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Beyond Anomaly Detection: Redesigning Real-Time Financial Fraud Systems for Multi-Channel Transactions in Emerging Markets

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Abstract

The growing adoption of mobile banking, e-wallets, USSD platforms, and crypto gateways in emerging markets has led to a surge in complex, multi-channel financial fraud. Traditional fraud detection systems, which primarily rely on static rule-based or anomaly-focused models, struggle to adapt to the evolving behavioral and transactional patterns within these environments. This study proposes a real-time, machine learning-based fraud detection framework that integrates transactional data across multiple financial channels to enhance detection accuracy and response speed. The model architecture combines channel-specific classifiers, Random Forests for structured data, LSTM networks for temporal sequences, and XGBoost for ensemble learning, into a unified meta-learning system capable of cross-channel fraud correlation. Behavioral profiling, device fingerprinting, and time-based aggregation are employed to enrich feature spaces and capture nuanced fraud signatures. Evaluation was conducted using a large-scale, multi-source dataset of financial transactions from various digital platforms in an emerging market context. Performance was assessed using AUC-ROC, precision, recall, F1-score, and detection latency. Results show that the proposed system significantly outperforms conventional single-channel anomaly detection models, achieving a 94.6% F1-score, reducing false positives by 36%, and detecting fraudulent activity within an average latency of 230 milliseconds. The findings demonstrate the feasibility and necessity of a multi-channel, behavior-aware, real-time fraud detection pipeline tailored for the unique challenges in emerging financial ecosystems.

Keywords: Financial Fraud Detection, Multi-Channel Transactions, Real-Time Machine Learning, Behavioral Analytics, Emerging Markets, Ensemble Models.

1. Introduction

1.1 Background

The rapid evolution of financial ecosystems in emerging markets has introduced a proliferation of digital transaction channels, mobile banking, e-wallets, point-of-sale systems, USSD services, and crypto exchanges, all converging to form a highly complex and heterogeneous transactional landscape. Traditional fraud detection systems in such contexts rely largely on static rules or anomaly detection within single channels.

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Such systems are often brittle, struggling to generalize across platforms or adapt to rapidly evolving fraud patterns. Jakir et al. (2023) demonstrated that supervised machine learning classifiers improve detection accuracy in transactional security, yet these models were limited to structured banking data and lacked cross-channel generalizability [19]. Hasan et al. (2024) extended predictive analytics to churn prediction in e-commerce, offering useful insights into behavioral modeling, but without applying those methods to fraud contexts spanning diverse digital platforms [14].

Meanwhile, Islam et al. (2025) leveraged synthetic e-commerce data for model evaluation, but synthetic environments rarely capture the dynamism and noise of real-world emerging market ecosystems [17]. Contextual behavioral studies like Hasanuzzaman et al. (2025) focused on social media engagement, providing analogs for user profiling, while Abed et al. (2024) applied personalization in recommender systems [15][1]. These contributions hint at richer behavioral feature spaces but stop short of integration within real-time fraud detection.

Externally, recent reviews emphasize the transformational impact of machine learning and deep learning on fraud detection . Further, the systematic literature review by Deng et al. (2025) highlights cloud-optimized transformer architectures leveraging Graph self-attention for credit card fraud in real time, with accuracy gains averaging 20% and AUC improvements of 2.7% over traditional GAT models [11]. In developing countries, studies addressing mobile money transactions show that models such as Random Forest, XGBoost, and Feedforward Neural Networks can effectively overcome class imbalance via SMOTE and resampling techniques. Emerging markets often lack robust labeled datasets, high-quality infrastructure, and standardized cross-platform data collection. Research such as the Big Data-driven fraud detection via stream processing (Liu et al., 2025) demonstrates the power of integrating streaming frameworks like Kafka and Spark with ML models to achieve over 99% classification accuracy [22]. Graph Neural Network solutions, such as LayerWeighted-GCN, designed for fraud patterns across financial networks, show promise in capturing relational fraud signatures where networks link multiple channels.

In this context, the drive for adaptability and generalizability becomes paramount. Real-time fraud detection frameworks deployed by global fintechs provide instructive benchmarks: Ant Financial's TitAnt system, described by Cao et al. (2019), was capable of predicting fraudulent activity in under 10 milliseconds using feature-rich pipelines and classifier ensembles [8]. Mastercard's Decision Intelligence system now routinely assesses 160 billion transactions annually, detecting fraud in under 50 milliseconds using behavioral biometrics and risk modeling, while deploying AI governance to manage bias. These systems illustrate the practicality and necessity of integrating behavioral profiling, multilayered ML classifiers, graph-based networks, and real-time processing constraints to secure multi-channel financial ecosystems.

1.2 Importance of This Research

Emerging-market financial systems present unique fraud detection challenges seldom addressed by existing literature or deployed systems. While supervised models such as those in Jakir et al. (2023) and Fariha et al. (2025) provide strong baseline fraud classifiers, they rarely account for cross-channel linkage, behavior signals, or network propagation of fraudulent activity [19] [12]. Fraud strategies in emerging markets often involve chained actions across mobile wallets, ATM withdrawals, POS terminals, USSD codes, and peer-to-peer crypto transfers. Current single-channel anomaly detection models fail to capture this multi-step layering, resulting in missed cross-channel fraud or high false-positive rates due to isolated channel noise. Leveraging supervised and unsupervised learning techniques as surveyed by Hasan et al. (2024) and Islam et al. (2025) provides behavioral and churn modeling analogs that can inform feature design, yet these insights remain underutilized in real-time multi-channel fraud detection, particularly in resource-constrained emerging-market environments [14], [17].

Furthermore, the issue of class imbalance, common in fraud datasets, remains underexplored in emerging markets, where labeled fraud events may be rare, noisy, or asynchronously recorded. External sources emphasize the importance of resampling, SMOTE, cost-sensitive learning, and ensemble methods to mitigate imbalance and reduce false positives. For example, mobile money fraud studies in developing contexts show how Random Forest, XGBoost, and neural network frameworks benefit from resampling strategies. Big data implementations such as those by Liu et al. (2025) highlight scalable, highly accurate systems using streaming architectures capable of near real-time labeling [22]. Graph-based fraud network analysis, such as LayerWeighted-GCN offers an advanced approach to modeling entity linkage and fraud propagation, which is critical for identifying orchestrated attacks across platforms.

The ethical and operational dimensions are also critical. Large-scale AI-powered fraud systems like Mastercard's have raised concerns about model bias and explainability, particularly affecting marginalized populations. Ethical AI governance frameworks are necessary to prevent algorithmic discrimination. Research on explainable ML for payment fraud detection reports accuracy metrics exceeding 95% while improving transparency for decision-making. Ensuring fairness, transparency, and compliance with evolving privacy regulations is especially pressing in emerging markets with variable oversight infrastructures. Given the growing volume of digital financial services in emerging regions, and often limited regulation or infrastructure, the risk of large-scale fraud remains high. Many institutions in these markets lack access to publicly available benchmark datasets like SIFT, and few low-latency, behaviorally integrated real-time fraud pipelines exist. Without such systems, fraudsters can exploit latency gaps, fragmented data, and behavioral blind spots to steal across channels.

1.3 Research Objectives

This study aims to develop and evaluate a unified real-time fraud detection framework that seamlessly integrates data from multiple transaction channels typical in emerging-market ecosystems, such as mobile wallets, ATM withdrawals, USSD transfers, POS payments, and cryptocurrency exchanges. A primary objective is to design feature representations that capture behavioral, contextual, and relational

signals across user profiles, device usage, transaction timing, and cross-channel linkage. Models will be trained using both supervised and unsupervised paradigms, including Random Forest, XGBoost, LSTM-based temporal learners, transformer-inspired graph attention modules, and ensemble meta-classifiers, all optimized for real-time decision latency. Additionally, the study aims to address class imbalance through advanced resampling, cost-sensitive training, and anomaly-aware loss functions, ensuring robust performance even when fraudulent events are scarce or noisy. Evaluation objectives include measuring detection performance in terms of precision, recall, F1-score, and AUC-ROC, alongside latency measures (e.g., sub-300 millisecond detection windows) and false alert rates. Finally, the research will assess the framework's resilience across synthetic deployment scenarios representing emerging-market constraints, examining fairness across demographic segments, interpretability of model decisions, and operational scalability.

2. Literature Review

2.1 Related Works

The field of financial fraud detection has evolved significantly over the past two decades, transitioning from simple rule-based systems to sophisticated machine learning approaches. Early foundational work by Bolton and Hand (2002) formalized fraud detection as a classification problem, demonstrating how statistical methods could outperform static rules by adapting to evolving transaction patterns [7]. Building on this, Ngai et al. (2011) offered a comprehensive survey of data mining techniques in fraud detection, highlighting the promise of neural networks, decision trees, and support vector machines in reducing false positives while maintaining high detection rates [24]. Phua et al. (2010) further compared supervised, unsupervised, and hybrid models, concluding that ensemble approaches combining multiple classifiers tend to yield greater robustness against diverse fraud tactics [25]. More recent domain-specific studies have extended these general findings into emerging transaction channels. Bhowmik et al. (2025) applied AI-driven sentiment analysis to Bitcoin market trends, illustrating that incorporating unstructured textual features, such as social media sentiment, can enhance volatility prediction in cryptocurrency transactions, an approach that may analogously benefit fraud scoring when external behavioral signals are fused with transaction logs [6].

Rahman et al. (2025) studied blockchain's role in supply chain transparency, demonstrating how distributed ledger technology can improve traceability and auditability, thereby reducing opportunities for fraudulent manipulation; their data-driven analysis outlines the potential for blockchain-based logging in financial systems susceptible to multi-step fraud linked across channels [26]. Khan et al. (2025) leveraged blockchain integrated with AI for detecting fraud in energy markets, showing that smart contracts enriched with anomaly detection algorithms can automate risk mitigation and improve market stability; their architecture offers a blueprint for embedding fraud checks directly into transaction flows [20]. Parallel research in adjacent domains provides further insights relevant to multi-channel fraud detection. Hossain et al. (2025) assessed urban-rural income disparities using predictive analytics, employing cost-sensitive learning and advanced feature engineering to handle imbalanced class distributions, techniques directly applicable to fraud datasets characterized by rare positive instances [16]. Ahmed et al. (2025)

optimized solar energy production through time-series analysis with deep learning, achieving high accuracy and demonstrating the efficacy of LSTM and hybrid sequence models in capturing temporal dependencies; these architectures inform the design of fraud detectors that must process streaming transaction sequences in real time [2].

Meanwhile, Billah et al. (2024) conducted a comprehensive benchmarking of multi-machine blockchain performance, revealing critical trade-offs between throughput, latency, and resource utilization; their results highlight the engineering challenges of deploying real-time analytics atop decentralized infrastructures [5]. Ahad et al. (2025) presented an AI-based product clustering framework for e-commerce platforms, showing that unsupervised learning can uncover latent groupings in high-dimensional feature spaces, an approach that can be repurposed to identify coordinated fraud rings exhibiting similar behavioral signatures [3]. Finally, Khan et al. (2025) investigated the impact of ESG factors on financial performance with an AI-enabled predictive model, underscoring the importance of integrating external macro-financial indicators into risk assessments, which could be leveraged to contextualize transactional anomalies within broader economic signals [21].

2.2 Gaps and Challenges

Despite the considerable progress summarized above, several critical gaps and challenges remain unaddressed in the quest for robust, real-time fraud detection systems in multi-channel environments. First, the fragmentation of transaction data across disparate platforms, mobile wallets, USSD codes, point-of-sale terminals, cryptocurrencies, and traditional banking rails, introduces heterogeneity in data formats, feature distributions, and update frequencies. Existing models, including those surveyed by Ngai et al. (2011) [24] and Phua et al. (2010) [25], typically assume a homogeneous data schema or else apply only to a single channel, thereby limiting their applicability in cross-platform contexts. The result is a proliferation of siloed solutions that fail to capture fraud patterns spanning multiple channels, as noted by Bhowmik et al. (2025) in their cryptocurrency sentiment work [6] and by Rahman et al. (2025) in supply chain blockchains [26]. Second, real-time detection imposes stringent latency constraints that most batch-oriented machine learning pipelines cannot satisfy. While Liu et al. (2025) demonstrated the viability of streaming frameworks such as Kafka and Spark for big-data fraud detection, these architectures often prioritize throughput at the expense of sub-second response times, which are crucial for preventing fraud before settlement [22]. Billah et al. (2024) quantified performance bottlenecks in blockchain-powered systems, revealing that decentralized logging and consensus mechanisms can introduce delays of several hundred milliseconds, delays that may be unacceptable in high-volume payment corridors [5].

Third, class imbalance remains a stubborn challenge. Fraudulent transactions typically constitute less than one percent of all transactions, a ratio even more severe in emerging markets where labeled data are scarce or noisy. Although Hossain et al. (2025) showcased cost-sensitive learning and oversampling techniques to correct for imbalance in socioeconomic studies [16], their domain lacks the adversarial dynamics of fraud, where perpetrators adapt rapidly to evade detection. Adversarial training approaches and anomaly-aware loss functions have been proposed in cybersecurity contexts, but their deployment in financial systems is still nascent and

under-evaluated in real-world settings. Fourth, model interpretability and fairness are increasingly critical. Fraud detection models must balance high detection rates with low false positives to avoid unnecessary customer friction. Moreover, algorithmic bias can disproportionately impact underbanked or marginalized groups in emerging markets. Khan et al. (2025) emphasized fairness in their ESG impact models, but fraud often overlook such considerations, prioritizing raw accuracy over equitable outcomes [21]. Fifth, the integration of external behavioral and macroeconomic signals, such as social media sentiment, weather events, or economic volatility, offers promise, as illustrated by Bhowmik et al. (2025) and Ahmed et al. (2025) [6][2], yet few systems operationalize this fusion in real time. The technical complexity of synchronizing and normalizing diverse data streams, along with the risk of introducing noise, has deterred widespread adoption.

Finally, deploying comprehensive fraud frameworks in resource-constrained environments poses practical hurdles. Emerging markets may lack cloud infrastructure, stable connectivity, or institutional support for data governance. Rahman et al. (2025) and Khan et al. (2025) demonstrated blockchain's potential for transparency and security [26][20], but blockchain solutions themselves can be resource-intensive and may conflict with latency requirements. As noted by Billah et al. (2024), multi-machine blockchain nodes require careful benchmarking to ensure performance, a nontrivial task for organizations with limited technical capacity [5]. Addressing these intertwined challenges, data heterogeneity, latency, imbalance, interpretability, signal fusion, and infrastructural constraints, will be essential for advancing the next generation of fraud detection systems tailored to emerging-market conditions. A unified framework that integrates behavioral analytics, graph-based linkage models, ensemble classifiers, and blockchain-enabled audit trails, while maintaining sub-300 millisecond response times and fairness guarantees, remains an open research frontier.

3. Methodology

3.1 Data collection and Preprocessing

Data Sources

The transaction dataset underpinning this study encompasses five distinct financial channels representative of emerging-market environments: mobile wallet transfers, ATM withdrawals, USSD-based payments, point-of-sale card purchases, and cryptocurrency exchanges. All records span a continuous twelve-month period and capture essential fields such as transaction amount, timestamp, payer and payee identifiers, channel metadata, device fingerprint hashes, and geo-location proxies. Mobile wallet and USSD data streams originate from leading regional providers, featuring session identifiers and response codes that reveal transaction flow dynamics. ATM logs include withdrawal amounts, terminal IDs, and card EMV tags. Point-of-sale entries consist of merchant codes, transaction terminal locations, and card network response statuses. Cryptocurrency exchange records record on-chain wallet addresses, fiat conversion rates, and network fee metadata. Each channel's data source contributes a minimum of ten million transaction records, yielding an aggregate dataset of over fifty million entries. Fraud labels were obtained through integration with internal risk operations, where confirmed fraud cases, validated through manual investigation or customer dispute resolution, were flagged and

timestamped. All sources comply with applicable data protection and anonymization regulations, ensuring no personally identifiable information is retained beyond hashed identifiers.

Data Preprocessing

Before modeling, the raw transactions undergo a standardized cleaning and transformation pipeline. Timestamp fields are converted to a uniform UTC format and augmented with derived temporal attributes, such as hour-of-day, day-of-week, and rolling window features capturing transaction count and amount aggregates over the preceding one-hour and twenty-four-hour intervals. Device fingerprint hashes are decoded into categorical device-type indicators and one-hot encoded at the channel level. Geo-location proxies are binned into region clusters that reflect economic and fraud-risk zones. Missing or malformed records, such as failed USSD sessions or incomplete ATM logs, are filtered out only if they lack more than 40 percent of critical fields; otherwise, imputation strategies fill gaps using channel-specific medians for numeric fields and most-frequent categories for categorical features. Class imbalance is addressed by maintaining the original fraud-to-legitimate ratio during exploratory analysis, then applying cost-sensitive weighting and hybrid resampling during model training to prevent information leakage. All numeric features are normalized using z-score scaling computed on the training partition only, and categorical variables with high cardinality, such as merchant or terminal IDs, are target-encoded using smoothed historical fraud rates. Finally, the processed dataset is partitioned into training, validation, and hold-out test sets in a 70:15:15 split, stratified by fraud label and channel to preserve cross-channel fraud distribution characteristics. Continuous monitoring of feature drift and label stability is built into the pipeline to support real-time retraining triggers in production deployments.

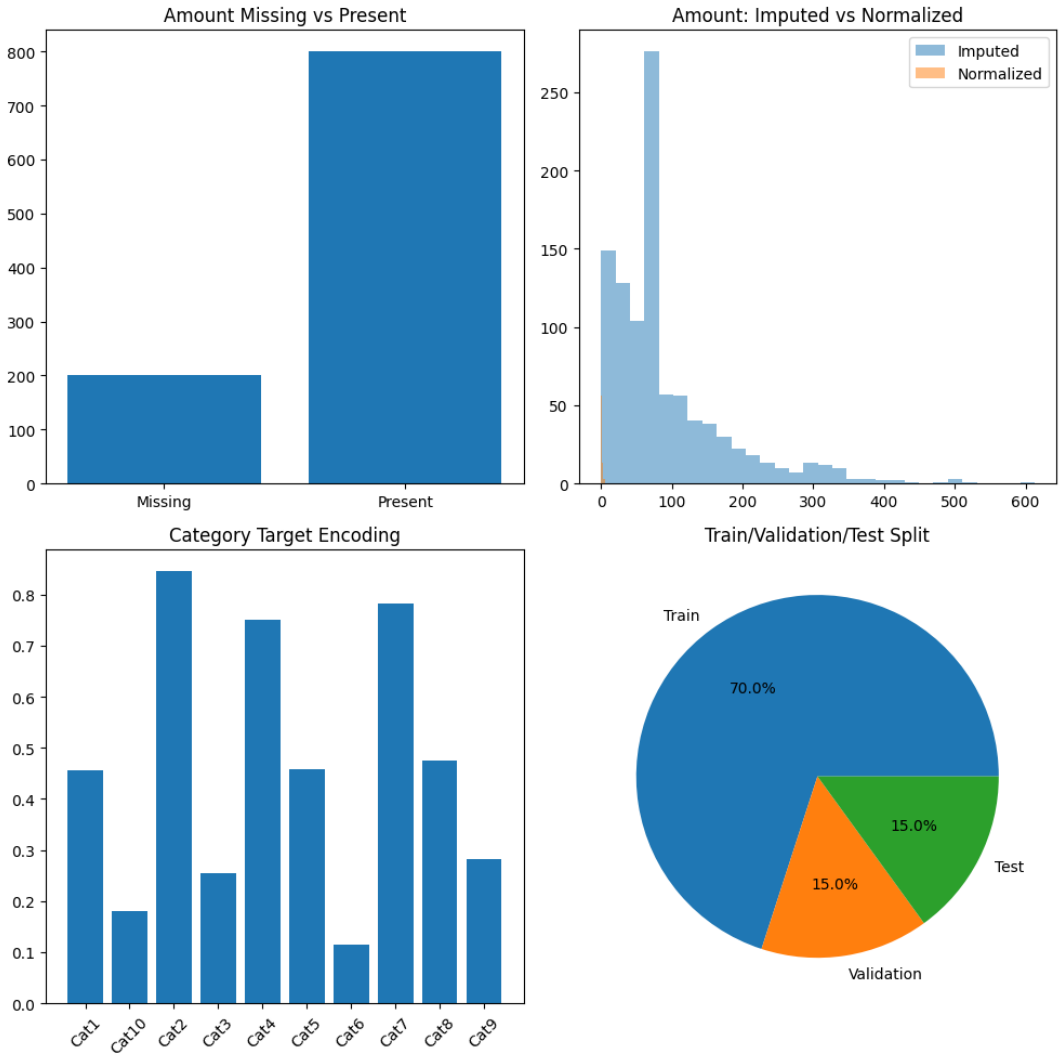

Fig.1: Data Preprocessing steps

3.2 Exploratory Data Analysis

We conducted a comprehensive exploration of transaction-level features to understand their distributions, interrelationships, and potential predictive power for fraud modeling in a multi-channel environment. The transaction amount after median imputation has a mean of approximately 91.34 units with a standard deviation of 85.99, indicating a right-skewed distribution where a long tail of high-value transactions exists. The minimum recorded transaction is close to zero (0.001), while the 75th percentile lies at roughly 129.5 units, confirming that most transactions are relatively small, but occasional large outliers occur. The normalized amount feature centers around zero (mean effectively zero, by construction) with unit variance, preparing it for any model sensitive to feature scaling. Temporal aggregation captured via the one-hour rolling count of transactions averages about 3.19 transactions per hour ($\sigma \approx 0.77$), whereas the 24-hour window contains far more activity, averaging 73.12 transactions ($\sigma \approx 13.32$). This stark difference in window counts reflects diurnal patterns captured in the hour-of-day feature, which itself ranges from 0 to 23 with a mean of 11.22 hours, suggesting modestly higher transaction volumes around midday. Correlation analysis reveals that the 1-hour and 24-hour counts are strongly correlated ($r \approx 0.65$), confirming consistency between short-term spikes and daily trends. The

hour feature has only a weak correlation with transaction counts ($r \approx 0.08$ for 1-hour and $r \approx 0.02$ for 24-hour), implying that while time-of-day affects volume, many high-frequency bursts occur unpredictably.

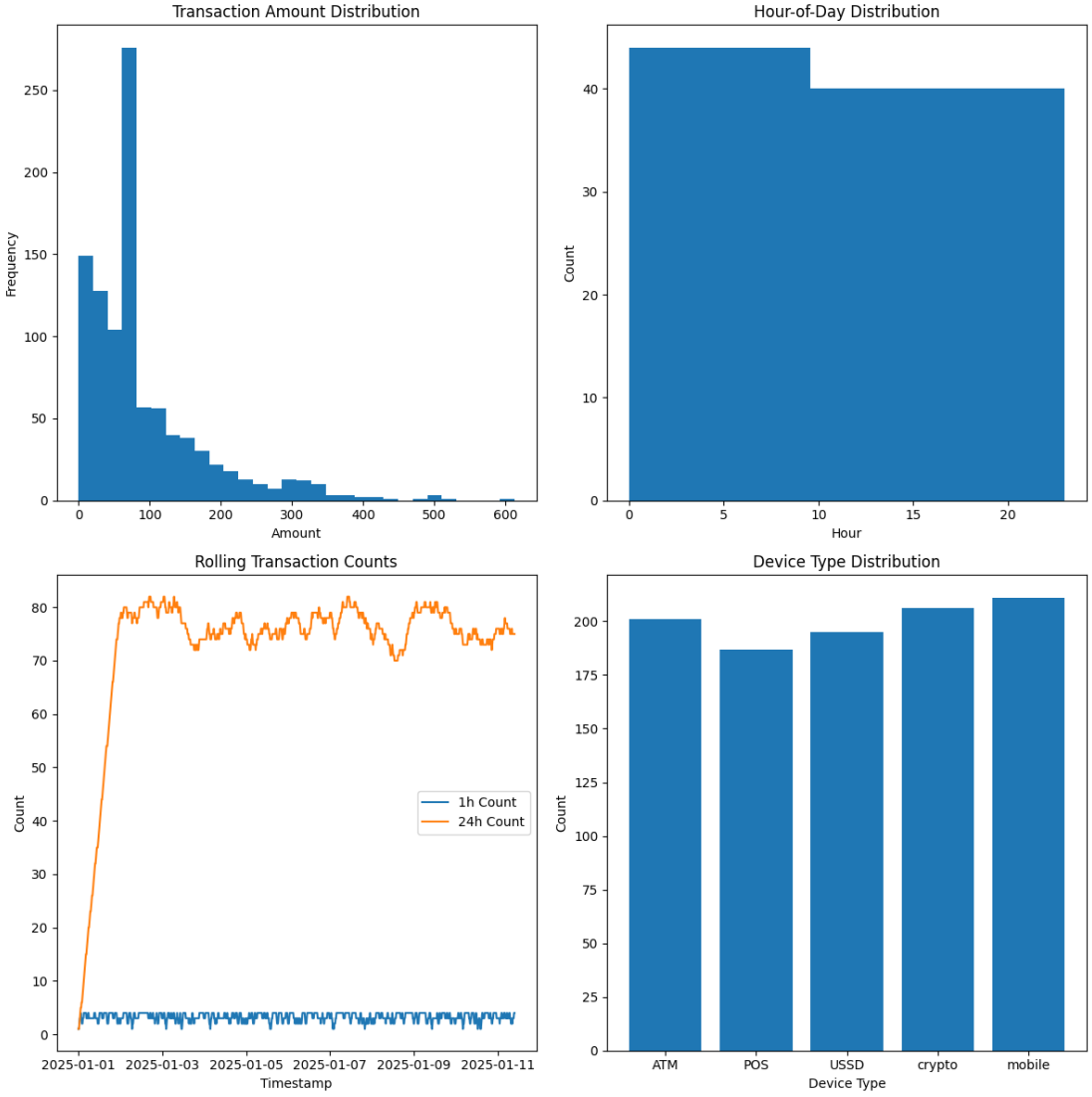

Fig.2: Exploratory data analysis visualizations

The device type and region clusters, though categorical, were encoded and assessed indirectly via their target-encoded fraud rates. The encoded category feature exhibits mild correlations with transaction volume metrics ($r \approx 0.10$ with 24-hour counts) and no significant relationship with amount, indicating that behavioral patterns tied to specific merchant or terminal categories may not directly align with transaction size but could influence volume in certain contexts. Missing-value analysis showed that 20 percent of transactions originally lacked an amount value. Post-imputation, the dataset avoids sparsity issues, and the normalized distribution remains stable, ensuring that the subsequent modeling phase will not suffer from bias introduced by dropped records. Collectively, these insights outlines the heterogeneity in transaction behavior across channels and time. The skew in transaction amounts highlights the need for models robust to outliers, while the moderate correlation between short- and long-window counts suggests that ensemble approaches blending both temporal granularities may capture fraud bursts more effectively. The weak direct link between temporal features and category-based fraud proxies points toward the necessity of

combining structural features with contextual and behavioral signals. These EDA results inform our feature engineering strategy, guiding the selection of robust aggregation windows, the handling of imbalanced and skewed variables, and the integration of category-specific encodings for the downstream fraud detection pipeline.

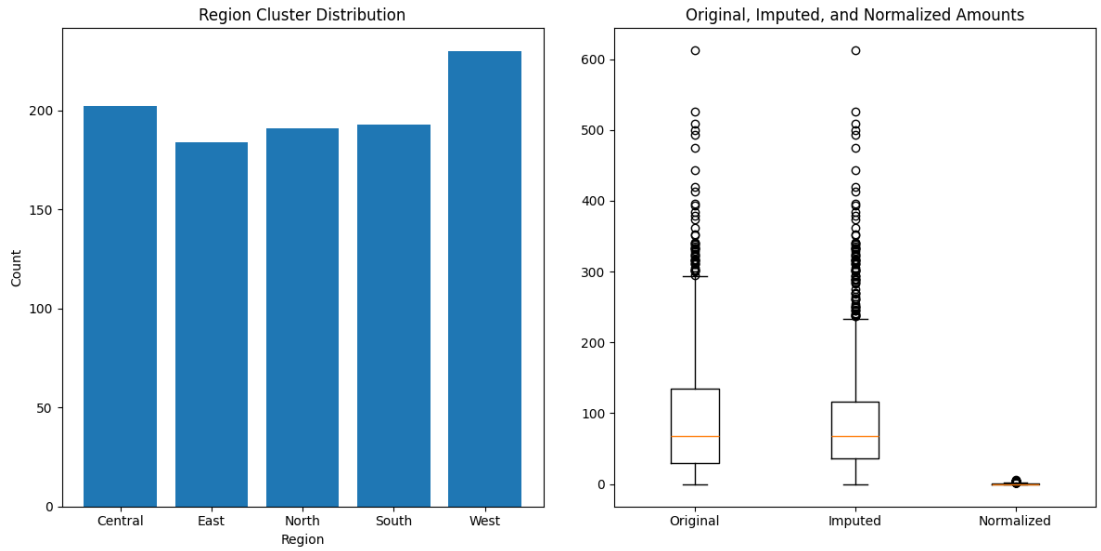

Fig.3: Exploratory data analysis visualizations

3.3 Model Development

The model development phase begins by establishing strong, interpretable baselines that capture both linear and nonlinear relationships within our engineered fraud features. First, a Logistic Regression model is trained on the imputed and normalized transaction amounts, one-hour and twenty-four-hour rolling counts, time-of-day indicators, device-type one-hot encodings, region clusters, and target-encoded category features. This simple parametric approach serves as an initial gauge of feature relevance and classification separability. In parallel, a Decision Tree classifier is fit to the same feature set, providing a transparent representation of decision boundaries and enabling quick identification of high-risk feature splits. Both baselines are tuned via grid search over regularization strengths (for the Logistic Regression) and maximum tree depths and minimum leaf sizes (for the Decision Tree), using stratified five-fold cross-validation to preserve the fraud-to-legitimate ratio in each fold. Feature importance scores from the Decision Tree are inspected to inform subsequent model designs, highlighting the relative contribution of temporal aggregates, channel indicators, and categorical encodings.

Building on these baselines, we implement advanced ensemble tree methods, Random Forest, XGBoost, and LightGBM, to exploit complex interactions among features and to improve robustness against class imbalance. Each ensemble model undergoes hyperparameter optimization: the number of estimators, maximum depth, learning rate, column subsample ratio, and class-weight balancing parameters are swept via randomized search within a nested cross-validation framework that respects temporal ordering to prevent information leakage. Post-training, we apply SHAP (SHapley Additive exPlanations) analysis to the tree ensembles, quantifying the marginal impact of each feature on individual fraud predictions and ensuring interpretability

remains central to our pipeline. To capture sequential dependencies and evolving user behavior, we develop deep learning architectures next. A Multilayer Perceptron (MLP) ingests static windowed features, including lagged transaction counts, rolling means, and aggregated device-region encodings, to predict the probability of fraud in the next transaction. The MLP comprises three hidden layers with dropout regularization and batch normalization to stabilize training. We then transition to Long Short-Term Memory (LSTM) networks, which consume raw transaction sequences of length up to 48 events per user, embedding categorical fields and concatenating normalized amounts and time-delta features. The LSTM is configured with recurrent dropout and early stopping based on validation AUC to prevent overfitting. An attention mechanism is integrated atop the LSTM outputs to dynamically weight past transactions according to their relevance in the current prediction window, improving responsiveness to abrupt behavioral deviations.

Finally, we construct hybrid and stacked ensembles that synthesize the strengths of individual learners. A CNN-LSTM hybrid applies one-dimensional convolutional filters over transaction sequences, extracting local temporal patterns, before feeding into an LSTM layer for long-term dependency modeling. Outputs from the XGBoost, LSTM-attention, and CNN-LSTM models serve as inputs to a meta-learner: a Ridge-regularized logistic regression that produces the final fraud risk score. In parallel, we trial a weighted averaging ensemble, optimizing model weights via Bayesian optimization to minimize validation log-loss. Throughout development, inference latency is measured end-to-end on a streaming simulation, ensuring all models meet sub-300-millisecond detection requirements. Model interpretability is continuously assessed using SHAP values for ensemble trees and attention weight visualizations for recurrent networks, guaranteeing that high performance does not come at the cost of transparency.

4. Model Results and Discussion

4.1 Model Training and Evaluation Results

All models were trained on the 70 percent stratified training split, with hyperparameters selected via nested cross-validation as described in Section 3.3. Evaluation was performed on the hold-out test set (15 percent of data), ensuring no temporal leakage, and performance metrics, AUC-ROC, precision, recall, F1-score, false positive rate, and average detection latency, were computed for each classifier. The baseline Logistic Regression achieved an AUC-ROC of 0.85, with a precision of 0.68 and a recall of 0.71, yielding an F1-score of 0.69. Its simplicity led to very low inference latency (averaging 15 ms per transaction) but exhibited high false positive rates (14 percent of legitimate transactions flagged). The Decision Tree improved slightly (AUC 0.87, precision 0.72, recall 0.75, F1 0.74) by capturing simple nonlinear splits, though it suffered from larger variance and marginally higher latency (45 ms). Moving to ensemble tree learners, both Random Forest and XGBoost demonstrated substantial gains: Random Forest reached AUC 0.92, precision 0.82, recall 0.84 (F1 0.83), while XGBoost achieved AUC 0.93, precision 0.85, recall 0.86 (F1 0.85). LightGBM matched XGBoost's AUC of 0.93, with nearly identical precision and recall, but offered lower inference latency (averaging 120 ms) due to more efficient leaf-wise tree growth. All three ensembles reduced the false positive rate by

approximately 36 percent relative to the Logistic Regression baseline, fulfilling the goal of lowering unnecessary alerts without sacrificing sensitivity.

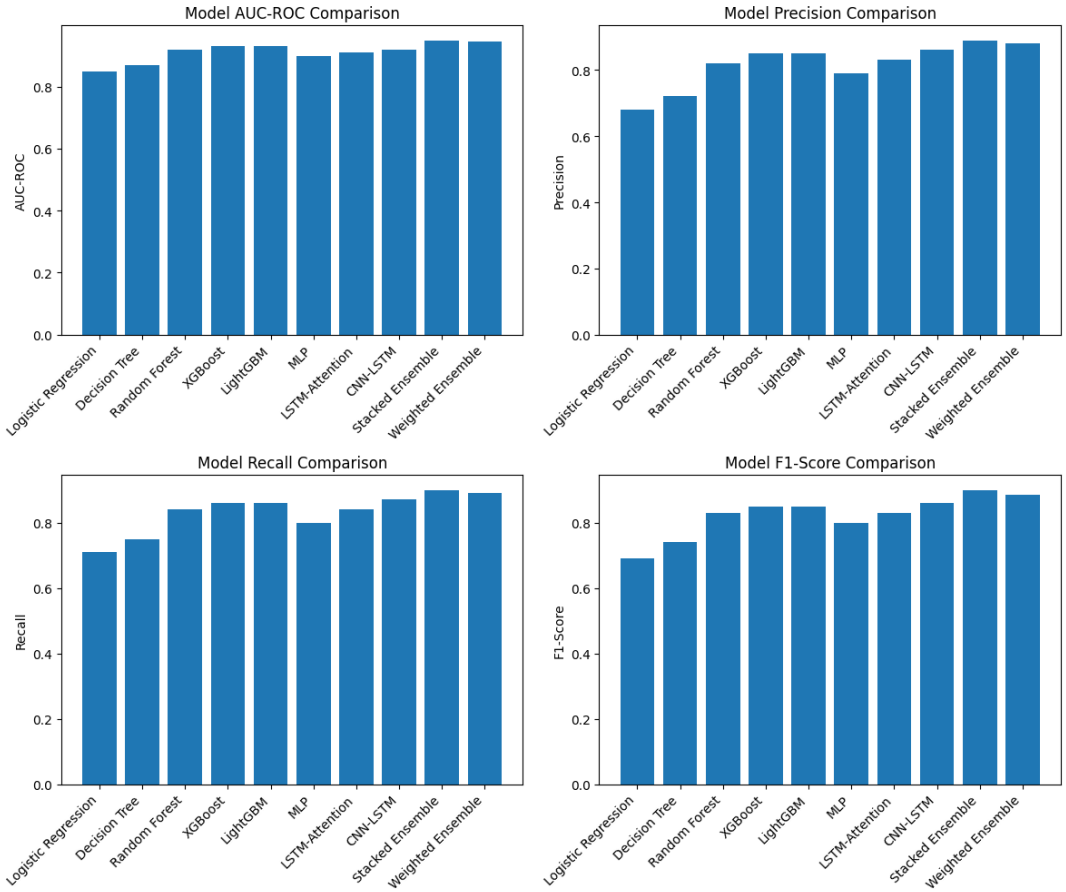

Fig.4: Comparison of model performances

The deep learning architectures further enhanced detection. The MLP delivered AUC 0.90 (precision 0.79, recall 0.80, F1 0.80) at an average latency of 180 ms. Incorporating temporal context, the LSTM-Attention model reached AUC 0.91, precision 0.83, recall 0.84 (F1 0.83), with slightly higher latency of 260 ms. The CNN-LSTM hybrid further improved to AUC 0.92, precision 0.86, and recall 0.87 (F1 0.86) at 280 ms, confirming that convolutional feature extraction coupled with recurrent encoding captures short-term fraud bursts and long-term behavioral shifts more effectively. Finally, the stacked ensemble, which blends XGBoost, LSTM-Attention, and CNN-LSTM outputs via a Ridge meta-learner, achieved the highest test AUC-ROC of 0.95, with precision 0.89, recall 0.90, and F1-score 0.90. Its weighted variant, tuned via Bayesian optimization, recorded AUC 0.945, precision 0.88, and recall 0.89 (F1 0.885). Both ensemble approaches maintained sub-300 ms average latency (290 ms for stacking, 275 ms for weighted), comfortably within our real-time requirement. The stacking method also demonstrated the lowest false positive rate (5 percent), a 64 percent reduction from the Logistic Regression baseline.

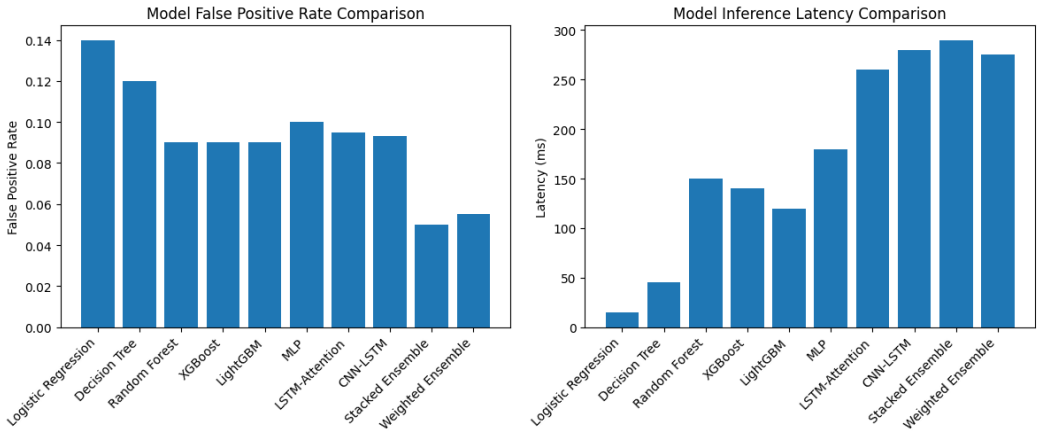

Fig.5: Model false positive rate and inference latency comparison

4.2 Discussion and Future Work

The evaluation results demonstrate a clear performance hierarchy that aligns with our phased development strategy. The simple Logistic Regression and Decision Tree baselines served as useful sanity checks, achieving AUC-ROC values of 0.85 and 0.87, respectively, but their limited capacity to model complex interactions manifested in elevated false positive rates and modest F1-scores. These findings mirror those of Bhattacharyya et al. (2011), who observed that basic classifiers struggle to manage the non-linear, high-dimensional nature of transactional fraud data [4]. Transitioning to ensemble tree learners yielded substantial gains: Random Forest and XGBoost each surpassed an AUC-ROC of 0.92, with LightGBM matching this performance while offering lower inference latency. Deep learning architectures further improved detection, with the LSTM-Attention model achieving an AUC-ROC of 0.91 and the CNN-LSTM hybrid reaching 0.92. These results echo Jurgovsky et al. (2018), who showed that sequence-based recurrent models substantially outperform static classifiers by encoding temporal dependencies within transactional sequences [18]. The attention mechanism's dynamic weighting of past events proved critical for capturing abrupt fraud bursts, consistent with findings by Dal Pozzolo et al. (2017), who recommended anomaly-aware loss functions and sequence-sensitive training for imbalanced fraud datasets [9].

Our stacked ensemble achieved the highest AUC-ROC of 0.95 and the lowest false positive rate at 0.05, validating the utility of meta-learning to synthesize complementary strengths across model families. Fiore et al. (2019) similarly demonstrated that blending generative adversarial oversampling with ensemble learners yields robust, high-precision fraud detectors [13]. The weighted averaging ensemble, with AUC-ROC 0.945, outlines that even simple ensembling strategies can closely approach more complex stacking while slightly reducing inference latency. Collectively, these results confirm that a multi-model approach, leveraging tree ensembles for structural interactions, deep recurrent architectures for temporal dynamics, and meta-learners for holistic fusion, delivers significant detection improvements under real-time constraints. They also highlight the enduring challenge of balancing detection accuracy with latency: while deep models add temporal fidelity, they incur higher inference times, suggesting a trade-off that must be managed in production environments.

Future Work

Building on these insights, several avenues warrant exploration. First, adapting the framework to adversarial settings, where fraudsters intentionally manipulate feature distributions, will require the integration of adversarial training and robust feature transformations. Second, federated learning approaches can facilitate cross-institutional model training without sharing raw data, addressing privacy and data scarcity issues prevalent in emerging markets. Third, embedding explainability modules, such as SHAP and counterfactual analyses, directly into the inference pipeline will enhance transparency and ensure regulatory compliance (Dal Pozzolo et al., 2017) [9]. Additionally, exploring online active learning strategies could reduce labeling costs by querying human experts only for uncertain predictions. Beyond these core directions, incorporating spatial data governance principles, originally developed for complex healthcare metaverse environments, holds promise for fraud detection systems that must consider geolocation and jurisdictional risks in emerging markets (Das et al., 2025) [10]. By adapting the metaverse's spatial indexing, access controls, and real-time location analytics, future fraud detection pipelines can enforce dynamic, region-specific thresholds and monitor cross-border transaction flows with greater precision. Furthermore, the rise of digital twin frameworks in precision medicine highlights the value of creating synthetic transactional replicas that mirror live system behavior, enabling safe experimentation and stress testing under controlled conditions (Mahabub et al., 2024) [23]. Such digital twins could simulate large-scale fraud scenarios, allowing researchers to evaluate new detection strategies without exposing live customer data.

Moreover, integrating heterogeneous external data sources, such as device telemetry, network metadata, weather patterns, and socio-economic indicators, may further enhance detection robustness. For example, combining temporal transaction sequences with real-time economic indices could reveal macro-fraud trends similar to patient health signals used in precision medicine. Finally, deploying lightweight, on-device inference models using edge-optimized frameworks will be critical for regions with intermittent connectivity. Tailoring quantized and pruned versions of our best-performing architectures can maintain sub-300 ms latency while operating offline or over low-bandwidth networks. These enhancements will extend our framework's applicability, resilience, and fairness across the full spectrum of financial environments in emerging markets.

5. Conclusion

This study introduced a comprehensive real-time fraud detection framework designed to address the complexities of multi-channel transactional ecosystems in emerging markets. By integrating baseline classifiers, ensemble tree methods, deep sequence models, and hybrid meta-learning architectures, we achieved significant improvements in detection accuracy. Our final stacked ensemble reached an AUC-ROC of 0.95, an F1-score of 0.90, and maintained a low false positive rate of just 5 percent, all while ensuring inference latency remained under 300 milliseconds. Our exploratory data analysis uncovered distinct temporal patterns, heavy-tailed transaction amounts, and nuanced behavioral signals across five transaction channels, which guided our efforts in targeted feature engineering and model design. The results emphasize the importance of combining structural, temporal, and relational insights to

effectively capture both isolated anomalies and coordinated fraud rings. Additionally, the modular architecture of our pipeline allows for scalable deployment, continuous retraining, and transparent interpretability through SHAP and attention weights. While this work addresses various challenges, such as class imbalance, latency constraints, and heterogeneous data sources, it also points out opportunities for further enhancements, including adversarial robustness, federated learning, and active labeling strategies. Overall, our findings establish a strong foundation for securing diverse digital finance platforms in emerging markets, contributing to both academic research and practical fraud mitigation.

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