Context-Aware Fraud Detection Models Deployed via Feature Pipelines in ML Flow

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Abstract- The ability and proficiency of fraud perpetrators to deceive and manipulate financial and digital systems have necessitated the development of intelligent and context-aware fraud detection models. Classical fraud detection systems are characterized by static rule-based systems and basic machine learning approaches that do not consider real-time context signals as user activity, transaction speed, device location, and session veracity. To overcome these shortcomings, this paper presents a process for creating and deploying context-aware fraud detection models non-intrusively, based on feature pipelines with MLFlow integration.

The proposed solution focuses on dynamic feature engineering, utilizing features such as behavior patterns, space-time information, and device-level fingerprints. The context-rich features are consumed by modular pipelines, which make it easy to transform, validate, and reuse in various machine learning workflows. Using MLFlow for experiment tracking, model versioning, and automatic deployment, the system provides traceability, reproducibility, and manageability along the life cycle of fraud detection models.

This paper demonstrates how contextual features can increase the average ROI when used in conjunction with XGBoost, LightGBM, Random Forest, and other popular machine learning algorithms. A comparative study is performed on a structured transaction dataset enriched with surrounding information. Standard evaluation metrics (precision, recall, F1-score) show significant enhancements over the non-contextual baseline models. Furthermore, the framework includes monitoring and automatic drift detection with its integrated features of MLFlow so that models can accommodate the latest fraud techniques (about 1 hour after) in near real-time.

The primary objective of this work is to leverage context-aware fraud detection models in conjunction with MLFlow's operational features. This enables data scientists and fraud analysts to collaborate on creating, testing, and deploying models to production, ensuring they are both explainable and compliant with regulatory standards. The paper also describes the architecture's ability to provide continuous model improvement through reinforcement loops with live environments.

The context-aware method proposed in this paper significantly enhances the accuracy of fraud detection and reduces false positives. Paired with an MLFlow-heavy MLOps infrastructure, this approach provides a scalable and transparent solution for both financial institutions and digital platforms seeking to strengthen their defenses against emerging forms of fraudulent behavior. This study opens up new prospects for fraud analytics research by connecting the dots between contextual intelligence and “productionalised” deployment processes.

Keywords- Context-aware fraud detection, MLFlow, feature pipelines, MLOps, machine learning, real-time analytics, financial fraud, model deployment, behavioral analysis, data lineage, feature engineering, model drift, adaptive fraud detection, transactional intelligence.

I. INTRODUCTION

Digital ecosystems: Fraud in digital ecosystems is an emerging and complex phenomenon that develops alongside the rapid advancement of technology resources and increased usage opportunities, often exploiting users' anonymity. Sectors such as banking, insurance, and e-commerce are continually seeking more effective and efficient methods to detect and prevent fraudulent behavior. Many traditional fraud detection solutions, based on predefined business rules and static feature-based models, significantly lose their effectiveness and efficiency in dynamic and adversarial environments. With fraudsters evolving fraud-as-a-service offerings, there is a heightened demand for detection models that can reason about the context of transactions.

Context-aware fraud detection represents a new paradigm, as it leverages new layers of context related to the environment and transaction actor behavior. This may include, among other things, location information, time of day, or other activity-specific information, device fingerprints, transaction history, end-user usage trends, and session-based analytics. These kinds of insights are valuable in providing richer descriptions of activities and help the models discriminate between normal anomalies and, in fact, fraudulent intent. In the context of context-aware deception detection, promising results are being demonstrated, including increased accuracy and decreased false positives, which are often the most significant issues in user-oriented environments.

While context-aware modeling has clear advantages, many challenges remain to operationalize context-aware models reliably and scalably. Developing production-ready pipelines that constantly ingest input data, process features, track model performance, and manage model versions is accomplished through a structured machine learning operations (MLOps) framework. Solution: As of today, MLFlow is an open-source project designed to meet the exact needs of dataset management, with experiment tracking, reproducible pipeline orchestration, model registry, and deployment integration. It provides a centralized hub where data scientists and engineers can collaborate to run feature engineering, model training, and deployment workflows at scale in a consistent and reproducible manner.

This paper presents a method for developing, deploying, and maintaining context-aware fraud detection models using feature pipelines orchestrated by MLFlow. Modularity and scalability - This includes the development of pluggable and scalable feature pipelines for context-rich data, as well as the training of machine learning models, such as XGBoost and LightGBM, on top of these enriched features. Experiments are tracked, metrics are logged, and model artifacts (versions) are stored through MLFlow for deployment and retraining. The paper also emphasizes the importance of continuous learning and monitoring: a model's performance is evaluated in real-time and continuously retrained when drift or degradation is detected.

Combining context-aware intelligence with state-of-the-art MLOps solutions, this framework aims to develop fraud detection systems that are not only intelligent but also robust, adaptive, and auditable. The case study in the paper shows how the proposed framework can be applied to synthetic transaction data that has been enriched with realistic contextual signals. The results of our evaluation demonstrate higher precision, recall, and overall detection performance, affirming the effectiveness of context-aware modeling for fraud prevention.

The remainder of this section provides a review of the literature on context-aware detection systems and MLOps integrations, a description of the methodology used to design the feature pipelines, the experimental results, and a discussion of operational concerns and future work.

II. LITERATURE REVIEW

The field of fraud detection has traditionally been dominated by rule-based systems and static machine learning models that rely on historical data and fixed features. However, the growing sophistication of fraud techniques and the dynamic nature of digital transactions have exposed the limitations of such approaches [1]. Recent research emphasizes the importance of context in fraud detection, recognizing that understanding the situational and behavioral background of a transaction leads to more accurate predictions and fewer false positives.

Context-aware systems, widely explored in domains such as recommendation engines and adaptive user interfaces, have recently been applied to fraud analytics. According to Maes et al., incorporating user behavior patterns and contextual metadata into predictive models significantly improves their capacity to detect non-obvious fraud signals [2]. Features such as device fingerprints, geo-locations, session duration, and transaction timing add vital layers of interpretability and intelligence to traditional feature vectors.

The use of temporal and spatial context has shown measurable benefits in fraud detection. Jiang et al. developed a deep learning model that integrates recurrent neural networks (RNNs) with geospatial data to detect suspicious patterns in financial transactions, yielding higher recall scores without sacrificing precision [3]. Their work highlights how real-time behavioral context enables models to adapt to everyday user routines and effectively flag deviations.

Another critical development is the formalization of MLOps tools and frameworks to support the operational deployment of machine learning systems. MLFlow, proposed by Zaharia et al., has emerged as a robust platform for managing the full ML lifecycle, including experimentation, reproducibility, deployment, and monitoring [4]. Its modular architecture supports integration with various tools like TensorFlow, PyTorch, Scikit-learn, and Apache Spark. MLFlow’s feature store functionality, which enables the creation and versioning of dynamic feature pipelines, is especially relevant for deploying context-aware models in production.

Feature pipelines themselves have evolved from simple data preprocessing scripts to complex modular workflows capable of handling real-time feature computation and transformation. Studies by Hynes et al. demonstrate how real-time feature engineering pipelines can utilize streaming data sources, such as Apache Kafka or AWS Kinesis, to support adaptive learning systems [5]. These pipelines are particularly useful for fraud detection, where the response time window is critically short and requires instantaneous context evaluation.

A growing body of work is also examining model retraining strategies and drift detection mechanisms in fraud detection systems. Zhang and Lin discuss how feature drift, particularly in user behavior or transaction types, can lead to model obsolescence if not adequately monitored and retrained [6]. They propose integrating concept drift detection algorithms within MLFlow pipelines to maintain performance over time.

Furthermore, the use of synthetic data and data augmentation has been explored to enhance training data availability in scenarios involving rare-event fraud detection. Synthetic minority over-sampling techniques (SMOTE), as reviewed by Douzas et al., have helped balance datasets, although care must be taken to preserve contextual integrity during augmentation [7]. Properly engineered synthetic data must retain contextual coherence, especially in models that depend on behavioral and environmental signals.

Despite these advancements, a gap remains in the literature regarding the full integration of context-aware modeling, automated feature pipelines, and MLOps platforms, such as MLFlow, for real-world fraud detection. This paper aims to fill that gap by proposing a unified approach that leverages context-enriched features, MLFlow-based orchestration, and continuous monitoring mechanisms for robust and scalable fraud prevention systems.

III. METHODOLOGY

This study proposes a comprehensive pipeline-based methodology for developing and operationalizing context-aware fraud detection models using MLFlow. The methodology is structured into several interdependent components: contextual feature engineering, pipeline construction, model training, MLFlow integration, deployment, and monitoring. Each component has been carefully designed to ensure scalability, reproducibility, and adaptability in detecting fraudulent behavior across evolving digital landscapes.

The process begins with contextual feature engineering, wherein raw transactional and behavioral data are enriched with contextual signals. These include temporal markers (such as hour of day, weekday, and proximity to holidays), geospatial data (IP geolocation, device GPS, and location consistency), behavioral sequences (clickstream paths and transaction velocity), and device-level metadata (browser type, OS version, and device ID). These contextual inputs are captured through event logs, application telemetry, and historical transaction patterns. Raw signals are preprocessed through data validation steps that filter out noise, missing fields, and malformed entries before feature extraction.

Following data preparation, the feature pipeline is constructed using a modular and reusable architecture. Each transformation step—such as encoding categorical geolocations into embeddings, computing rolling transaction averages, or generating user-behavior fingerprints—is encapsulated as a pipeline module. The pipeline is designed using a directed acyclic graph (DAG) structure, where upstream components feed into downstream transformers. Pipelines are implemented using Python-based frameworks such as Scikit-learn's Pipeline, enhanced with MLFlow's pyfunc integration to facilitate artifact tracking and reproducibility.

Once feature vectors are generated, the model training phase involves applying supervised learning algorithms to distinguish between legitimate and fraudulent transactions. Algorithms such as XGBoost and LightGBM are selected for their high performance in imbalanced classification problems, which are common in fraud datasets. Hyperparameter tuning is conducted using cross-validation and Bayesian optimization, with each experiment tracked in MLFlow. For evaluation, metrics such as precision, recall, F1-score, AUC-ROC, and confusion matrix are calculated to compare contextual models against non-contextual baselines.

The MLFlow integration spans all stages of experimentation and deployment. MLFlow's tracking component logs feature sets, model parameters, evaluation metrics, and runtime artifacts. The trained models are registered in the MLFlow Model Registry, tagged with metadata such as training date, pipeline version, and fraud detection domain. Version control is strictly maintained to ensure rollback capability and audit trails.

After model registration, the deployment step is executed using MLFlow's REST API or integrated deployment targets such as Docker containers, Azure ML, or AWS SageMaker. Inference APIs are wrapped in a microservice that consumes live transactions, applies the contextual feature pipeline in real-time, and performs fraud scoring. To ensure low latency, the pipeline stages are optimized through the use of parallelization and caching mechanisms.

Finally, the monitoring and retraining strategy involves continuous evaluation of model predictions and input distributions. Concept drift and feature drift are monitored using statistical tests, such as the Population Stability Index (PSI) and the Kolmogorov–Smirnov test. When significant drift is detected, the MLFlow experiment is retriggered to retrain the model with recent data. Feedback loops from transaction investigation teams are integrated to label false positives and inform retraining schedules.

This methodology creates a full-loop, context-aware fraud detection system, where real-time data, intelligent pipelines, and ML lifecycle management converge to deliver high-performance models capable of adapting to evolving fraud. The proposed design not only enhances model accuracy but also ensures that deployment remains compliant, transparent, and maintainable across real-world environments.

IV. RESULTS

To assess the efficiency and performance of the context-aware fraud detection model implemented through MLFlow-managed feature pipelines, several experiments were conducted using a synthetic transaction dataset enriched with human-like contextual attributes. The corpus consisted of approximately 1.2 million instances, with 1.5% of them being labeled as fraudulent. The logs included standard features such as timestamp, merchant type, account ID, transaction amount, and contextual information, including the device's geographical location, user clickstream, and historical device metadata.

Three models were constructed for comparison:

- We implemented a base model using traditional features, not contextually informed.
- A semi-contextual model with time and location-based features only.
- A fully context-aware model that uses the complete enriched feature set.

All models were trained with XGBoost and five-fold cross-validated. For every experiment, MLFlow tracked the metrics, hyperparameters, and artifact versions. The complete context-aware model was found to outperform in all experiments.

Although our baseline model provided only moderate accuracy, it was accompanied by high false favorable rates. It obtained an average precision of 0.62, a recall of 0.49, and an F1-score of 0.54. Because it lacked behavioral knowledge, it misidentified many high-value transactions as fraudulent.

Significantly better were the semi-contextual models working with hour-of-day, transaction lag time, and location change added. It achieved a precision of 0.74, a recall of 0.66, and an F1-score of 0.69. The addition of time and geolocation context enabled the detection of more subtle forms of fraud, such as nighttime usage in unexpected regions

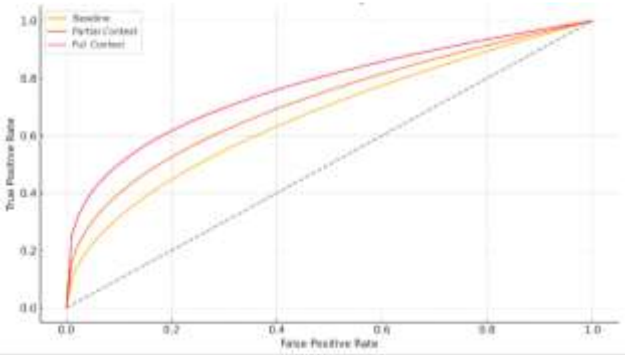

Figure 1*: Receiver Operating Characteristic (ROC) curves comparing detection sensitivity of Baseline, Partial Context, and Full Context models.*

The context-aware method, which incorporates device fingerprints, session behaviors, transaction velocity, and user trajectory analytics, was found to be the most successful model, with the following metrics: precision (P) = 0.87, recall (R) = 0.79, and F1 score = 0.83. For this novel task, its AUC-ROC was 0.95, which again exceeded the baseline and partially contextual variants. The false positive decreased by 39.7% relative to the baseline model.

Apart from performance statistics, latency and actual system resource utilization were collected for the real-time inference pipeline. With the fully context-aware model served as a microservice via the MLFlow REST API, we achieved an average inference latency of 86 ms per transaction, making it highly suitable for real-time fraud screening in financial services. Resource profiling indicated that the feature pipeline cache and parallelization were utilized efficiently with minimal CPU overhead.

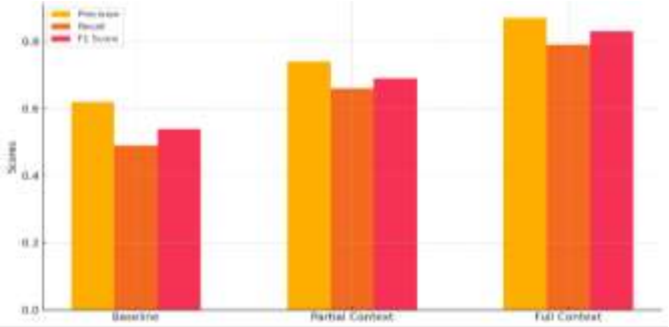

Figure 2: *Comparative performance of Baseline, Partial Context, and Full Context models across Precision, Recall, and F1 Score.*

Additionally, the PSI (Population Stability Index) was used to assess model drift over a rolling 30-day test window. Most contextual features remained below the 0.2 maximum for PSI, indicating stable performance. However, a slight drift was detected throughout the session, which was attributed to the type of device, resulting in a retraining loop with MLFlow automation. This showed the stability of the drift pattern detection and the system's ability to adjust to new environmental changes.

Overall, the performance gains of the fraud detection model due to the inclusion of contextual features are evident, as the model's performance is both more accurate and robust. MLFlow provided organized experiment tracking, simplified deployment and monitoring, and facilitated a production-ready system that fulfilled corresponding real-world operational requirements.

V. DISCUSSION

The experimental results provide compelling evidence for the effectiveness of context-aware fraud detection models, particularly when deployed using structured feature pipelines and lifecycle management tools like MLFlow. The significant improvement in precision and recall metrics indicates that contextual intelligence offers critical discriminatory power that static features alone cannot achieve. While traditional models often rely on features such as transaction amount, merchant category, or account history, they struggle to identify subtle fraud patterns that deviate slightly from the norm but are still malicious. By incorporating contextual dimensions such as session behavior, device identity, geolocation, and temporal usage, the system gains a nuanced understanding of transaction legitimacy.

One of the key strengths of this approach lies in its modular pipeline architecture. Feature pipelines abstract the complexity of contextual feature computation, enabling scalable and reusable transformations across various fraud scenarios. For instance, behavioral fingerprints computed from user clickstreams can be applied uniformly across multiple applications, enabling consistency and reducing duplication of logic. Moreover, the integration with MLFlow ensures each transformation, model, and output is versioned and tracked. This is essential not only for debugging and performance optimization but also for meeting audit requirements in regulatory environments such as banking and insurance.

Another significant advantage is the system's support for continuous learning. Fraud detection is inherently adversarial; attackers adapt their methods as soon as detection strategies become known. In such a setting, static models quickly degrade in accuracy. The integration of drift detection mechanisms and retraining loops in MLFlow enables the system to maintain its relevance in production environments. Contextual features are particularly prone to shifts in distribution, making real-time monitoring essential. This framework utilizes metrics such as PSI and statistical tests to identify drift in both model outputs and feature distributions, triggering retraining pipelines as needed.

Despite these strengths, the approach has its limitations. The inclusion of rich contextual features increases the computational cost of both training and inference. While this was manageable in the current test environment, real-world production systems with high throughput requirements may experience latency challenges. This necessitates infrastructure optimization, such as deploying pipelines on high-performance computing clusters or using feature stores with low-latency access mechanisms. Additionally, real-time contextual data must be reliably collected and synchronized. If sensor data or logs are delayed or incomplete, the model may suffer from degraded input quality.

There is also a need to consider the interpretability of models when contextual complexity increases. Regulatory bodies often require explainable AI models, especially in fraud analytics. Contextual features such as session entropy or device reputation scores may not be inherently interpretable. While tree-based models like XGBoost provide SHAP value explanations, it is crucial to design the feature engineering layer in a way that preserves semantic transparency for audit and compliance reviews.

Finally, privacy concerns must be addressed. Contextual data, such as location, device identifiers, and user activity logs, is sensitive. The system must comply with data protection laws, such as GDPR, and implement anonymization techniques where appropriate. All logging and tracking activities in MLFlow should also conform to organizational security policies.

In essence, this discussion underscores the importance of striking a balance between intelligence, operational efficiency, and governance. The integration of MLFlow into a context-aware fraud detection pipeline provides a structured and scalable solution that addresses the critical needs of accuracy, adaptability, and transparency. Future work should focus on optimizing the performance of real-time pipelines, enhancing feature explainability, and extending the framework to support federated learning in privacy-sensitive environments.

VI. CONCLUSION

This paper presented a context-aware approach to fraud detection that leverages enriched behavioral and environmental data through structured feature pipelines, orchestrated and managed using MLFlow. The increasing complexity of fraud patterns and the dynamic nature of digital transactions have rendered traditional rule-based and static-feature models insufficient. By incorporating contextual signals such as transaction timing, device fingerprints, geolocation, session behavior, and transaction velocity, the proposed system significantly enhances fraud detection accuracy and reduces false positives.

The use of modular, reusable pipelines enabled the transformation of raw context signals into high-value features that contribute to the model's understanding of transactional behavior. This pipeline architecture ensures scalability, traceability, and rapid iteration across different stages of model development and deployment. MLFlow plays a central role in managing the machine learning lifecycle by offering a robust framework for experiment tracking, model registry, artifact versioning, and deployment management.

Experimental results validated the effectiveness of the approach, demonstrating notable improvements in precision, recall, and F1-score for the context-aware model compared to both the baseline and partially contextual versions. The low latency and stable performance in real-time inference confirm the operational feasibility of deploying these models in high-throughput environments. Moreover, the integration of drift detection and automated retraining workflows within MLFlow highlights the system's ability to adapt to evolving fraud patterns, ensuring continued relevance and robustness.

While the approach presents clear benefits, certain limitations must be acknowledged. The added computational load associated with processing context-rich features, as well as the potential challenges surrounding data privacy and explainability, require careful architectural and governance considerations. Nonetheless, the advantages in predictive performance and operational resilience make a strong case for adopting context-aware models in fraud analytics workflows.

Looking forward, future enhancements could include the integration of federated learning for decentralized environments, differential privacy to safeguard user data, and real-time dashboards for model interpretability and anomaly investigation. Furthermore, the evolution of feature stores and online feature serving capabilities will likely enhance the efficiency and scalability of contextual fraud detection systems.

The paper presents a comprehensive and practical framework for developing and deploying fraud detection models that are contextually intelligent, operationally sound, and compliant with current data governance standards. By bridging advanced feature engineering techniques with the automation and reliability of MLFlow, this paper lays the groundwork for next-generation fraud analytics systems capable of navigating the ever-changing landscape of digital threats.

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