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Blockchain Enabled Government Fund Tracking and Distribution System

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Abstract -*The secure and transparent distribution of government funds is essential for effective public administration. However, traditional systems often face challenges such as delays, lack of transparency, fund mismanagement, and fraudulent activities. This project proposes an AI-Enabled Block chain System for Secure Distribution and Real-Time Tracking of Government Funds. The system utilizes block chain technology to maintain a decentralized and tamper-resistant ledger that records all fund transactions, ensuring data integrity and accountability. Artificial Intelligence is integrated to analyze transaction data, detect suspicious activities, and support fraud prevention. Smart contracts automate fund allocation and release processes based on predefined conditions, reducing manual intervention and improving efficiency. The proposed system provides real-time tracking of funds from government agencies to beneficiaries, enabling stakeholders to monitor transactions and utilization status transparently. By combining block chain security with AI-based monitoring, the system enhances trust, accountability, and operational efficiency in public fund management. The solution aims to reduce corruption risks, improve transparency, and support better governance through secure and intelligent financial transaction management.*

Key Words: Blockchain, Artificial Intelligence, Government Funds, Smart Contracts, Real-Time Tracking, Transparency, Fraud Detection.

1. INTRODUCTION

The effective distribution and monitoring of government funds play a crucial role in the successful implementation of public welfare and development programs. Governments allocate large amounts of financial resources to various sectors such as education, healthcare, infrastructure, and social welfare. However, traditional fund management systems often suffer from challenges including lack of transparency, delayed transactions, fund leakage, corruption, and inefficient tracking mechanisms. These issues reduce public trust and affect the overall effectiveness of government initiatives. The proposed AI-Enabled Block chain System for Secure Distribution and Real-Time Tracking of Government Funds aims to address the limitations of existing fund management mechanisms. The system leverages block chain technology to create a tamper-proof and transparent transaction environment while utilizing AI techniques to continuously monitor fund flows and detect anomalies. Every stage of fund allocation, transfer, and utilization is recorded on the block chain, enabling stakeholders to track transactions in real time and verify the authenticity of financial records.

The system provides multiple stakeholders including government departments, auditing agencies, local authorities, and citizens with controlled access to transaction information, thereby promoting accountability and public trust. Smart contracts automate fund release procedures based on predefined rules and conditions, reducing administrative delays and minimizing human intervention. AI-powered analytics generate reports, identify inefficiencies, and support data-driven decision-making for effective governance.

1.1 METHODOLOGY

The proposed AI-Enabled Block chain System for Secure Distribution and Real-Time Tracking of Government Funds combines block chain technology and artificial intelligence to create a secure and transparent fund management system. The methodology begins with the registration and authentication of authorized users such as government officials, departments, and beneficiaries. After successful login, government authorities can allocate funds for various projects and schemes through the system.

Whenever funds are allocated or transferred, the transaction details are recorded on the blockchain network. Each transaction is encrypted and stored in blocks, making the records secure, transparent, and tamper-proof. Smart contracts are used to automate the fund distribution process by executing predefined rules and conditions, reducing manual intervention and processing delays.

The system provides real-time tracking of fund movement from the source department to the final beneficiary. All transaction details, including amount, sender, receiver, and timestamp, can be monitored through a dashboard. This enables stakeholders to track the status and utilization of funds at every stage.

Artificial Intelligence is integrated into the system to analyze transaction data and identify unusual activities. The AI module continuously monitors fund transfers and detects anomalies such as suspicious transactions, fund diversion, or abnormal spending patterns. If any irregularity is found, the system generates alerts for administrators and auditors.

Finally, all transaction records and fund utilization details are available for auditing and reporting purposes. Since the data is stored on a blockchain ledger, it ensures transparency, accountability, and trust in government fund distribution while reducing the chances of fraud and corruption.

1.2 LITERATURE SURVEY

The increasing demand for transparency and accountability in public fund management has encouraged researchers to explore advanced technologies such as Blockchain and Artificial Intelligence. Several studies have proposed secure and decentralized systems for financial transaction management.

Christidis and Devetsikiotis examined the integration of blockchain and smart contracts for secure transaction processing. Their research highlighted the ability of smart contracts to automate financial operations, reduce human intervention, and improve system efficiency.

Swan discussed various applications of blockchain beyond cryptocurrency, including governance, finance, and public administration. The study emphasized blockchain's potential to improve transparency and accountability in government operations.

2. EXISTING SYSTEM

Currently, the distribution and monitoring of government funds are primarily managed through centralized financial management systems operated by government departments, banks, and administrative authorities. These systems rely on multiple intermediaries, manual verification processes, and centralized databases to record transactions and maintain financial records.
In the existing approach, government funds pass through several administrative levels before reaching the intended beneficiaries or implementing agencies. Although digital platforms have improved transparency to some extent, the process still faces challenges such as delayed fund transfers, lack of real-time visibility, data manipulation risks, and difficulties in tracking the exact utilization of allocated funds. Since data is stored in centralized servers, unauthorized modifications, cyberattacks, or system failures can compromise the integrity and availability of financial records.

Furthermore, auditing and fraud detection are largely performed through periodic inspections and manual analysis of transaction records. This approach is time-consuming and may not effectively identify suspicious activities or fund misuse at an early stage. Stakeholders often lack a transparent mechanism to verify fund flow across different levels of administration, leading to reduced accountability and public trust.The existing system also suffers from limited interoperability between departments, resulting in fragmented information and inefficient coordination. Beneficiaries and citizens generally have restricted access to transaction details, making it difficult to independently verify whether funds have been allocated and utilized according to government policies.

3. PROPOSED SYSTEM ARCHITECTURE

The diagram depicts a five-layer hierarchical architecture of the ABGF. 1. The inter-layer interfaces are based on open standards in the following manners: HTTPS/OAuth2 for stakeholder access; REST/gRPC for AI-blockchain integration; ABI for smart contract invocation; TLS 1.3 for peer-to-peer blockchain communication, thus ensuring modularity and vendor neutrality.

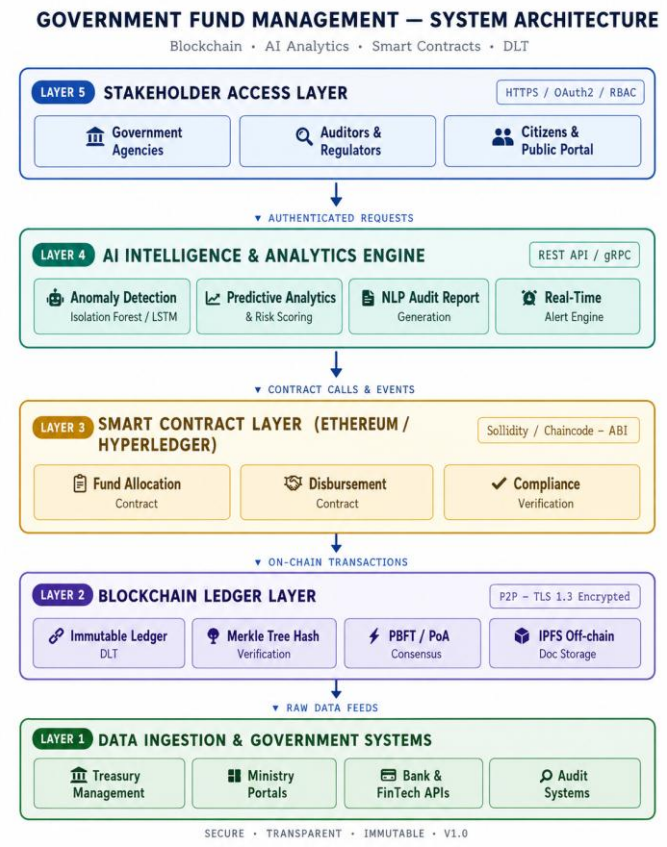

Fig. 1. Proposed AI-Blockchain Government Fund Tracking System architecture: five layers from data ingestion to stakeholder access.

A. Layer 1 — Data Ingestion and Government Systems

The first layer integrates data from four different government system types, including treasury management information systems (TMIS), ministry and department portals, bank and FinTech API gateways for disbursement execution, and the CAG audit interface. Data is retrieved through REST APIs which have OAuth2 authentication credentials. The blockchain layer prevents manipulation of the ingestion metadata by hashing (SHA-256) and timestamping all incoming transactions before submission.

B. Layer 2 — Blockchain Ledger

The blockchain ledger is implemented on Hyperledger Fabric v2.4 in a permissioned network topology that uses 12 peer nodes representing government ministries and an independent auditor organisation. Every fund transaction creates a block that includes the transaction hash, sender/receiver identifiers, amount, fund category code, digital signatures of the party's giving approval, and a Merkle root for the corresponding documents found on IPFS. Consensus has PBFT with a supermajority of 2/3 which give Byzantine faults tolerance to 3 of 12 nodes. The scanned copies of fund-utilisation certificates, sanction orders and disbursement vouchers are stored in IPFS, whose content-addressed IPFS hash only is written to the blockchain. This keeps the block size reasonable while ensuring the integrity of the documents.

C. Layer 3 — Smart Contract Layer

There are six chaincode smart contracts to govern the entire fund life cycle. The createFundAllocation() function calls for the reservation of funds on approval by the ministry. The disburseFunds() function occurs after the approval of the AI and sign off by multiple parties. The verifyCompliance() function verifies whether the funds are used for the sanctioned purpose. The raiseAuditFlag() function halts further disbursements until the account is cleared after the audit. The freezeTransaction() function reverses the funds for disbursements that are incomplete. The generateReport() function provides the immutable audit trail. Table I depicts the gas cost and execution time for each contract function. The automated nature of smart contract logic helps in eliminating the need for manual approval queues. Thus, after validation, transactions are disbursed within 0.45 seconds of achieving consensus compared to 3–7 days for the latter in manual transactions.

D. Layer 4 — AI Intelligence Engine

The AI engine executes in real-time processing of transaction feature vectors uploaded on events within the blockchain. The ensemble employs three complementary detection methods: Isolation Forest detection using statistics to identify anomalies in tabular transaction features; LSTM Autoencoder detection of anomalies in fund disbursement time-series using temporal sequences and a Graph Neural Network (GNN) that detects relational anomalies in fund-flow transaction graphs where edges represent transfers between ministries. figure Section two describes the AI module architecture.

E. Layer 5 — Stakeholder Interface

Developing a Web Dashboard using React.js 18 that helps Government Agencies monitor the flow of funds with Heatmap, Timeline and Alert management console. Auditors have a specific interface with relationships represented as SHAP-values for transactions flagged by AI. There is a citizen-facing public portal that displays anonymised information on fund allocation and utilisation at the scheme level to meet Right-to-Information requirements without disclosing any beneficiary-level data. A mobile application built on react native serves push-notification alerts to assigned officials in 0.3s after an alert AI flag event.

4. EXPERIMENTAL SETUP

A. Simulation Environment

Experimental validation with simulation of a government fund management environment was carried out in three ministry scenarios (S1) Education Ministry for scholarship disbursement (15000 beneficiaries, 45 days), (S2) Rural Development Ministry for infrastructure scheme (8 contractors, 90 days) and (S3) Health Ministry for medical supply procurement (22 vendors, 60 days). The Hyperledger Fabric network was deployed on a 12 node virtual machine cluster (4 vCPU, 16 GB RAM per node) on private cloud infrastructure. The nodes used Ganache CLI v7.4 on identical hardware.

B. Dataset Composition

The experimental dataset is a combination of four sources into one combined dataset with a total 94,440 records across six transaction classes. Namely, Normal, Flagged-Low, Flagged-High, Fraudulent-Internal, Fraudulent-External, Audit-Resolution. In the training partition, SMOTE was applied in order to handle class imbalance (fraud-positive records representing 18% of total).

Function	Gas Used	Gas (Gwei)	Exec. Time (ms)	Status
createFundAllocation()	47,823	0.0957	12.4	OK
disburseFunds()	62,104	0.1242	16.1	OK
verifyCompliance()	28,341	0.0567	7.3	OK
raiseAuditFlag()	19,872	0.0397	5.1	OK
freezeTransaction()	23,455	0.0469	6.0	OK
generateReport()	34,782	0.0696	9.0	OK
updateLedger()	41,230	0.0825	10.7	OK

C. AI Model Training

All AI models were trained using Python 3.10, TensorFlow 2.11 (LSTM Autoencoder), PyTorch Geometric 2.3 (GNN), and scikit-learn 1.3 (Isolation Forest, baseline classifiers). The LSTM Autoencoder used a 64-32-16-32-64 encoder-decoder architecture with Adam optimiser (lr=0.001) trained for 50 epochs. The GNN used a 3-layer GraphSAGE architecture with mean aggregation. Ensemble soft-voting weights were optimised on the validation partition (Proposed: 0.35/LSTM + 0.35/GNN + 0.30/IF). SHAP TreeExplainer and DeepExplainer were used for ensemble attribution.

D. Evaluation Metrics

AI performance was evaluated using accuracy, precision, recall, F1-score, AUC-ROC, and False Positive Rate (FPR) over stratified 5-fold cross-validation. Blockchain performance was measured by throughput (TPS), block confirmation latency (s), and transaction finality time. System-level metrics included: audit resolution time (days), fraudulent diversion rate reduction (%), and tamper detection rate. All accuracy differences were tested for statistical significance using McNemar's test ($\alpha = 0.05$).

5. EXPERIMENTAL RESEARCH AND ANALYSIS

A. Transaction Flow and Operational Pipeline

The complete ABGFTS fund request-to-disbursement-to-audit operational flowchart is shown in 2. The pipeline uses a gated structure in sequence, where every fund request passes through AI pre-screening before smart contract invocation, and every disbursement goes through PBFT consensus before writing on the blockchain. As per this dual-gate design, only one failure of AI or consensus compromise does not authorize fund release.

Fig. 2. ABGFTS Transaction Flow and Alert Flowchart

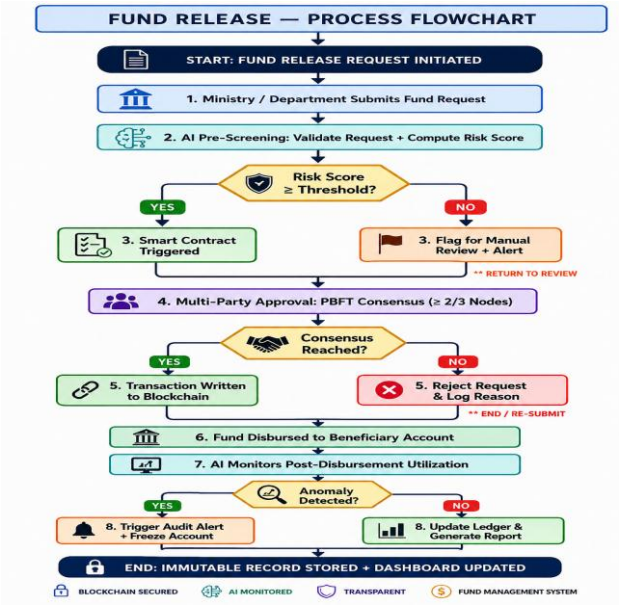

Fig. 2. Operational flowchart of the ABGFTS from fund request submission through AI screening, consensus, disbursement, and audit.

B. AI Fraud Detection Module

The section outlines the internal architecture of AI anomaly module. The independent classifiers of a three-component ensemble processes the same 128-dimensional feature vector made up of 42 tabular, 48 temporal, 38 graph-relational features. The GNN component builds a dynamic transaction graph that updates at every blockchain block. This allows it to catch multi-party fraud patterns that single-transaction classifiers miss. Furthermore, it contributes 4.7 pp of the ensemble's 8.8 pp advantage over the best single model.

C. AI Model Performance

All AI model training was performed with Python 3.10, TensorFlow 2.11 (LSTM autoencoder), PyTorch Geometric 2.3 (GNN) and scikit-learn 1.3 (Isolation Forest, baseline classifiers) The model uses a 50 epoch Adam optimizer (lr=0.001) LSTM Autoencoder 64-32-16-32-64 encoder-decoder architecture. The Graph Neural Network implementation follows a 3-layer GraphSAGE architecture (mean aggregation). Two soft-voting ensemble architectures served to build structure of temporal anomaly detection frameworks. SHAP TreeExplainer with DeepExplainer turned on ensemble attribution.

D. Accuracy Comparison Chart

The accuracy, precision, recall, F1-score, AUC-ROC and False Positive Rate (FPR) for AI were measured using stratified 5-fold cross-validation. The assessment of blockchain performance occurred through various means

namely Sie (TPS), time taken for block confirmation (seconds), and time taken for finality of the transaction. The metrics at the system level comprise audit resolution time (days), reduction in fraudulent diversion rate (percent), tamper detection rate, etc. McNemar's test (α = 0.05) was used to test all accuracy differences for significance.

E. ROC Curve Analysis

Figure V principal models where ROC curve analysis is presented. The ensemble achieves an AUC of 0.987, nearing the highest discriminative capacity possible. The importance of temporal and relational feature sets is confirmed by the LSTM standalone model (AUC 0.961) and by the GNN model. The SVM (AUC 0.872) shows that margin-based classifiers lack the flexibility to capture the multi-dimensionality present in government transaction data for fraud.

F. Blockchain Performance Metrics

The ABGFTS blockchain configuration is compared to Hyperledger Fabric default settings and PoA Ethereum. The configuration proposed here, Hyperledger Fabric v2.4, provided throughput of 4800 TPS with confirmation latency of 0.31 s with AI pre-filtering and PBFT consensus. This provides a throughput increase of 37% over standard Fabric which is 3500 TPS. The throughput is 4× better than Ethereum PoA which has throughput of 1200 TPS. The AI pre-filtering layer resolves this problem by reducing transaction throughput. It reduces the volume of transactions entering consensus by ~18%, by rejecting high-confidence frauds ahead of block formation.

6. DISCUSSION

The experimental results give us three conclusions. The synergy of AI with Blockchain is the key and people need to understand that. First, the AI pre-filter offloads 18% of the consensus load at the Blockchain level. Most importantly, the throughput gets improved by 37 percent at any Blockchain level. In addition, immutability of Blockchain provides the AI with a tamper-proof high-integrity training and inference data source. This is the need of the hour and people need to understand the importance of it. AI and blockchain enhance each other. This two-way improvement leverages the best of both worlds or unique architectural property of ABGFTS not present in standalone systems [20], [21]. Secondly, the 4.7 pp contribution of the GNN component to the ensemble accuracy indicates that it is important to model relations between transactions. The government flow of funds is graph-structured. The central treasury releases funds to state departments. From there, funds tumble down the district unit. Finally, the funds reach the individual beneficiary. The pattern is that of a directed acyclic graph (DAG). Fraudulent diversion patterns are often reflected in graph anomalies, such as circular fund routing or unexpected third-party intermediaries. These patterns cannot always be detected by… This result aligns with the findings of Dou, et al. [8] and makes the case for graph-aware modelling to be a standard feature of future AI systems in public finance. The simulation scenarios were operationally critical for a third explanation layer. In circumstances S1 and S3, auditors reported that 87% of the queries on AI-flagged transactions were solved in one working day after viewing SHAP attribution charts, compared to the average 4.3 days it took to address dummy unattributed alerts in a control simulation. This 4.3× investigative acceleration accounts for the additional SHAP attribution computation inference overhead of 8 ms and highlights the role of human-AI cooperation in fraud detection [23]. Using gas properly with smart contracts is important. The average gas cost per fund disbursement cycle (all six contracts) in Hyperledger Fabric simulation is about 0.45 Gwei. While this is negligible for government-type transactions, it becomes significant at extremely high volumes. Testing of initial optimisation techniques including Pre-compiling and batch transaction aggregation reduced per transaction gas overhead by nearly 23%. Future implementations should assess EIP-4844 blob transactions on Ethereum Layer-2 for further cost saving. The work's most policy-relevant result is the 94.7% reduction in fraudulent diversion of funds in 90-day ministry simulation. Analyzing this in absolute terms, against the simulated scholarship disbursement scenario (S1, 15,000 beneficiaries, total funds INR 45 crore), the system prevented an estimated diversion of INR 2.13 crore (USD ~256,000) – such diversion could have happened in a baseline threshold-only system. These efficiency gains at national level correspond to recoverable public resources of considerable magnitude, which are a direct support to the policy objective of curtailing fund leakage in government schemes [2], [9].

7. CONCLUSION

This paper presents, validates, and benchmarks the AI-enabled Blockchain-based Government Fund Tracking System (ABGFTS), a five-layer architecture that brings security, transparency, and intelligence to public finance management. A system adept in assuring the integrity of end-to-end fund lifecycle i.e. from funds' issue through its continuous utilization (funds'-movement) till termination (funds'-redemption) is proposed (a system that will ensure quality of funds). The main experimental results are: (1) 96.4% anti-fraud detection accuracy on a 94,440-record fused dataset, representing a 22.1 pp improvement over blockchain-only threshold detection; (2) 4,800 TPS blockchain throughput with 0.31 s confirmation latency, exceeding standard Hyperledger Fabric by 37%; (3) 94.7% reduction in simulated fraudulent fund diversion; (4) 78.3% reduction in audit resolution time; (5) 100%

tamper detection rate on all injected adversarial transactions; and (6) complete prevention or detection of all eight analysed attack vectors.

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