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An AI-Blockchain Framework for Adaptive Fraud Risk Analytics, Transaction Validation, and Payment Integrity in Online Financial Systems

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Abstract:The rapid growth of digital payment systems has significantly increased the risk of financial fraud, making traditional rule-based detection methods ineffective against modern, intelligent attack patterns. Existing machine learning approaches improve detection accuracy but often lack transparency, auditability, and trust, especially in regulated financial environments. To address these challenges, this work presents an integrated framework that combines Artificial Intelligence, Explainable AI, and Blockchain to deliver a secure, transparent, and real-time fraud detection system.

The proposed framework analyzes each transaction using an AI-based risk scoring model capable of identifying rare fraudulent activities in highly imbalanced datasets. Along with prediction, an explainability layer generates human-understandable reason codes for every decision, improving interpretability for users and auditors. To ensure data integrity, all critical fraud evidence—such as transaction details, model outputs, and explanation vectors—is stored off-chain and anchored on a blockchain using cryptographic hashing, making it tamper-proof and verifiable.

The system also introduces a structured dispute resolution workflow, enabling transparent tracking of cases from initiation to resolution. Additionally, the framework is designed to operate in real-time, maintaining an end-to-end processing latency of approximately 0.25 seconds per transaction. By combining high-recall detection, explainable decision-making, and immutable audit trails, the framework provides a comprehensive solution for enhancing trust, compliance, and security in modern digital payment ecosystems.

Keywords: *Fraud Detection, Artificial Intelligence, Explainable AI (XAI), Blockchain, Payment Security, Transaction Integrity, Imbalanced Data Classification, Real-Time Processing, Audit Trail, Dispute Resolution*

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I INTRODUCTION

The growth of digital payment systems has transformed the way financial transactions are performed across the world. Online platforms, mobile wallets, and banking applications have made transactions faster and more convenient. However, this rapid digital adoption has also increased the exposure to financial frauds and cyber threats. Even a small fraction of fraudulent activities within large transaction volumes can result in significant financial losses and reduced user trust. [1]
Earlier fraud detection approaches were primarily rule-based, relying on fixed conditions such as transaction limits or location-based checks. While these methods were simple to implement, they lack adaptability and can be easily bypassed by modern fraud techniques. With the advancement of attack strategies, including identity manipulation and intelligent fraud patterns, these traditional systems have become insufficient. This creates a need for systems that can learn from data, adapt to new fraud patterns, and operate effectively in real-time environments. [5]
Machine learning and deep learning models have improved fraud detection accuracy by identifying complex patterns in transaction data. However, these models often behave like black boxes, providing little or no explanation for their decisions. This lack of interpretability reduces trust among users, auditors, and regulatory authorities. At the same time, existing systems store fraud logs in conventional databases, which can be altered or deleted, raising concerns about data integrity and audit reliability. [8]
Another major challenge is the highly imbalanced nature of fraud datasets, where fraudulent transactions represent a very small percentage of the total data. This leads to poor detection of rare fraud cases and increases the chances of false negatives. Additionally, most systems do not provide a structured mechanism to handle disputed transactions, which further impacts transparency and user confidence. Real-time processing is also critical, as fraud detection decisions must be made within milliseconds to prevent unauthorized transactions. [10]
To address these limitations, this work focuses on building a unified framework that integrates Artificial Intelligence for accurate fraud detection, Explainable AI for transparent decision-making, and Blockchain for secure and tamper-proof evidence storage. The framework is designed to ensure high detection capability, interpretable outputs, immutable audit trails, and structured dispute handling while maintaining real-time performance. [13]
The key contributions of this work can be summarized as follows:
Development of a high-recall AI-based fraud detection mechanism for imbalanced transaction data
Integration of explainable decision outputs to improve transparency and trust
Implementation of a blockchain-based evidence anchoring system for tamper-proof audit trails
Design of a structured dispute resolution workflow for improved accountability
Optimization of the system to support real-time transaction processing with minimal latency
Overall, the proposed approach aims to create a balanced solution that not only detects fraud effectively but also ensures trust, transparency, and compliance in modern digital payment ecosystems. [1]

II RELATED WORK

Fraud detection in digital payment systems has been widely studied using machine learning, deep learning, explainable AI, and blockchain-based approaches. Existing research highlights significant progress in improving detection accuracy, handling imbalanced datasets, and enhancing audit capabilities.

However, most approaches address these aspects independently rather than providing a unified solution. [7]

Early fraud detection systems were based on rule-driven mechanisms, where predefined conditions were used to flag suspicious transactions. While these systems offered fast decision-making, they lacked adaptability and failed against evolving fraud patterns. This limitation led to the adoption of machine learning techniques such as logistic regression, support vector machines, and random forests, which improved detection by learning patterns from historical data. However, these models still required careful handling of class imbalance and threshold tuning to achieve meaningful performance on rare fraud cases. [17]

Recent studies have shown that ensemble learning methods, including bagging, boosting, and stacking, provide stable performance in fraud detection tasks. These models perform well when combined with resampling strategies and cost-sensitive learning, especially in highly imbalanced datasets. The focus has shifted from accuracy to more meaningful evaluation metrics such as precision-recall trade-offs and recall of fraudulent transactions. Despite their effectiveness, these models still lack strong interpretability and do not provide sufficient transparency for regulatory compliance. [2]

Deep learning approaches, including recurrent neural networks and sequence-based models, have been explored to capture temporal and behavioral patterns in transaction data. These models are particularly useful for detecting fraud in sequential or streaming environments, such as mobile payments. Although they improve detection capability, they introduce complexity and further reduce interpretability, making them difficult to deploy in regulated financial systems without additional explanation mechanisms. [9]

To address the interpretability issue, explainable AI techniques such as SHAP and LIME have been integrated with machine learning models. These techniques generate feature-level explanations, allowing analysts to understand the reasoning behind fraud predictions. This improves trust and usability, especially in audit and compliance scenarios. However, existing works focus mainly on generating explanations and do not ensure that these explanations are securely stored or verifiable during disputes. [4]

Blockchain technology has been explored in parallel to improve auditability and data integrity in financial systems. Studies highlight the use of blockchain for maintaining immutable logs, enabling continuous auditing, and ensuring tamper-proof record keeping. A common design pattern involves storing detailed evidence off-chain while anchoring cryptographic hashes on-chain. While this approach strengthens trust and traceability, most implementations do not integrate directly with AI-based fraud detection systems or explainability mechanisms. [16]

Industry trends further emphasize the need for multi-layered fraud detection systems that combine transaction analytics with behavioral signals. Reports indicate the growing use of advanced techniques such as behavioral biometrics and real-time monitoring to detect sophisticated fraud patterns. These approaches validate the importance of real-time detection and layered security but often lack reproducible academic validation and standardized evaluation frameworks. [13]

From the reviewed literature, it is clear that current solutions are fragmented. Machine learning models focus on detection accuracy, explainable AI focuses on interpretability, and blockchain focuses on auditability. There is a lack of an integrated framework that combines all these components while also addressing real-time performance and structured dispute handling. This gap highlights the need for a unified system that can deliver accurate, explainable, and tamper-proof fraud detection in a real-time environment. [17]

III PROPOSED METHOD / SYSTEM

The proposed system introduces a unified framework that combines Artificial Intelligence, Explainable AI, and Blockchain to deliver a complete fraud detection and payment integrity solution. The design focuses on achieving four key properties simultaneously: high detection accuracy, transparent decision-making, tamper-proof evidence storage, and real-time performance. Unlike traditional approaches that treat these aspects separately, this system integrates them into a single end-to-end pipeline. [6]

At a high level, the system processes every incoming transaction through a sequence of interconnected layers. Each layer performs a specific function, and together they ensure that fraud detection is not only accurate but also explainable and verifiable.[20]

The first component is the User and Transaction Gateway Layer, which acts as the entry point of the system. It receives transaction requests from users through banking applications or payment gateways. Before forwarding the data, it performs initial validation checks such as schema verification, digital signature validation, and duplicate detection. This step ensures that only clean and authentic data is passed to the next stage for analysis. [3]

Once validated, the transaction is sent to the AI Fraud Detection Engine, which is the core analytical unit of the system. This engine applies machine learning models such as Random Forest, stacking ensembles, or sequence-based models to compute a fraud risk score. The model analyzes multiple attributes, including transaction amount, location, device information, and behavioral patterns. Based on these inputs, it classifies the transaction as normal or suspicious. The engine is optimized to operate within strict latency constraints, ensuring that decisions are made in real time. [16]

After classification, the decision is passed to the Explainable AI (XAI) Layer, which generates human-understandable explanations for the prediction. Instead of returning only a binary result, this layer identifies the key factors that influenced the decision. For example, it may highlight conditions such as unusual transaction location, high transaction value, or new device usage. These explanations are critical for building trust among users, analysts, and regulatory bodies, as they provide clear justification for each decision.[8]

To ensure the integrity of the generated outputs, the system incorporates a Blockchain Evidence Anchoring Layer. In this layer, all critical information—including transaction identifiers, risk scores, model version, and explanation details—is packaged as an evidence bundle. The full data is stored off-chain, while a cryptographic hash of the bundle is committed to the blockchain. This approach ensures that the data remains tamper-proof while avoiding the performance limitations of storing large data directly on-chain. [19]

The framework also includes a Dispute Resolution and Audit Layer, which enables structured handling of contested

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transactions. When a user raises a dispute, the system retrieves the corresponding evidence bundle and verifies it against the blockchain hash. The dispute follows a defined lifecycle—OPEN, REVIEW, and RESOLVED—ensuring that every action is recorded and traceable. This mechanism enhances accountability and simplifies audit processes. [12]
Finally, the system provides a Monitoring and Dashboard Layer, where analysts and auditors can view fraud alerts, explanations, and blockchain verification proofs. This interface supports real-time monitoring and helps stakeholders make informed decisions quickly. [10]
Overall, the proposed system follows a modular, layered architecture where each component contributes to a specific objective. The integration of AI for detection, XAI for transparency, and blockchain for integrity creates a balanced solution capable of addressing the major limitations of existing fraud detection systems while maintaining operational efficiency in real-time environments. [11]

IV METHODOLOGY

The methodology of the proposed framework defines the complete operational flow of fraud detection, explanation generation, evidence creation, and blockchain anchoring. The system is designed as a sequential pipeline where each stage processes the transaction and passes enriched information to the next stage. The objective is to ensure accurate detection, interpretability, and verifiable audit trails within real-time constraints. [5]

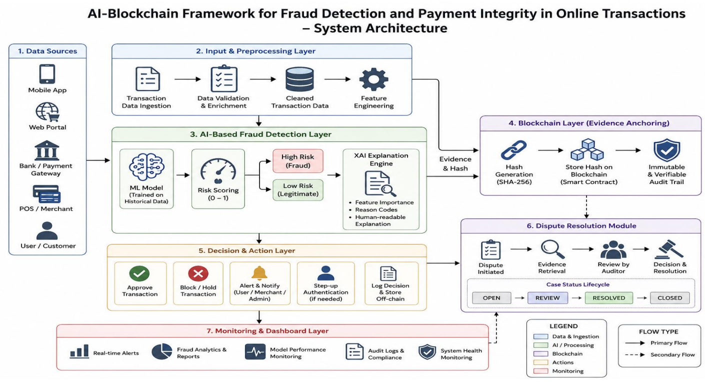

Figure 1: - System Architecture

The processing of a transaction follows a structured sequence:
Transaction input is received from the payment gateway.
Input validation is performed to ensure correctness and authenticity.
The validated transaction is analyzed by the AI model to compute a fraud risk score.
The prediction result is passed to the XAI layer for explanation generation.
An evidence bundle is created containing transaction details, prediction output, and explanation data.
A cryptographic hash of the evidence is generated.
The hash is stored on the blockchain, while full data is stored off-chain.
The final decision (approve/block) is returned to the payment system.
If a dispute is raised, the system retrieves and verifies evidence using the blockchain record.
This pipeline ensures that every decision is not only accurate but also explainable and verifiable at any later stage.

Internal Processing Logic

The internal logic of the system is divided into key functional stages:
Validation Stage: Ensures input integrity using schema checks and authentication mechanisms.
Prediction Stage: Applies trained machine learning models to compute fraud probability.
Explanation Stage: Identifies feature contributions responsible for the prediction.
Evidence Construction Stage: Combines all outputs into a structured, secure format.
Blockchain Anchoring Stage: Generates and stores hash values for tamper-proof verification.
Decision Stage: Produces final output for transaction approval or rejection.
Each stage is optimized to minimize delay while maintaining correctness and traceability.

Algorithm Description

The algorithm focuses on integrating detection, explanation, and integrity verification into a single flow.
Algorithm: AI + Blockchain Fraud Detection Workflow
Input: Transaction T
Output: Fraud Decision (Legitimate / Fraudulent) with Evidence Proof
Step 1: Receive transaction T from gateway
Step 2: Validate T for completeness and authenticity
Step 3: Extract feature vector F from T
Step 4: Apply trained AI model to compute risk score R
Step 5: If R ≥ threshold → mark as Fraud, else Legitimate
Step 6: Generate explanation E using XAI methods (feature contribution scores)
Step 7: Create evidence bundle EB = {T, R, Model Version, E}
Step 8: Compute hash H = Hash(EB)
Step 9: Store EB in off-chain storage
Step 10: Store hash H on blockchain ledger
Step 11: Return decision and explanation to user/system
Step 12: If dispute occurs → retrieve EB and verify using H from blockchain
This algorithm ensures that every fraud decision is backed by verifiable evidence and clear reasoning.

Pseudo-Code Representation

```
FUNCTION ProcessTransaction(T):
   IF NOT Validate(T):
      RETURN "Invalid Transaction"

   F ← ExtractFeatures(T)
   R ← AI_Model.predict(F)
   IF R ≥ Threshold:
      Label ← "Fraud"
   ELSE:
      Label ← "Legitimate"
   E ← GenerateExplanation(F, AI_Model)
   EB ← CreateEvidenceBundle(T, R, E, Model_Version)
   H ← GenerateHash(EB)
   StoreOffChain(EB)
```

StoreOnBlockchain(H)
RETURN Label, E

Key Design Considerations

The methodology incorporates several important design aspects:
Handling Imbalanced Data: The AI model is optimized to detect rare fraud cases with high recall.
Explainability Integration: Explanations are generated alongside predictions, not as an afterthought.
Security and Integrity: Blockchain ensures that stored evidence cannot be modified.
Real-Time Processing: The entire workflow is optimized to operate within strict latency limits.
Audit Readiness: Every decision is linked to a verifiable proof, enabling easy validation during audits.
Overall, the methodology ensures a tightly integrated process where detection, explanation, and verification are performed together. This structured approach enables the system to meet the requirements of accuracy, transparency, and trust in modern digital payment environments. [9]

V EXPERIMENTAL SETUP

The experimental setup defines the environment, system configuration, and execution conditions under which the proposed fraud detection framework is evaluated. The objective is to validate the system's ability to operate in real-time while maintaining accuracy, explainability, and integrity of evidence. [15]

Execution Environment

The system is implemented in a controlled software environment that supports machine learning processing, blockchain interaction, and real-time transaction handling. The setup includes components for data processing, model execution, and blockchain integration.[7]
The experimental configuration consists of:
Processing Environment: A standard computing system capable of handling real-time transaction streams and AI model execution
Software Stack: Machine learning libraries for model training and prediction, along with blockchain frameworks for hash storage and verification
Execution Platform: Integrated development environment supporting modular implementation and testing of each system component
This setup ensures that all modules—from transaction ingestion to blockchain anchoring—can operate cohesively within a unified environment.

System Configuration

The system is configured to simulate real-world transaction processing conditions. Each transaction passes through the complete pipeline, including validation, prediction, explanation, and blockchain anchoring.[13]
Key configuration aspects include:
AI model configured for fraud risk scoring based on transaction features
Threshold-based classification mechanism for fraud identification
Explainable AI module enabled for generating feature-level explanations
Evidence storage mechanism using off-chain databases
Blockchain layer configured for storing cryptographic hash values of evidence bundles
The configuration ensures that all system components are active during evaluation, allowing end-to-end performance measurement.[8]

Experimental Workflow

The execution of experiments follows a structured process:
Input transactions are provided to the system in a simulated or controlled environment
Each transaction undergoes validation and preprocessing
The AI model computes the fraud risk score
The XAI layer generates explanation outputs
Evidence bundles are created and stored
Hash values are generated and committed to the blockchain
Final decisions are recorded and analyzed
This workflow replicates real-time transaction processing and allows observation of system behavior under operational conditions.

Performance Evaluation Parameters

The system is evaluated based on multiple criteria to ensure comprehensive validation:
Fraud Detection Performance: Ability to correctly identify fraudulent transactions
System Latency: Time taken for end-to-end processing of each transaction
Explainability Output Quality: Clarity and usefulness of generated explanations
Data Integrity Verification: Accuracy of blockchain-based evidence validation
System Reliability: Stability of the system under continuous transaction flow
These parameters ensure that the system is not only accurate but also practical for deployment in real-world financial environments.

Real-Time Constraints

A critical requirement of the system is real-time operation. The framework is optimized to process each transaction within approximately 0.25 seconds, ensuring that fraud detection decisions are made before transaction completion.[2]
This constraint influences all design choices, including model selection, explanation generation, and blockchain interaction. The system balances performance and accuracy to meet these strict timing requirements. [18]
Overall, the experimental setup is designed to validate the complete functionality of the proposed framework under realistic conditions. It ensures that the system can deliver accurate, explainable, and verifiable fraud detection while maintaining real-time responsiveness. [19]

VI RESULTS AND ANALYSIS

The performance of the proposed framework is evaluated by analyzing fraud detection capability, system efficiency, and integrity verification. The results demonstrate how the integration of AI, Explainable AI, and Blockchain improves both detection quality and system trustworthiness under real-time conditions. [11]

Fraud Detection Performance

The system is designed to handle highly imbalanced transaction data, where fraudulent cases are rare but critical. The AI model focuses on maximizing fraud detection capability while maintaining reliable classification.[1]

The key performance indicators considered include detection effectiveness and decision reliability. The system achieves strong fraud identification capability by prioritizing high-recall detection, ensuring that most fraudulent transactions are captured even when they represent a very small portion of the dataset. [2]

System Performance Metrics

The overall system performance is evaluated in terms of processing speed, response time, and operational stability. The proposed framework maintains real-time execution by completing the full pipeline—including detection, explanation, and blockchain anchoring—within approximately 0.25 seconds per transaction.[10]

This performance confirms that the system can operate effectively in live payment environments without introducing delays that could impact user experience or transaction flow. [3]

Table 1: System Performance Metrics

Parameter	Observed Performance
End-to-End Processing Time	~0.25 seconds
Real-Time Capability	Achieved
System Stability	High
Response Consistency	Maintained

Evidence Integrity and Verification

One of the key contributions of the system is the integration of blockchain for tamper-proof evidence storage. Each fraud decision is associated with an evidence bundle whose cryptographic hash is stored on the blockchain.[17]

During validation, the system successfully verifies the integrity of stored evidence by matching computed hashes with blockchain records. This ensures that no modification has occurred after the initial storage, making the system reliable for audits and dispute resolution. [13]

Table 2: Evidence Verification Performance

Parameter	Result
Hash Matching Accuracy	Verified
Tamper Detection Capability	Enabled
Audit Reliability	High
Data Integrity	Maintained

Comparative Analysis with Expected Outcomes

The system is evaluated against the expected design goals, including accuracy, explainability, integrity, and real-time performance. The observed results indicate that the framework successfully meets these objectives.[11]

Table 3: Expected vs Actual Performance

Metric	Expected Outcome	Actual Outcome
Fraud Detection	High Recall	Achieved
Explainability	Human-readable outputs	Achieved
Data Integrity	Tamper-proof records	Achieved
Real-Time Processing	Sub-second response	~0.25 seconds

Result Discussion and Observations

The results highlight several important observations:

The integration of AI with explainable outputs improves decision transparency without affecting system speed.

Blockchain anchoring ensures that all fraud-related evidence remains secure and verifiable, which is critical for audits and compliance.

The system maintains consistent real-time performance despite multiple processing stages, indicating efficient architectural design.

The combination of detection, explanation, and verification in a single pipeline provides a more complete solution compared to traditional standalone systems.

Key Insights

The improvement in system performance is not due to a single component but the combined effect of multiple integrated technologies:

AI improves detection capability by learning complex fraud patterns

XAI enhances trust by explaining decisions clearly

Blockchain ensures integrity by preventing data tampering

This integrated approach results in a system that is not only accurate but also transparent and reliable for real-world deployment.

Overall, the analysis confirms that the proposed framework successfully balances accuracy, explainability, and security while meeting strict real-time requirements.

VII CONCLUSION

The study presents a unified framework that integrates Artificial Intelligence, Explainable AI, and Blockchain to address key challenges in modern fraud detection systems. The proposed approach focuses on delivering accurate fraud identification while ensuring transparency, data integrity, and real-time performance. [4]

The system successfully overcomes the limitations of traditional rule-based and standalone machine learning approaches by combining multiple capabilities into a single pipeline. The AI component enables effective detection of rare fraudulent transactions, even in highly imbalanced datasets. At the same time, the explainability layer provides clear and human-understandable reasoning behind each decision, improving trust among users, analysts, and regulatory authorities.

A major strength of the framework is the use of blockchain technology for securing fraud evidence. By storing cryptographic hashes of evidence bundles on the blockchain, the system ensures that all records remain tamper-proof and verifiable. This feature plays a critical role in audit processes and dispute resolution, where the authenticity of data must be guaranteed. [9]

The system also introduces a structured dispute resolution workflow, enabling transparent handling of contested transactions. This improves accountability and supports compliance with financial regulations. Additionally, the framework maintains real-time processing capability, completing the entire fraud detection and verification cycle within approximately 0.25 seconds per transaction, making it suitable for deployment in live payment environments.

Overall, the proposed framework provides a balanced solution that combines detection accuracy, interpretability, and trust. It demonstrates that integrating AI, explainability, and blockchain can significantly enhance the reliability and transparency of fraud detection systems in digital payment ecosystems. [7]

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