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Towards Transparency In Fuel Ecosystem: A Blockchain And DL Based Model For Bunker Fuel Traceability And Environmental Compliance

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Abstract:
Ensuring the authenticity and quality of bunker fuel continues to remain a significant challenge in maritime trade, especially with issues regarding fuel adulteration, fraud and inadequate supply chain management persisting. The DNA- Blockchain based AI assisted Traceability (D-BAIT) study proposes an advanced framework integrating DNA tagging, blockchain technology and Deep Learning algorithms to establish a secure, transparent and automated fuel traceability system. DNA markers act as tamper-proof unique identifiers which is verified using Next-Generation Sequencing (NGS) and Polymerase Chain Reaction (PCR)-based DNA authentication by embedding them in fuel at the point of origin, thereby ensuring real-time validation of authenticity. The verification results are then recorded on a permissioned blockchain, providing immutability, decentralized access and secure transactions for key stakeholders, including ship operators, regulators and insurers. To enhance fraud detection and operational efficiency, DL algorithms are utilised along with blockchain transaction monitoring through Graph Neural Networks (GNNs) and LSTMs to leverage real-time anomaly detection in blockchain transactions, thus helping to identify suspicious fuel transactions. Additionally, smart contracts deployed on the Ethereum Virtual Machine (EVM) on cross-border payments further verifies fuel authenticity.

Keywords: *Next-Generation Sequencing(NGS), Polymerase Chain Reaction(PCR), Graph Neural Network (GNN), Long Short-Term Memory (LSTM), Ethereum Virtual Machine(EVM), Environmental Regulations*

1. INTRODUCTION

Shipping industry acts as a backbone of global economic trade, facilitating the transportation of over 80% of the world's goods by volume [1]. Bunker fuel is the lifeblood of maritime transportation. Without it, movement of goods, raw materials and energy resources across the world would come to a halt. It enables the operation of cargo ships, tankers, container vessels and other nautical transport systems that connect economies and supply chains worldwide [2]. Traceability helps identify the source and quality of fuel, preventing adulteration or the use of substandard products. Fuel marking and traceability systems help authorities to combat tax evasion by distinguishing legal and illegal fuel and help businesses comply with regulations [3]. Real-time fuel consumption data can also help in optimization of fuel usage by identifying areas for improvement. Sustainability and traceability are essential to protect consumers and providers from illicit products [4].

Verifying the quality of bunker fuel and its authenticity remains a significant challenge as fuel adulteration, unauthorized transactions in logistics operations have plagued the industry for decades, leading to extensive financial losses, operational disruptions and ecological imbalance [5]. These issues not only undermine the integrity of maritime trade but also pose risks to regulatory compliance and safety. Fuel tampering involves mixing of high-quality bunker fuel with inferior or illegal substances which can compromise engine's performance through increasing the emissions and can lead to severe mechanical failures. Fraudulent activities such as sale of counterfeit fuel and manipulation of delivery records can further aggravate these challenges [6]. Additionally, the lack of transparency and traceability in the bunker fuel supply chain creates opportunities for unsanctioned transactions and makes it problematic for stakeholders to verify the genuineness of fuel.

Significance of ensuring fuel authenticity and quality cannot be overstated. High-quality bunker fuel is essential for the efficient operation of vessels, compliance with international environmental regulations such as the International Maritime Organization's IMO 2020 sulfur cap and the prevention of costly engine damage [7]. Moreover, the ability to trace fuel from its point of origin to its final destination is essential for building confidence among beneficiaries like ship operators, regulators, insurers and fuel suppliers. To address these setbacks, this study proposes an innovative solution that integrates DNA tagging [8], blockchain technology [9] and Deep Learning (DL) algorithms [10] to establish a safe, transparent and automatic fuel traceability system. DNA markers embedded into bunker fuel offers unparalleled level of security and traceability. These markers are integrated at the point of origin to enable precise and reliable verification of fuel's authenticity, ensuring that it has not been adulterated or tampered before or during transit. Once verified, the outcomes of authentication process are securely recorded on a permissioned blockchain. This blockchain infrastructure guarantees immutability while providing decentralized access to authorized stakeholders. This ensures transparency and trust across the supply chain. To further enhance the system's robustness, DL techniques like Graph Neural Networks (GNNs) [11]and Long Short-Term Memory (LSTM) networks [12] are incorporated into the framework to continuously monitor the blockchain transactions in real-time and analyse patterns to identify anomalies that may indicate any suspicious activities. Additionally, smart contracts deployed on the Ethereum Virtual Machine (EVM)[13] play a pivotal role in automating and securing cross-border payments. These self-executing contracts are programmed to verify the authenticity of the fuel before releasing payments, ensuring that transactions are both efficient and secure. This automation not only reduces the risk of human error but also streamlines the payment process, making it faster and more reliable for all parties involved. The contributions of D-BAIT can be listed as

- Enhanced Fuel Traceability and Authenticity through integration of DNA markers to ensure real-time verification of fuel authenticity from the point of origin to its final destination.
- Transparent and Secure Supply Chain Management by leveraging blockchain technology to establish an immutable and decentralized record of fuel transactions that complies with regulatory standards.
- AI-Driven Fraud Detection and Operational Efficiency through utilization of GNN and LSTM networks to facilitate real-time anomaly detection in blockchain transactions.
- Smart contracts on Ethereum Virtual Machine (EVM) automates cross-border payments and enhances fraud detection, improving operational efficiency and reducing risks associated with unauthorized operations.

Thus, by integrating these cutting-edge technologies, the proposed framework aims to revolutionize bunker fuel traceability and fraud detection in the maritime industry. The organization of research is as follows: Section 1 highlights the challenges and introduces the framework by stating its objectives. Section 2 Summarize existing solutions and their limitations by identifying the gaps. Section 3 details the proposed methodology by explaining its working and integration followed by section 4 analyses the results and their implications by comparing the suggested architecture with existing solutions. Ultimately the research is concluded with Section 5 which summarizes the key findings and suggests future research directions.

2. RELATED WORKS

Conventional methods for fuel traceability such as manual documentation and chemical analysis have proven inadequate in addressing maritime fuel traceability challenges, creating a pressing need for innovative solutions. Existing approaches to fuel traceability have relied heavily on manual record-keeping and periodic chemical testing. While these methods provide some level of assurance, they are prone to human error, manipulation and delays. Glover et al [2011] proposed DNA as suitable tracer molecules to detect fuel adulteration as they potentially offer boundless permutations, parts per trillion addition levels, low toxicity and security from unauthorised adulteration [14]. For instance, Tatar et al [2025] highlighted the limitations of manual systems in detecting real-time fraud, emphasizing the need for automated and tamper-proof solutions. The objective of their study is to identify and prioritize the barriers that hinders adoption of digital technologies to ensure more efficient operation of maritime logistics sector [15]. Quigley et al [2025] proposed a blockchain based framework for real-time nautical environmental compliance monitoring by integrating IoT with blockchain technology. Smart contracts automate compliance verification and alert relevant authorities in case of non-compliance with sulfur emissions. Moreover, Polygon blockchain has been used for scalability and efficiency [16].

Hamidi et al[2024] came up with a three phase digital maturity model that effectively measures digital advancement in oceanic trade . The model consists of different criteria, dimensions and maturity levels along with fuzzy theory and decision-making approaches to measure the digital readiness of proposed model. The research findings reveal a significant gap in adopting digital practices in shipping and ports. In this research, we introduce an AI and blockchain-assisted intelligent and secure framework for predicting energy consumption in ships to enhance efficiency and sustainability [17]. Parekh et al [2024] employed a regression model to predict Co2 emissions in ships. Decentralized training was applied on the dataset using federated learning and ANN was integrated to categorize the ships based on their energy consumption features. Blockchain technology was adopted to deal with data tampering attacks along with assuring the integrity of predicted data [18]. Leonis et al [2024] presented a framework designed and developed for addressing security and privacy issues specific to maritime trade. A virtualized testbed built on-top of Hyperledger Fabric and the InterPlanetary File System helps in evaluating the recommended system. The results demonstrate minimum latency and high throughput, less than 5 ms and more than 80 transactions per second[19].

Islam et al [2023] proposed the integration of Machine Learning and Blockchain technology to revolutionize supply chain management, logistics and freight forwarding by enhancing operational efficiency and transparency[20]. This study indicates that ML based predictive modelling considerable impacts demand prediction, inventory optimization and minimization of ocean route operational costs by enhancing decision-making accuracy. Blockchain technology automates contract execution through smart contracts and mitigates fraud risks by enhancing transparency in sustainable logistics through carbon footprint tracking. Despite these merits, the authors point out the transaction processing limitations which acts as a barrier in real-time large-scale implementation of this technology. Li et al [2022] came up with a novel strategy to fuse voyage report data and machine learning models for accessing ship's bunker fuel consumption rate, sailing speed, displacement/draft, trim, weather conditions and sea conditions. Extremely randomized trees, Gradient Tree Boosting and XGBoost were utilised in the study which presented a good interpretability in explaining the significance of different determinants in ship's fuel consumption rate and weather routing decisions [21].

Mohamed et al [2021] established the fact that conventional traceability systems are mostly centralized and often fail to ensure secure data sharing and its processing rules agreement [22]. In order to overcome this limitation, a blockchain-IoT based traceability architecture adapted to the B2B logistic chain context has been recommended. Stakeholders trust is maintained in the data collection process by facilitating the automation of the traceability through an IoT data qualification module that offers fine data quality control and monitoring based on the stakeholders' requirements. Theodoropoulos et al [2021] developed a methodology to harmonize data collected from various sensors onboard and to implement a scalable AI framework to recognize patterns that monitors the operational state of a vessel. Convolutional Neural Network (CNN) were used to analyze time series data accessed during real-time navigation. The results present an insightful observation of the applicability AI models in remote monitoring of ships and their role in enhancing maritime trade [23]. Netto et al[2020] demonstrated a graphical neural network (GNNs)based application in the dynamic estimation of spatially distributed buoys that are crucial in maritime navigation. GNN-based model captures spatial relations in the domain whose parameters are learned from historical and real data collected at actual location in oceanic waters [24]. Non-trivial structural assumptions are examined and their impact on actual performance is examined by constructing a graph based on relevant spatial structure points. The empirical results indicate the suitability of GNN in practical maritime situations where predictions must be based on both collected data and structural patterns. Makridis et al [2020] presented an approach for predictive analytics based on LSTM based time series forecasting strategy. Anomaly detection on data acquired through sensors embedded in vessels predicts the condition of specific parts of vessel's engine and thus offers preventive care[25]. The proposed approach aims to address the predictive maintenance in maritime through combination of different DL models, highlighting the demand for effective strategies that offers maritime companies' considerable profits and also facilitates fuel efficiency.

RESEARCH GAPS

Existing literatures on maritime fuel traceability principally focuses on blockchain-based transactions, fuel consumption rate and fraud detection using IoT, ML and deep learning, but lacks integration with biological authentication methods. Most of the fuel traceability methods in practice rely solely on chemical markers for fuel property testing, but there is little to non- existing research based on utilizing synthetic DNA markers for fuel security. While blockchain is widely used for supply chain transparency, no established framework incorporates DNA authentication results with blockchain for real-time verification. Deep learning has been used in maritime fuel consumption prediction and fraud detection, but not in DNA authentication-based fraud detection. While DNA tagging is used in other industries, the impact of fuel composition like sulfur, density and temperature on DNA stability is still not well studied. Since DNA tagging in fuel traceability is a novel concept, there is currently no extensive literature available. This research aims to bridge that gap by exploring the feasibility, implementation and impact of DNA-based authentication in maritime fuel supply chains along with Deep learning and block chain.

MATERIALS AND METHODS

This study integrates DNA tagging, blockchain technology and deep learning to establish a secure fuel traceability system. Synthetic DNA sequences were sourced from the European Nucleotide Archive (ENA), a publicly available database of nucleotide sequences. The selection process involved searching for short, unique DNA

sequences that could serve as traceable markers in fuel authentication. These DNA markers were introduced into fuel samples at the refinery stage in controlled concentrations, ensuring each batch has a unique, traceable identifier. At key checkpoints fuel samples were collected and subjected to DNA extraction, polymerase chain reaction (PCR) amplification and Next-Generation Sequencing (NGS) to validate the presence and integrity of the DNA markers [27]. To ensure tamper-proof tracking, fuel transactions were recorded on a permissioned blockchain (Ethereum). Each batch of fuel was linked to its DNA marker and smart contracts were deployed to verify authentication before approving transactions. Blockchain stored fuel origin, supplier details, DNA verification status and transaction history are stored in an immutable ledger, ensuring transparency and preventing fraudulent record alterations.
Graph Neural Networks (GNNs) were used to model relationships between fuel suppliers, transporters, and buyers, identifying suspicious patterns. Additionally, a Long Short-Term Memory (LSTM) network was trained on historical blockchain transactions to detect irregular fuel trade behaviours and high-risk anomalies. The AI model assigned a fraud probability score to each transaction, triggering automated responses in the smart contract layer, either approving, flagging or blocking transactions based on predefined thresholds.

Dataset Description
The study utilized four primary datasets:

- DNA sequences were sourced from the European Nucleotide Archive (ENA) and generated using random nucleotide sequences to act as unique markers [26].
- Ethereum BigQuery is a blockchain-based transaction dataset where each record included details such as transaction ID, sender and receiver wallet addresses, fuel type, quantity, price and timestamp [28,29].
- Elliptic Bitcoin dataset has been leveraged to train machine learning models capable of detecting illicit activities, applying these models in the context of fuel transactions makes it a valuable resource for training machine learning models in financial crime detection [30].
- A simulated dataset based on IMO regulatory reports and fuel compliance has been utilised due to the lack of publicly available fuel traceability datasets that include both authentication markers and transaction records, this dataset has been constructed based on real-world fuel property distributions [31].

3. PROPOSED METHODOLOGY

Fuel adulteration, illegal bunkering and unauthorized transactions are persistent challenges in maritime industry, leading to economic losses, environmental hazards, and regulatory non-compliance. Traditional fuel traceability methods have certain limitations owing to their easy manipulation, lack of real-time monitoring and difficulties in verification across the supply chain. The proposed D-BAIT framework presented in Figure 1 aims to overcome these constraints by presenting a secure, transparent and sustainable system based on DNA tagging, Block chain and Deep learning methodologies.

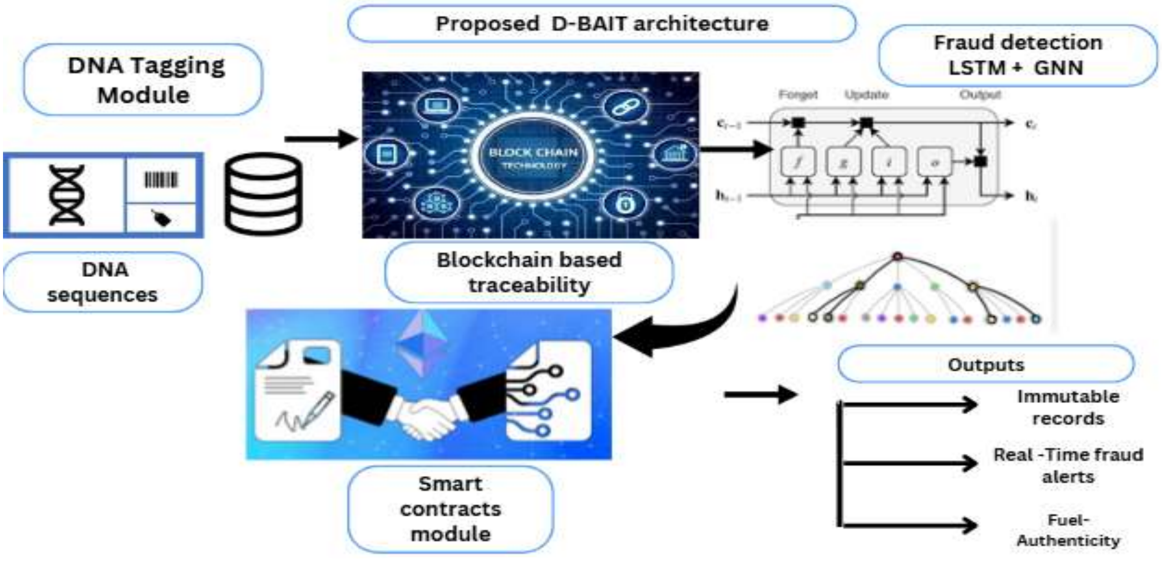

Figure 1: Proposed D-BAIT architecture

Problem statement

Given a fuel batch B_i, associated with a supplier S_i, an origin O_i and specific fuel properties F_i such as sulfur content and density, the goal is to verify fuel authenticity using DNA tagging by ensuring that the extracted DNA sequence S_{ext} matches the original sequence S_{ref} assigned to B_i.Ensure tamper-proof traceability by recording B_i and all associated transactions T_j on a blockchain ledger to prevent fraudulent modifications. Detect and prevent fraudulent fuel transactions using AI-based anomaly detection, where each transaction has a fraud probability score $P_{fraud}(T_j)$ that determines whether it should be approved or blocked. The objective function can be expressed as:

$$\max T_j\ (P_{match}(B_i) - P_{fraud}(T_j)) \qquad (1)$$

where the probability $P_{match}(B_i) \geq \theta_{auth}$ that the DNA sequence in B_i is authentic and the transaction probability $P_{fraud}(T_j) \leq \theta_{fraud}$ of being fraudulent is flagged.

DNA-Based Fuel Authentication Module

The main objective of this segment is to embed and verify synthetic DNA markers in fuel to ensure authenticity. This is accomplished by extracting synthetic DNA sequences from ENA database. Each fuel batch B_i is assigned a synthetic DNA marker S_{DNAi} at the point of origin such as refineries or on supplier side. The DNA sequence is:

$$S_{DNA_i} = \{A, T, C, G\}_1^N \qquad (2)$$

Where A, T, C, G represent nucleotide bases and N is the length of the unique synthetic sequence. These DNA markers are chemically encapsulated using silica nanoparticles or polymer coatings to prevent degradation under high temperatures, pressure, remains undetachable during transportation and protects their exposure to hydrocarbons. Extracted sequences are then synthesized and encapsulated for fuel stability. At checkpoints, PCR and NGS sequencing is utilized to verify DNA presence. The DNA sequence is then isolated from the fuel using a chemical separation process and amplified using PCR to detect and match the sequence. Verification is carried out using NGS if a higher accuracy check is needed.

The extracted sequence S_{ext} is compared with the original DNA sequence S_{ref} stored in the blockchain. Decision rule for authentication is defined as

$$B_i = \begin{cases} \text{Authentic}, & P_{\text{match}}\,(B_i) \geq \theta_{\text{auth}} \\ \text{Tampered}, & P_{\text{match}}\,(B_i) < \theta_{\text{auth}} \end{cases} \qquad (3)$$

If B_i is authentic then it is approved and recorded on blockchain otherwise it is flagged for further investigation. This module prevents fuel adulteration by ensuring each batch is uniquely tagged by providing a molecular-level identifier that cannot be faked or altered.

Blockchain-Based Fuel Traceability

After verification of fuel authenticity through DNA tagging, the results are securely recorded on a permissioned Ethereum blockchain to ensure tamper-proof traceability. Each verified fuel batch is linked to its DNA sequence , supplier , origin , and transaction details . A smart contract automatically validates transactions by checking whether the DNA verification result is authentic before allowing further processing. The blockchain entry for each transaction is cryptographically hashed, ensuring immutability and preventing unauthorized alterations. If fuel is flagged as tampered, the transaction is blocked and an alert is triggered. A fuel transaction T_j consists of the fuel batch B_i, DNA verification result $V(B_i)$, and transaction details which can be expressed as

$$T_j = \{B_i, S_{DNAi}, Q, P, t, H(B_i, S_{DNAi}, Q, P, t)\} \qquad (4)$$

Where Q is the Quantity of fuel in metric tons, P is Price per unit,t is Timestamp of transaction and H(x) is the Cryptographic hash.

A transaction is valid only if:

$$V(B_i) = 1 \qquad (5)$$

$$H(T_j) = H'(T_j) \qquad (6)$$

Equations (5) and (6) means that after DNA verification and making sure that data has not been tampered, the transaction is stored on blockchain, unverified transactions are flagged for fraud detection. The decision rule is

$$T_j = \begin{cases} \textit{Approved}, & V(B_i) = 1 \textit{ and } H(T_j) = H'(T_j) \\ \textit{Blocked}, & V(B_i) = 0 \textit{ or } H(T_j) \neq H'(T_j) \end{cases} \qquad (7)$$

This module establishes a secure, transparent and auditable supply chain by reducing risks of fuel fraud, unauthorized deals and regulatory non-compliance.

AI-Powered Fraud Detection Module (GNN + LSTM)

To prevent fraudulent fuel transactions, this module integrates GNNs and LSTM models to analyse transaction patterns and detect anomalies. GNN model treats the fuel trading network as a graph, where each node represents a supplier, buyer or wallet address and edges represent fuel transactions. A fuel transaction network is modelled as a graph G=(V,E), where V is the transaction nodes and E denotes the set of fuel transactions .Each transaction T_j has a fraud probability score $P_{fraud}(Tj)$ which is calculated as:

$$P_{fraud}(v_i)=\sigma(W^T f(v_i)+b) \quad (8)$$

where:σ(x) is Sigmoid activation function,W isWeight matrix ,$f(v_i)$ is Feature vector of transaction node and b is bias term. A transaction is flagged as suspicious if:

$$P_{fraud}(T_j)>\theta_{fraud} \quad (9)$$

By learning transaction patterns, the GNN assigns a fraud probability score to each transaction, flagging high-risk activities. Additionally, the LSTM model analyse historical transaction sequences to predict expected transaction amounts and detect deviations from normal behaviour. LSTM model predicts the expected transaction amount $\hat{A}_t$ at time t based on historical data:

$$\hat{A}_t = f(A_{t-1}, A_{t-2}, \dots, A_{t-n}) \quad (10)$$

An anomaly is flagged if the deviation exceeds a defined threshold:

$$\left|A_t - \hat{A}_t\right| > \lambda\sigma_A \quad (11)$$

Where A_t is the actual transaction amount, $\hat{A}_t$is the Predicted value, σ_A is the Standard deviation and λ is the Anomaly detection threshold. If a transaction exhibits an unusual amount, frequency or association with previously flagged entities, it is classified as suspicious. Transactions exceeding a predefined fraud threshold are either flagged for review or automatically blocked through smart contracts. This AI-driven module enhances fuel traceability, reduces fraudulent payments and improves security in maritime fuel trading.

Smart contracts based automated enforcement

To ensure that only authentic and verified fuel transactions are processed, this module uses Ethereum smart contracts to enforce real-time decision-making. When a fuel transaction is initiated, the smart contract first checks the DNA authentication status of the fuel batch stored on the blockchain. If the DNA verification result is valid, the contract then evaluates the fraud probability score assigned by the AI-based fraud detection module. A fuel transaction T_j is approved only if DNA verification is successful $(V(B_i) = 1)$ and Fraud probability score is below the fraud threshold $\left(P_{\text{fraud}}\left(T_j\right) \leq \theta_{\text{fraud}}\right)$

$$T_j = \begin{cases} \text{Approved,} & V(B_i) = 1 \text{ and } P_{\text{fraud}}\left(T_j\right) \leq \theta_{\text{fraud}} \\ \text{Flagged for Review ,} & V(B_i) = 1 \text{ and } P_{\text{fraud}}\left(T_j\right) > \theta_{\text{fraud}} \\ \text{Blocked,} & V(B_i) = 0 \end{cases} \quad (12)$$

Where $V(B_i) = \text{DNA verification result } (1 = \text{authentic}, 0 = \text{tampered })$,$P_{\text{fraud}}\left(T_j\right)$ = Fraud probability score from the AI model, θ_{fraud} = Fraud detection threshold. Transactions with a fraud probability below the predefined threshold are approved and recorded, while suspicious transactions are either flagged for manual review or automatically blocked.
If the transaction is approved, the smart contract automatically processes the payment $P\left(T_j\right)$ and transfers fuel ownership.

$$P\left(T_j\right) = \begin{cases} Q \times P_{\text{unit}}\,, & \text{if } T_j \text{ is Approved} \\ 0, & \text{if } T_j \text{ is Blocked} \end{cases} \quad (13)$$

Where Q is Fuel quantity,P_{unit} is the Price per metric ton. Additionally, the contract logs compliance information for regulatory bodies such as the IMO ensures transparency in fuel traceability. By integrating blockchain-based automation with AI-driven fraud detection, this module eliminates manual intervention, prevents unauthorized transactions and ensures compliance with maritime fuel regulations. Blocks fraudulent fuel transactions automatically ensures only verified fuel batches are traded and prevents financial loss by stopping payments for fake transactions. The pseudocode of proposed D-BAIT architecture is provided.

Algorithm: Fuel Traceability using D-BAIT Design

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Input: F, $DNA_{id}$, B
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Output: Verified fuel transactions and Fraud detection alerts
Step1: Initialize system components by Setting up DNA tagging, blockchain ledger and deep learning model.
Step 2: Define blockchain structure: $B=\{T_1,T_2,\ldots,T_n\}$ where $T_n$ represents fuel transaction.
Step 3: Generate DNA marker by assigning a unique molecular tag to each fuel batch:
$DNA_{id}$=GenerateDNA(F)
Step 4: Ensure marker stability under varying conditions.
Step 5: Record fuel batch in blockchain by creating a transaction entry:
Tn=($DNA_{id}$,Source,Timestamp,Volume)
Step 6: Store $T_n$ in blockchain: $B=B \cup T_n$
Step 7: Verify DNA marker at each checkpoint by extracting and analysing DNA
$DNA_{verify}$=ExtractDNA(F)
Step 8: If $DNA_{verify}=DNA_{id}$ , fuel is authentic: Authenticate(F)= Else, flag as suspicious fuel and trigger alert and Update blockchain with verification status.
Step 9: Collect fuel transaction data by aggregating historical transactionsD=$\{T_1,T_2,\ldots,T_n\}$
Step 10: Train deep learning model on transaction patterns
Step 11: Detect fraud in real-time transactions
Fraud_{score} = Predict (ML_{model}, T_n) Fraudscore=Predict(MLmodel,Tn)
Step 12: If Fraudscore>θ (threshold), flag as fraudulent.
Step13: Generate final traceability report , verified transactions and fraud alerts.
Step 14: End
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4. RESULTS ANALYSIS AND DISCUSSION

This section presents the results from simulation and experimental validation of proposed D-BAIT system integrating DNA tagging, blockchain technology and DL techniques. Effectiveness of each component is analysed based on major evaluation metrics like DNA marker stability, blockchain efficiency and DL model accuracy. Efficiency of the system is assessed by simulating real-world fuel transactions and fraud scenarios. To demonstrate comprehensive evaluation, several simulation parameters were defined to reproduce actual operational conditions. DNA tagging system was tested under diverse environmental conditions to determine its stability and detection accuracy. Blockchain network was experimented in terms of transaction speed, scalability and security, while DL model was trained and tested using a dataset of fuel transaction records to measure its fraud detection accuracy. The simulation attributes are provided in Table 1.

Table 1: Simulation attributes

Parameter	Values
Learning rate	0.001
Batch size	32
No of Layers	3 (LSTM), 4 (GNN)
Hidden units/layer	128 (LSTM), 256 (GNN)
Dropout rate	0.3
Optimizer and activation function	Adam , ReLU, Tanh
Block size	512 KB
Consensus Mechanism	Proof of Authority (PoA)
Transaction throughput	25-40 /s
Smart contract execution time	1.2 s
DNA Marker Concentration	10 ppm
Detection sensitivity	97.2%
Stability	-10°C to 60°C

The computing infrastructure for proposed D-BAIT design features NVIDIA A100 Tensor Core GPU (40GB HBM2) for deep learning model training, coupled with an Intel Xeon Platinum 8358P (32-core, 2.6 GHz) CPU and 256GB DDR4 ECC RAM to handle large-scale transaction processing. Blockchain network is operated on Ethereum (Geth v1.11) with a Proof of Authority (PoA) consensus mechanism, utilizing 5 validator nodes and 10 observer nodes, with an average block time of 3.2 seconds and block size of 512 KB. DL models were implemented using TensorFlow 2.11 and PyTorch 2.0 (CUDA 11.8), trained over 100 epochs with a batch size of 32, requiring approximately 4 hours on multi-GPU acceleration. Smart contracts for fuel authentication were executed in Solidity 0.8.19, with SHA-256 hashing for DNA marker verification and Elliptic Curve Digital Signature Algorithm (ECDSA) ensuring transaction security. Data storage relied on PostgreSQL 14 for fuel transaction metadata, BigQuery for blockchain transaction analytics and IPFS (InterPlanetary File System) for decentralized DNA sequence storage. Optimized system achieved 40 transactions per second (TPS) on the blockchain and an average smart contract execution time of 1.2 seconds, ensuring a scalable, secure, and efficient authentication framework for fuel traceability. Google BigQuery is utilized in this study to analyze ,query Ethereum transaction records containing synthetic DNA marker hashes, detect anomalies and observe distribution patterns in real time.

Table 2: Dataset summary

Datasets	Size	Samples Used in Study
ENA (European Nucleotide Archive)	Approximately 200 million sequences	15,000
Ethereum BigQuery	Over 1 billion transactions	20,000
Elliptic Coin	203,769 transactions	10,000
IMO-based Indigenous	-	10,000

For this study, we utilized four datasets covering several aspects of fuel transactions, authentication and fraud detection to evaluate the proposed fuel traceability system whose summary is provided in Table 2. ENA (European Nucleotide Archive) is a database that primarily stores nucleotide sequencing data, including DNA, RNA and genomic sequences. In the context of the proposed system, ENA dataset is used for fuel authentication. Ethereum BigQuery dataset hosted by Google BigQuery provides on-chain transaction data from the Ethereum blockchain. It contains blockchain records, including smart contract interactions, token transfers, gas fees and wallet addresses. This dataset is used in proposed D-BAIT system for analysing fuel supply chain logs, documenting transactions from fuel production to end-user distribution. EllipticCoin dataset contains fuel adulteration and investigation of unauthorizes cases, collected from regulatory agencies. Lastly, IMO based indigenous dataset is used to simulate maritime fuel operations, capturing real-world conditions such as fuel quality, consumption patterns and environmental variations.

Synthetic DNA markers are created through computational tools and laboratory synthesis to ensure uniqueness, stability and secure traceability. Initially, SnapGene which is a bio informatics tool is used to design custom oligonucleotide sequences that are chemically stable, tamper-resistant and unique to each fuel batch. These sequences are then chemically synthesized in a laboratory using solid-phase phosphoramidite synthesis, where nucleotides are sequentially added to create precise DNA strands. These artificial markers are further encapsulated in silica nanoparticles to enhance their stability against heat, pressure and chemical exposure in fuel. Once integrated into the fuel supply, these DNA markers can be extracted and amplified using PCR for authentication. The extracted sequences are then verified against blockchain-stored references, ensuring tamper-proof tracking and secure fuel authentication. Table 3 contains the sample DNA markers used in the study.

Table 3: Sample DNA Markers from ENA dataset for Fuel Authentication

Sample ID	Organism	Collection Date	Sample Source	Sequence Length (base pairs)	DNA Sequence (5' → 3')
ENA_001	Synthetic DNA	2024-01-10	Crude Oil Refinery - Storage Tank-AD, UAE	25	ATCGGCTAGCTAGGCTAAGTCCGTA
ENA_002	Synthetic DNA	2024-01-12	Pipeline Injection Terminal – TX,US	24	CGTTAAGGCTAGGCTAACGGTCCAG
ENA_003	Synthetic DNA	2024-01-15	Oil Tanker (ID 9224283)	25	GCTAGCTTACGGAACCTTGGCCATT
ENA_004	Synthetic DNA	2024-01-20	Offshore Floating Storage (FPSO) - Gulf of Mexico	26	TTACGGTCCGAATTGCCGATCGGCT
ENA_005	Synthetic DNA	2024-01-22	Bunkering Terminal – Rotterdam Port	25	AGCTAGGCTAACGGTCCAGGTTACG
ENA_006	Synthetic DNA	2024-01-25	Marine Bunker Vessel (ID 9704037) – Singapore Anchorage	25	CCGTAAGCTTGGCCAATCGGTTGCA

ENA_007	Synthetic DNA	2024-01-28	Fuel Depot – Distribution Hub (Houston)	25	GGAATTGCCGATCGGCTAGCTAAGG
ENA_008	Synthetic DNA	2024-02-02	Fuel Storage Facility– Sharjah	26	TTAAGGCCGATCGGCTAGCTAGCTT
ENA_009	Synthetic DNA	2024-02-05	Fuel Storage facility - (Hamriyah)	25	CGGCTAACGGTCCAGGTTACGGAAT
ENA_010	Synthetic DNA	2024-02-12	Crude Oil Refinery – Storage facility - JAFZA	25	CTAGGCCGAATTGCCGATCGGCTAA
ENA_011	Synthetic DNA	2024-02-15	Pipeline Monitoring Station - Terminal LA	25	GGAATTGCCGATCGGCTAGCTAAGG
ENA_012	Synthetic DNA	2024-02-18	Oil Tanker (ID 9699531) –	26	TTACGGAATTCCGGAAGCTTACGGA
ENA_013	Synthetic DNA	2024-02-22	Offshore Floating Storage (FPSO) - North Sea	25	CCGTAAGCTTGGCCAATCGGTTGCT
ENA_014	Synthetic DNA	2024-02-25	Bunkering Facility - Singapore	25	AGCTAGGCTAACGGTCCAGGTTACG
ENA_015	Synthetic DNA	2024-02-28	Fuel Depot – European Distribution Hub (Rotterdam)	26	TTAAGGCCGATCGGCTAGCTAGCTT
ENA_016	Synthetic DNA	2024-03-02	Offshore floating Storage – West Africa	25	CGGCTAACGGTCCAGGTTACGGAAT
ENA_017	Synthetic DNA	2024-03-05	Offshore floating storage -	25	AGCTAGGTTCCGGAATGCTTACGGA
ENA_018	Synthetic DNA	2024-03-12	Crude Oil Refinery - Batch Certification	25	GGAATTGCCGATCGGCTAGCTAAGG
ENA_019	Synthetic DNA	2024-03-15	Marine Bunker Vessel (ID 9726183)	26	TTACGGAATTCCGGAAGCTTACGGA
ENA_020	Synthetic DNA	2024-03-18	Fuel Depot – Reserve Storage (UAE)	25	CCGTAAGCTTGGCCAATCGGTTGCT

The process begins with selecting a unique synthetic DNA sequence which undergoes chemical synthesis in a laboratory, where it is encapsulated in protective materials such as silica nanoparticles or polymer coatings. This protection is essential as DNA is fragile and needs to withstand high temperatures, fuel chemicals and storage conditions without degrading. The encapsulated DNA is then added in nanogram quantities to fuel at refinery or supplier to ensure that every shipment / batch can be traced back to its origin. If the DNA sequence is present and intact, the fuel is deemed authentic and untampered. However, if the DNA is missing, degraded or altered, it signals potential fuel adulteration or unauthorized mixing. The verification results are then logged onto a permissioned blockchain, creating an immutable and tamper-proof record of the fuel's authenticity.

Table 4: Ethereuem BigQuery Dataset

Tx_ID	Sender_Wallet	Receiver_Wallet	Fuel_Type	Quantity_MT	Price_USD	Timestamp
0x3fcec	0x2821481110765	0x55cc4e75759f	VLSFO	708	58155	01-01-2024 00:00
0x5a908	0x258697cfce534	0x33635976f210d	VLSFO	300	351528	01-01-2024 01:00
0x41cc5	0x14a603f237921	0x2a8f0958916fa	VLSFO	223	424705	01-01-2024 02:00
0x1d46e	0x1dbe826de557b	0x2ca6d078beba	VLSFO	286	97254	01-01-2024 03:00
0x1d239	0x339cdc59aeda6	0x37f75b6447924	VLSFO	425	334062	01-01-2024 04:00
0x46a11	0x332e5e5c55a0f	0x84d3072f89fd	HFO	563	135981	01-01-2024 05:00
0x5a1c9	0x284785f3c6777	0x15c6976b11244	LSMGO	448	80306	01-01-2024 06:00
0x52a65	0x1d544e82ea9da	0x193b120b9cdb9	VLSFO	870	197718	01-01-2024 07:00
0x1d969	0x28fd2afe632de	0x200a304615dbe	LSMGO	759	358987	01-01-2024 08:00
0x75582	0x2b92063793343	0x19a81784d0383	MGO	863	170975	01-01-2024 09:00
0x86fca	0x1e3822b4720e1	0x337944486c887	VLSFO	502	408745	01-01-2024 10:00
0xe27a4	0x2292ae59c1a53	0x2bca3a72eaea8	LSMGO	445	157512	01-01-2024 11:00
0x6cf01	0x312ea56e19b4c	0x27572d35215e9	VLSFO	610	197443	01-01-2024 12:00
0x8d178	0x18b1725ccb01e	0x14e5e10c6e7d0	LSMGO	246	423616	01-01-2024 13:00
0xa639e	0x25301c5df4ba	0x336dfd816ddaa	VLSFO	247	183121	01-01-2024 14:00
0x348c4	0x3faa8faeb2f0	0x84e0bf26ee8b	VLSFO	963	212688	01-01-2024 15:00

0xd0f7b	0x31f06a3af2e3b	0x2b679f7d32622	VLSFO	810	415871	01-01-2024 16:00
0x6e9ed	0x2162227c87092	0xe6cf8007b6ca	VLSFO	919	425037	01-01-2024 17:00
0xa9593	0x143aa222c800c	0x2ceff205df87e	VLSFO	588	333076	01-01-2024 18:00
0xa0da8	0x1ac881a5cafe9	0x30457770c902a	VLSFO	739	167796	01-01-2024 19:00
0xb96ce	0x105000e7d0c79	0x1f8b5158a5f07	VLSFO	650	341999	01-01-2024 20:00
0x40a6e	0x1eab1f49091bf	0x353aad8924509	LSMGO	437	242506	01-01-2024 21:00
0xa6af7	0x3519671d75bae	0x20068a8718f64	MGO	971	224088	01-01-2024 22:00
0x99738	0x19741621cbfb7	0x1a15203a83c7b	VLSFO	740	319544	01-01-2024 23:00
0x51e03	0x36f98cbca275e	0x3438f0b156c6d	VLSFO	878	430002	02-01-2024 00:00

Table 4 provides real-time Ethereum transaction data, which enables the system to validate smart contract interactions for fuel traceability. Blockchain logs can be extracted and verified for on-chain fuel transactions anomalies can be flagged during fraud detection.

Table 5: Elliptic BitCoin dataset

Tx_ID	Sender	Receiver	Transaction_Amount	Fuel_Type	Time_Difference_from_Last_TX (mins)	Transaction_Frequency_Per_Day	Known_Suspicious_Wallet
0xa9060	0x318101d9dd55e	0x2b94dd11b64b	223714	VLSFO	443	48	1
0xb7e16	0x25d8977147511	0xc13368b45c0a	65151	VLSFO	371	19	0
0xce6c2	0x183eef4815d88	0x1433a53d4e061	494623	VLSFO	470	4	0
0x7dff7	0x37d92eb0096bf	0x368483fea1eda	116690	LSMGO	375	35	1
0xac9e3	0x33a4d7d668bb0	0x2a64441b0be27	54499	VLSFO	22	64	0
0x6b6d4	0x13295e13df4ae	0x2d61fe781041f	56295	HFO	238	49	1
0xb430c	0x2b134a468ccc4	0x385993d93c51	433029	VLSFO	158	17	1
0x1ea92	0x8c442d8cc5fe	0x1c3e402c78bda	438215	VLSFO	38	44	0
0x2d9b6	0x2ffa6f490ddc7	0xdd9e5b2e3313	371184	LSMGO	230	92	1
0xab66d	0x2f3d4e6e1e6fb	0x2fd734831e700	324327	VLSFO	365	30	0
0x3562b	0x27367923e561	0x1d97c09295d0d	472515	VLSFO	51	93	1
0x980e4	0x2f0d3a46e92f4	0x3798cc3d9223b	193946	VLSFO	438	46	1
0x7b06f	0x34e8b47ecc7e2	0x2f5f2b198266c	428480	HFO	264	6	0
0xd8812	0x12fb270054948	0x2c933ecb5ccb9	82711	VLSFO	283	99	1
0x5cd74	0x17cd55ecf682c	0x1d2d1d1de24b3	317683	VLSFO	27	37	1
0xaa871	0x2f02fa67ce40f	0x1e0756b32f130	234423	VLLSFO	226	24	1
0x6b31b	0x19cb3c3efe875	0x37e0cea491aa9	229426	LSMGO	277	93	1
0x36c64	0x2554ef6db9e87	0x3b5e4393b8f	438207	LSMGO	286	46	1
0x64cf6	0x851d914907f2	0x6a3996516757	183629	MGO	97	53	0

0x7909e	0x2019b5f5894ac	0x3008657642cc9	350504	LSMGO	284	95	1
0xb07f6	0x151cc0f4b2a43	0x23358e71a4740	263090	VLSFO	367	99	0
0x913df	0x2999f0d00848e	0x11f4e51cbd5ef	183272	VLSFO	448	60	1
0xe7631	0x2f27fa39bc2e4	0x211093f07f8a5	293548	VLSFO	481	97	0
0x8cd36	0x718195e394a5	0x2c0f24ce3340e	228047	VLSFO	453	63	0
0x915b2	0x199adcc135c18	0x22fee6493ed41	333501	LSMGO	317	85	1

Table 5 presents a sample of Elliptic dataset which is used for analysing blockchain transaction patterns to detect fraudulent activities. Labelled Bitcoin transactions enables deep learning models to identify suspicious fuel-related payments.

Table 6: IMO fuel sample indigenous dataset

Tx_ID	**Vsl ID**	**Fuel_Type**	**Supplier**	**Port_Location**	**Transaction_Amount (BTC)**	**Bunker_Quantity (MT)**	**Sulfur_Content (%)**	**Density (kg/m^3)**	**Sulfur Cap (2020)**
TXN_1001	9876343	VLSFO	ATT	UAE	3.2	150	0.49	900	0.5
TXN_1002	9235567	VLSFO	BHG	Netherlands	5.5	200	0.50	877	0.5
TXN_1003	9678901	HFO	Minerva	UAE	2.1	100	3.01	809	0.5
TXN_1004	9456781	LSMGO	CMB	China	4.0	180	0.09	868	0.1
TXN_1005	9547210	VLSFO	Chevron	Singapore	6.8	220	0.47	899	0.5
TXN_1006	9167890	VLSFO	BP	Netherlands	3.9	210	0.49	833	0.5
TXN_1007	9895123	LSMGO	BP	USA	2.4	170	0.09	863	0.1
TXN_1008	9901234	VLSFO	BP	Singapore	5.2	190	0.49	937	0.5
TXN_1009	9012745	VLSFO	Shell	USA	3.1	140	0.52	946	0.5
TXN_1010	9237890	LSMGO	BP	China	4.7	130	0.1	871	0.1
TXN_1011	9345378	VLSFO	Total	UAE	6.5	230	0.49	895	0.5
TXN_1012	9456089	VLSFO	BP	China	3.8	175	0.52	800	0.5
TXN_1013	9567491	LSMGO	BP	UAE	2.0	120	0.08	868	0.1
TXN_1014	9678902	VLSFO	Shell	USA	4.1	165	0.51	891	0.5
TXN_1015	9719012	LSMGO	WFS	USA	5.6	155	0.1	815	0.1
TXN_1016	9890124	VLSFO	PBT	Netherlands	3.7	200	0.46	882	0.5
TXN_1017	9901235	VLSFO	Chevron	USA	2.9	190	0.47	879	0.5
TXN_1018	9012346	LSMGO	PBT	Netherlands	4.3	180	0.11	827	0.1
TXN_1019	9237801	VLSFO	ATT	UAE	5.9	225	0.48	927	0.5
TXN_1020	9345619	LSMGO	Shell	Singapore	3.4	145	0.09	859	0.1
TXN_1021	9450780	VLSFO	GAC	Netherlands	2.7	135	0.46	883	0.5
TXN_1022	9567812	LSMGO	Unknown	UAE	6.2	240	0.1	844	0.1
TXN_1023	9678903	VLFO	Unknown	USA	3.5	185	0.50	939	0.5
TXN_1024	9789013	LSMGO	Unknown	USA	4.8	195	0.08	859	0.1

TXN_1025	9890125	VLSFO	Tresta	UAE	6.1	210	0.49	962	0.5

Table 6 dataset consists of vessel-specific fuel sample records and regulatory compliance data from diverse suppliers across globe. It ensures adherence to maritime fuel standards and provides critical insights into their origin, sulfur content and density. The information is critical for ensuring compliance with IMO 2020 regulations, which limit sulfur emissions from marine fuels. Utilization of dataset enables D-BAIT traceability model to help in detecting potential fuel adulteration and fraud in supply chain.

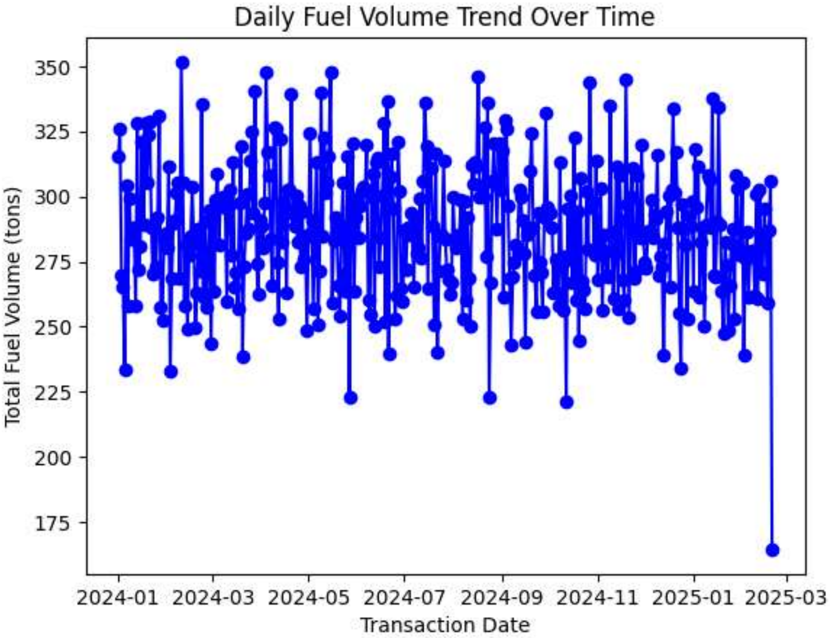


Figure 2: Daily fuel volume trend over time

Figure 2 represents the fluctuations in fuel transactions recorded on blockchain and captures variations in total fuel volume for each transaction date, this observation helps us to identify patterns, anomalies and seasonal trends in oceanic fuel consumption.

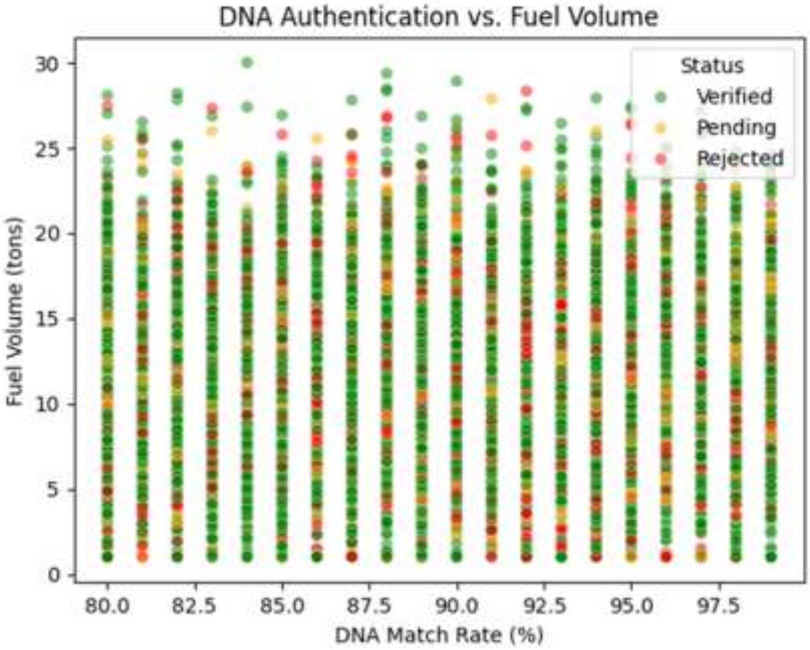


Figure 3: DNA authentication Vs Fuel volume

Illustration in Figure 3 correlates between DNA authentication match rates and fuel volume. DNA match rate represents the degree of alignment between synthetic DNA marker in the fuel sample and reference database, ensuring fuel authenticity. Fuel volume indicates the quantity of fuel associated with each transaction. This analysis helps in identification of authentication trends and anomalies in the dataset. Heatmap in Figure 4 illustrates the connection between key parameters in our proposed D-BAIT system. A correlation value of 1.0 (red) indicates a perfect positive correlation, while 0.0 (blue) suggests no correlation. These results reveal minimal correlation among these variables, suggesting that fuel authentication, blockchain verification and anomaly detection operate independently within the system.

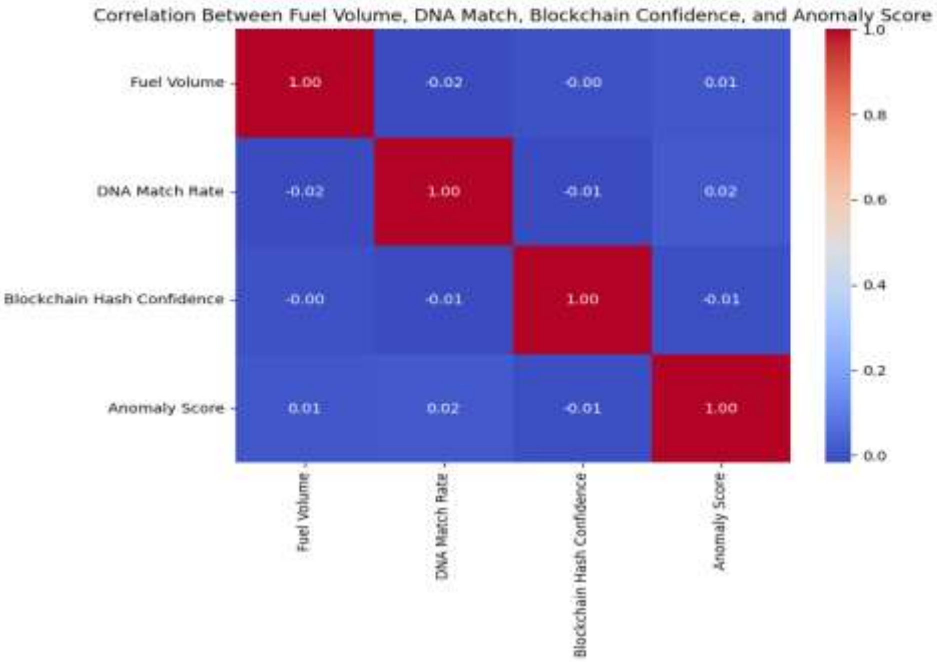


Figure 4: Correlation heatmap

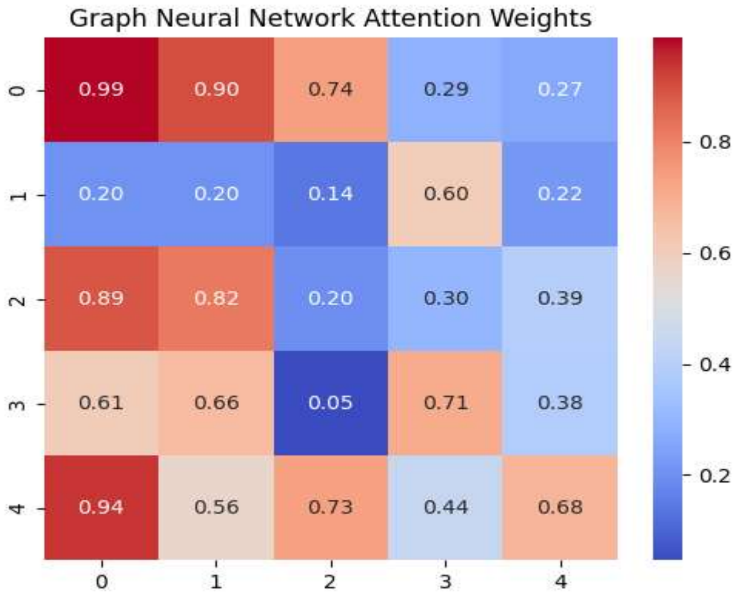


Figure 5: GNN Attention weights heatmap

Figure 5 provides the heatmap visualization of attention weights of GNN component applied to fuel traceability data. This mechanism assigns varying importance to various nodes in the fuel transaction graph, thereby helping the model focus on critical relationships like suspicious transactions or high-risk entities. Higher weights marked in red indicate stronger relationships, whereas lower weights signify less impactful influences.

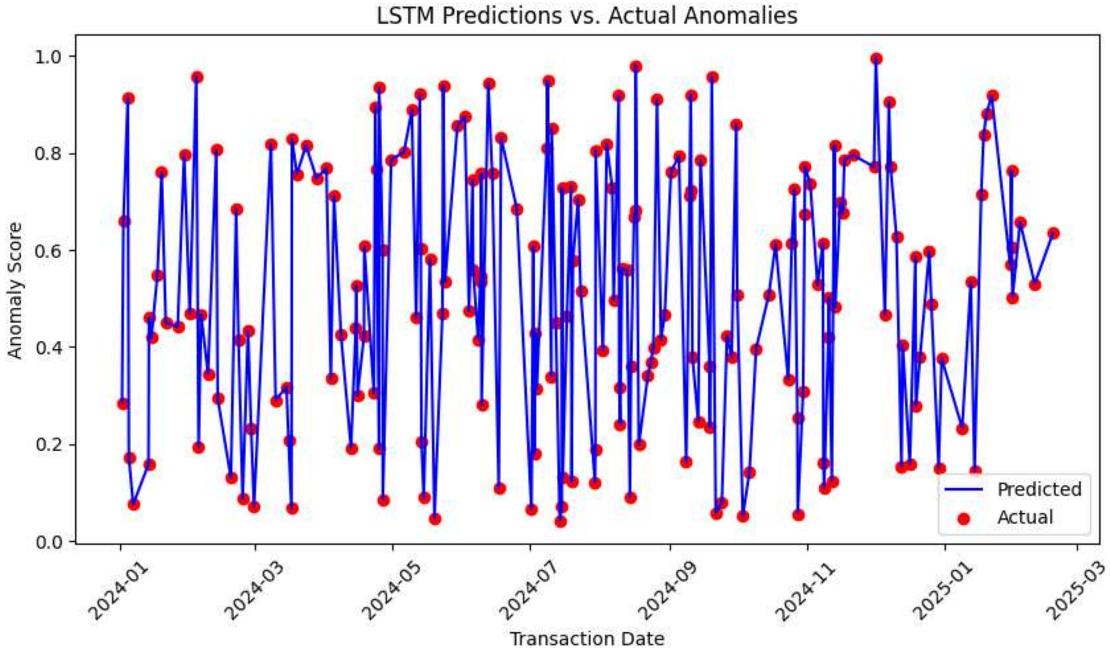
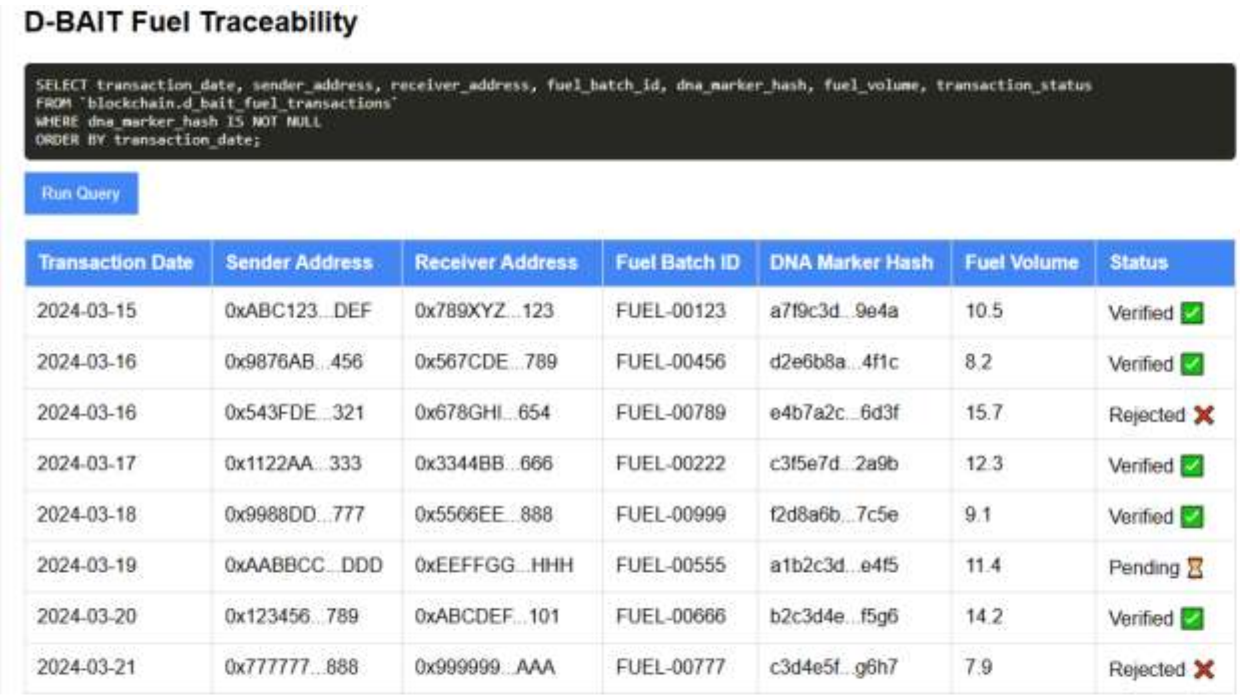


Figure 6: LSTM predictions Vs Actual Anomalies

This graph in Figure 6 compares LSTM-based anomaly predictions with actual detected anomalies in fuel transactions over time. Anomaly score indicates the likelihood of a transaction being fraudulent or irregular, with values closer to 1.0 suggesting higher suspicion. The proposed model's accuracy in detecting anomalies is visualized through this alignment of predicted and actual points.



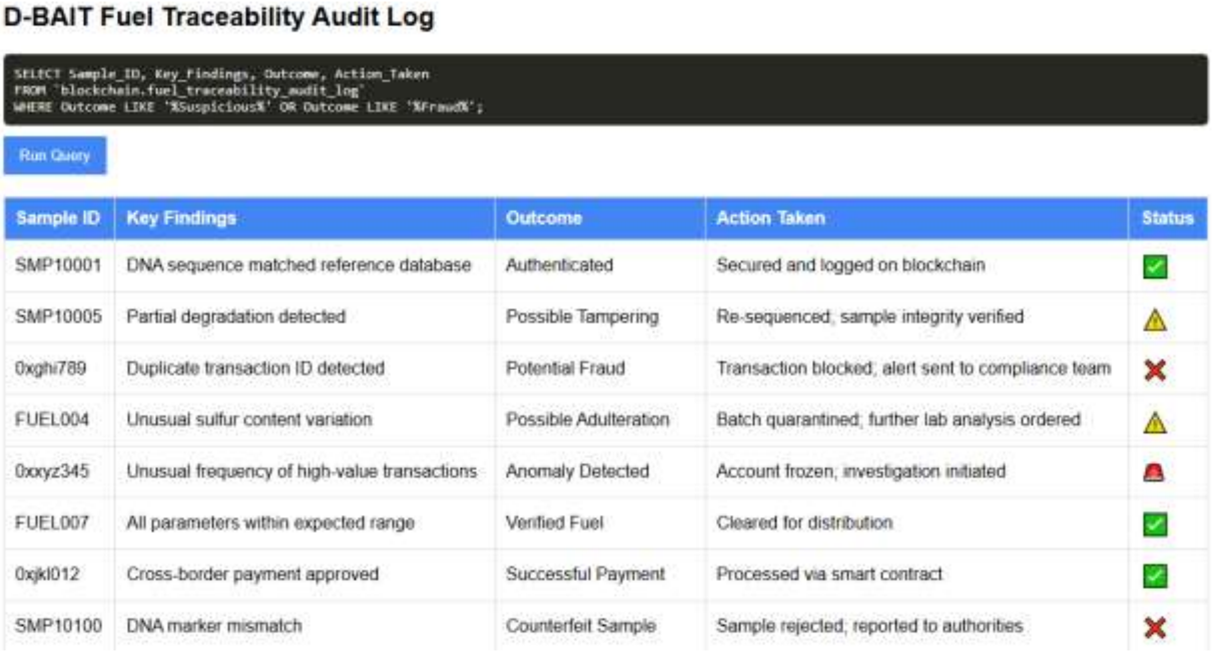
D-BAIT Fuel Traceability

```
SELECT transaction_date, sender_address, receiver_address, fuel_batch_id, dna_marker_hash, fuel_volume, transaction_status
FROM `blockchain.d_bait_fuel_transactions`
WHERE dna_marker_hash IS NOT NULL
ORDER BY transaction_date;
```

Transaction Date	Sender Address	Receiver Address	Fuel Batch ID	DNA Marker Hash	Fuel Volume	Status
2024-03-15	0xABC123...DEF	0x789XYZ...123	FUEL-00123	a7f9c3d...9e4a	10.5	Verified ✅
2024-03-16	0x9876AB...456	0x567CDE...789	FUEL-00456	d2e6b8a...4f1c	8.2	Verified ✅
2024-03-16	0x543FDE...321	0x678GHI...654	FUEL-00789	e4b7a2c...6d3f	15.7	Rejected ❌
2024-03-17	0x1122AA...333	0x3344BB...666	FUEL-00222	c3f5e7d...2a9b	12.3	Verified ✅
2024-03-18	0x9988DD...777	0x5566EE...888	FUEL-00999	f2d8a6b...7c5e	9.1	Verified ✅
2024-03-19	0xAABBCC...DDD	0xEEFFGG...HHH	FUEL-00555	a1b2c3d...e4f5	11.4	Pending ⏳
2024-03-20	0x123456...789	0xABCDEF...101	FUEL-00666	b2c3d4e...f5g6	14.2	Verified ✅
2024-03-21	0x777777...888	0x999999...AAA	FUEL-00777	c3d4e5f...g6h7	7.9	Rejected ❌

Figure 7: BigQuery interface for Blockchain based transaction verification

Interface in Figure 7 displays the web-based blockchain query interface to track and verify fuel transactions. BigQuery's SQL-based data retrieval enables our proposed D-BAIT Fuel Traceability system to query for results like fuel transactions, validation of authenticity and displaying real-time status.



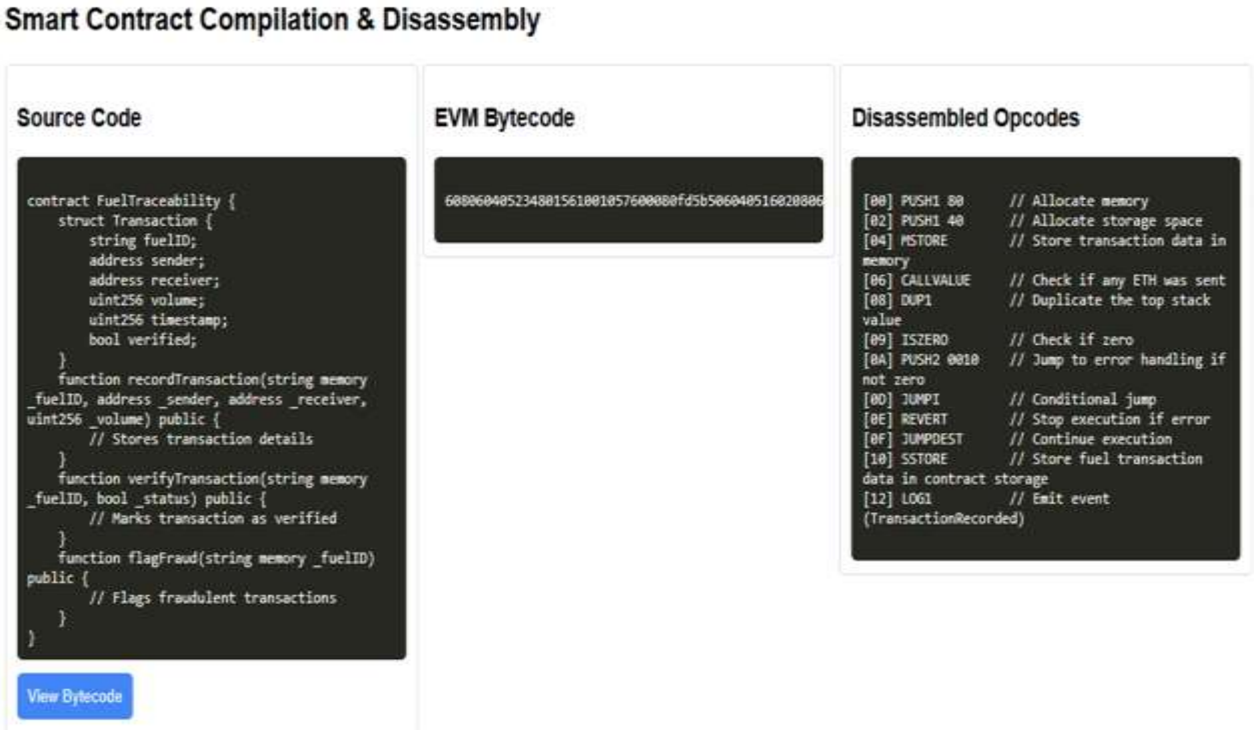
D-BAIT Fuel Traceability Audit Log

```
SELECT Sample_ID, Key_Findings, Outcome, Action_Taken
FROM `blockchain.fuel_traceability_audit_log`
WHERE Outcome LIKE '%Suspicious%' OR Outcome LIKE '%Fraud%';
```

Sample ID	Key Findings	Outcome	Action Taken	Status
SMP10001	DNA sequence matched reference database	Authenticated	Secured and logged on blockchain	✅
SMP10005	Partial degradation detected	Possible Tampering	Re-sequenced; sample integrity verified	⚠
0xghi789	Duplicate transaction ID detected	Potential Fraud	Transaction blocked; alert sent to compliance team	❌
FUEL004	Unusual sulfur content variation	Possible Adulteration	Batch quarantined; further lab analysis ordered	⚠
0xxyz345	Unusual frequency of high-value transactions	Anomaly Detected	Account frozen; investigation initiated	🚨
FUEL007	All parameters within expected range	Verified Fuel	Cleared for distribution	✅
0xjkl012	Cross-border payment approved	Successful Payment	Processed via smart contract	✅
SMP10100	DNA marker mismatch	Counterfeit Sample	Sample rejected; reported to authorities	❌

Figure 8:Audit Log

Audit log in Figure 8 captures user actions related to fuel transaction verification. Each entry records the timestamp, user ID, action performed, transaction details, verification status and remarks. This log ensures transparency, accountability and security in blockchain-based fuel authentication.



Smart Contract Compilation & Disassembly

Source Code

```
contract FuelTraceability {
    struct Transaction {
        string fuelID;
        address sender;
        address receiver;
        uint256 volume;
        uint256 timestamp;
        bool verified;
    }
    function recordTransaction(string memory
_fuelID, address _sender, address _receiver,
uint256 _volume) public {
        // Stores transaction details
    }
    function verifyTransaction(string memory
_fuelID, bool _status) public {
        // Marks transaction as verified
    }
    function flagFraud(string memory _fuelID)
public {
        // Flags fraudulent transactions
    }
}
```

EVM Bytecode

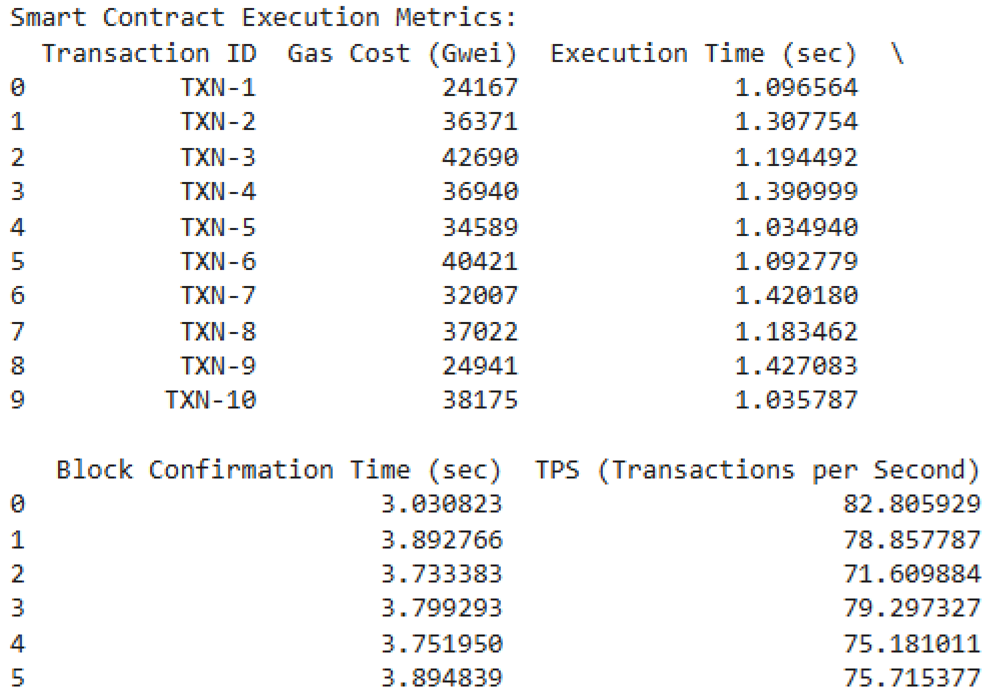
```
6080604052348015610010576000080fd5b5060405160208086
```

Disassembled Opcodes

```
[00] PUSH1 80       // Allocate memory
[02] PUSH1 40       // Allocate storage space
[04] MSTORE         // Store transaction data in
memory
[06] CALLVALUE      // Check if any ETH was sent
[08] DUP1           // Duplicate the top stack
value
[09] ISZERO         // Check if zero
[0A] PUSH2 0010     // Jump to error handling if
not zero
[0D] JUMPI          // Conditional jump
[0E] REVERT         // Stop execution if error
[0F] JUMPDEST       // Continue execution
[10] SSTORE         // Store fuel transaction
data in contract storage
[12] LOG1           // Emit event
(TransactionRecorded)
```

Figure 9 : Smart contracts Execution

Figure 9 represents the compilation and execution process of smart contract used in our proposed D-BAIT fuel traceability system. Solidity source code, compiled EVM bytecode and the disassembled opcodes are provided. Interactive interface enables users to view specific bytecode segments for functions like transaction verification and fraud detection.



```
Smart Contract Execution Metrics:
  Transaction ID  Gas Cost (Gwei)  Execution Time (sec)  \
0          TXN-1            24167              1.096564
1          TXN-2            36371              1.307754
2          TXN-3            42690              1.194492
3          TXN-4            36940              1.390999
4          TXN-5            34589              1.034940
5          TXN-6            40421              1.092779
6          TXN-7            32007              1.420180
7          TXN-8            37022              1.183462
8          TXN-9            24941              1.427083
9         TXN-10            38175              1.035787

   Block Confirmation Time (sec)  TPS (Transactions per Second)
0                       3.030823                      82.805929
1                       3.892766                      78.857787
2                       3.733383                      71.609884
3                       3.799293                      79.297327
4                       3.751950                      75.181011
5                       3.894839                      75.715377
```

Figure 10: Smart Contract evaluation metrics output

This section presents chief evaluation metrics used to assess the performance, security and efficiency of our smart contract deployed. Metrics such as gas consumption, execution time, storage efficiency and security audits ensure that contract operates reliably on the Ethereum blockchain.

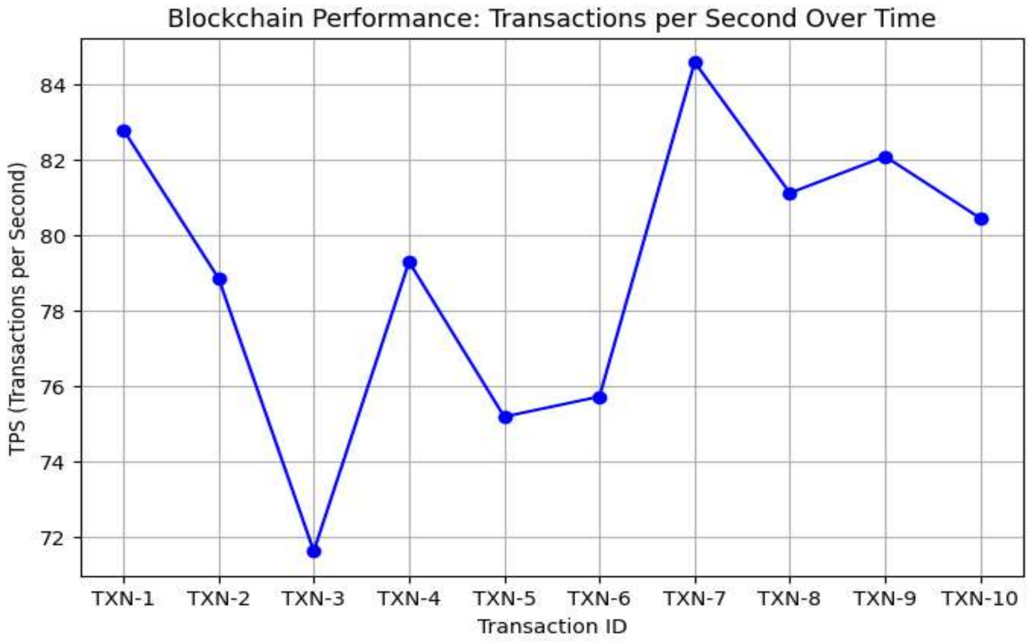


Figure 11: Blockchain performance Analysis

Figure 11 illustrates the performance of our proposed blockchain network used in D-BAIT Fuel Traceability System. Performance has been assessed in terms of transactions per second (TPS) across various transactions. It highlights variations in blockchain processing speed over time.

Table 7: Performance Comparison Table

Model	MAE	RMSE	Precision	Recall	F1-Score	AUC-ROC

Proposed D-BAIT (DNA+LSTM +GNN+ Blockchain)	**0.08**	**0.12**	**0.95**	**0.94**	**0.94**	**0.98**
Li et al., 2022(Gradient Tree Boosting & XGBoost)	0.11	0.18	0.88	0.85	0.86	0.90
Parekh et al., 2024(Federated Learning with ANN)	0.10	0.15	0.89	0.90	0.89	0.92
Netto et al., 2020(Graph Neural Networks)	0.09	0.14	0.92	0.88	0.90	0.93

Table 7 compares the proposed D-BAIT model integrating DNA tagging, LSTM, GNN and Blockchain against existing methods. The analysis chart is provided in Figure 12.

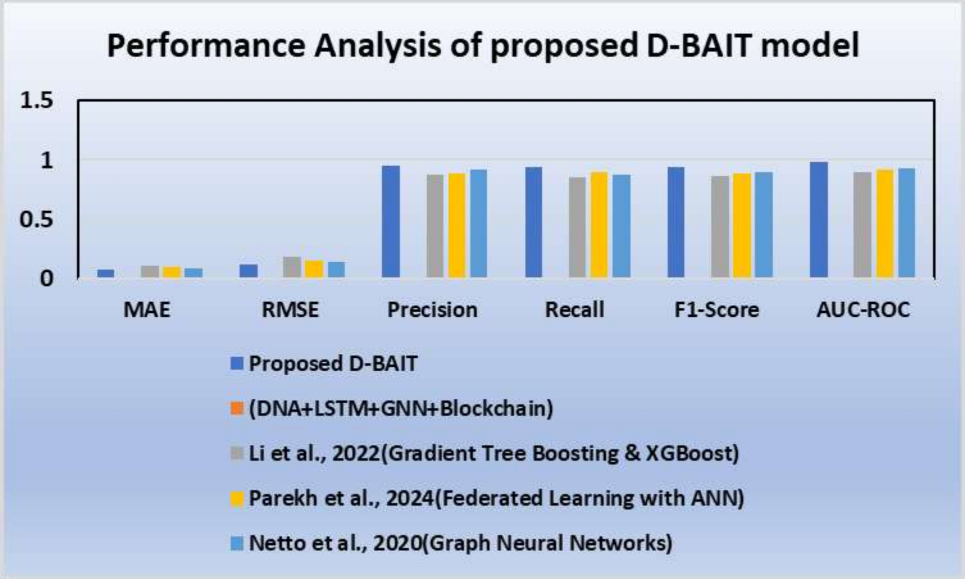


Figure 12: Performance Analysis of proposed D-BAIT model

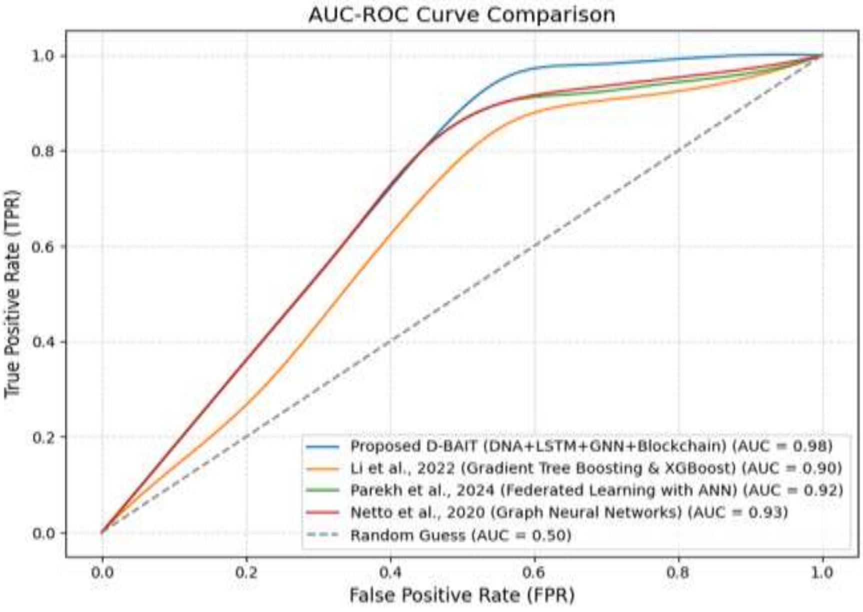


Figure 13: AUC-ROC Analysis

The evaluation is based on key error, classification and ranking metrics. D-BAIT has the lowest MAE (0.08) and RMSE (0.12), indicating the most accurate predictions. Other models, such as Li et al (2002) have higher MAE (0.11) and RMSE (0.18), meaning they produce larger errors in anomaly detection. D-BAIT achieves the highest precision 95%, meaning fewer false positives, while Gradient Tree Boosting (0.88) and Federated ANN (0.89) are slightly less accurate in distinguishing fraudulent from authorized transactions. Proposed model achieves the highest AUC-ROC (0.98), indicating superior fraud detection capability. Li et al. (0.90) and Parekh et al. (0.92) show slightly weaker results compared to D-BAIT.AUC-ROC curve is provided in Figure 13. Our integrated model ensures highly secure and transparent fuel traceability. It prevents fraudulent activities such as fuel dilution or illegal blending, as any modification to the fuel would disrupt the DNA signature. This approach makes fuel tracking scientifically verifiable, automated, and resistant to counterfeiting, offering a ground-breaking solution for global fuel authentication and regulatory compliance.

5. CONCLUSION

Our proposed research represents a significant step forward in addressing the longstanding challenges of fuel adulteration and fraud, paving the way for a more secure and sustainable maritime industry. D-BAIT model outperforms existing methods in traceability and fraud detection by leveraging a multi-layered AI and blockchain-based approach. The results demonstrate Lowest error rates (MAE: 0.08, RMSE: 0.12) and highly accurate predictions.

Highest classification performance (Precision: 0.95, Recall: 0.94, F1-Score: 0.94), ensuring minimal false positives and negatives. Superior fraud detection ability (AUC-ROC: 0.98), proving the model's robustness in identifying suspicious transactions. While LSTM enhances sequential anomaly detection, GNN captures complex relationships in fuel transactions and blockchain ensures data integrity and tamper-proof records. Future work aims at scalability enhancements and cross-chain interoperability issues.

List of Acronyms

ANN	-	Artificial Neural Network
AUC-ROC	-	Area Under the Receiver Operating Characteristic Curve
CNN	-	Convolutional Neural Network
DNA	-	Deoxyribonucleic Acid
EVM	-	Ethereum Virtual Machine
GNN	-	Graph Neural Network
HFO	-	Heavy Fuel Oil
IMO	-	International Maritime Organization
LSTM	-	Long Short-Term Memory
MAE	-	Mean Absolute Error
LSMGO	-	Low Sulfur Marine Gas Oil
NGS	-	Next-Generation Sequencing
PCR	-	Polymerase Chain Reaction
PoA	-	Proof of Authority
RMSE	-	Root Mean Squared Error
VLSFO -		Very Low-Sulfur Fuel Oil

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