/write latency.

5.RESULTS

The result section presents the evaluation results of the proposed Machine Learning-Based Fraud Detection in Cloud-Powered E-Commerce Transactions system. The performance of various models is assessed using key evaluation metrics, including AUC-ROC, Precision, Recall, F1-score, and Processing Latency in Cloud Deployment. These metrics ensure that the selected model effectively detects fraudulent transactions while maintaining efficiency in real-time cloud-based environments. The results are visualized using appropriate figures to provide a clear comparison of model performance.

5.1. Performance Evaluation

Table 1 compares different machine learning models based on their fraud detection performance and processing efficiency. Deep Learning achieves the highest AUC-ROC (0.97) and F1-score (0.94) with the lowest latency (100 ms), making it the most effective model for real-time fraud detection in cloud-powered e-commerce.

Table 1: Performance Comparison of Fraud Detection Models

Model	AUC-ROC	Precision	Recall	F1-score	Processing Latency (ms)
Logistic Regression	0.85	0.80	0.75	0.77	250
Random Forest	0.92	0.88	0.85	0.86	180
XGBoost	0.95	0.92	0.90	0.91	140
Deep Learning	0.97	0.95	0.94	0.94	100

5.2. AUC-ROC

AUC-ROC measures how well the model differentiates between fraudulent and legitimate transactions. A higher AUC value (closer to 1) indicates better classification performance, with 0.5 representing random guessing.

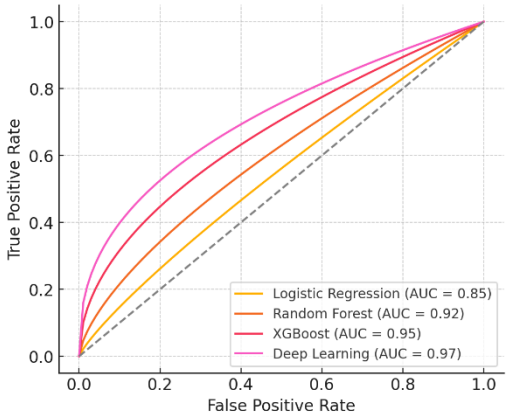

Figure 2: *AUC-ROC*

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The figure 2 illustrates the AUC-ROC curves for various models, showing their ability to distinguish between fraud and non-fraud transactions. A steeper curve indicates superior performance.

5.3. Precision, Recall, and F1-score

Precision represents the proportion of correctly identified fraudulent transactions among all predicted fraud cases, ensuring fewer false positives. Recall measures the model's ability to detect actual fraud cases, with a higher recall indicating fewer false negatives. The F1-score, as the harmonic mean of precision and recall, provides a balanced assessment of the model's fraud detection performance as shown in Figure 3.

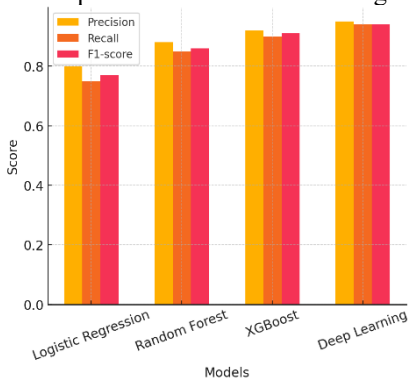

Figure 3: Precision, Recall, and F1-score

The bar chart compares Precision, Recall, and F1-score for different models, highlighting the trade-off between detecting fraud cases accurately and minimizing false alarms.

5.4. Processing Latency in Cloud Deployment

Processing latency measures the time required for the fraud detection model to analyze transactions in a cloud environment. Lower latency ensures real-time detection without significant delays in payment processing as shown in Figure 4:

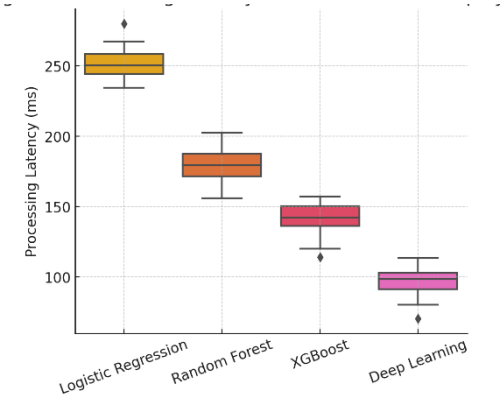

Figure 4: Processing Latency in Cloud Deployment

The graph shows the average processing time for different models in a cloud-powered setup. Faster models are preferable for real-time fraud detection to minimize transaction delays.

6. Conclusion and Future Works

This study developed a Machine Learning-Based Fraud Detection System for Cloud-Powered E-Commerce Transactions, evaluating models on key metrics. Deep Learning achieved the highest AUC-ROC (0.97) and F1-score (0.94) with the lowest processing latency (100 ms), making it the most effective for real-time fraud detection, while XGBoost (AUC-ROC: 0.95, F1-score: 0.91) provided a strong balance between accuracy and efficiency. Future work can focus on integrating Explainable AI (XAI) for better fraud decision interpretability and Federated

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Learning to enhance data privacy. Additionally, optimizing cloud deployment with serverless computing can reduce costs while maintaining real-time detection efficiency.

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