

Blockchain-Based Intelligent Carbon Credit Trading and Verification System Using AI

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Abstract

Aim of the article: To propose a decentralized, intelligent carbon credit trading and verification framework integrating blockchain and Artificial Intelligence (AI) to resolve double-counting and manual verification inefficiencies.

Methods: The study utilizes smart contracts for credit lifecycle automation and a hybrid CNN-LSTM deep learning model processing satellite imagery and IoT sensor data for real-time emission verification.

Findings: The AI-blockchain model achieved 96.3% verification accuracy and 94.1% fraud detection precision, outperforming manual methods. System throughput reached 1,247 TPS while cutting gas costs by 67%.

Conclusions: Integrating AI with blockchain creates a highly scalable, tamper-proof, and efficient carbon market, effectively mitigating greenwashing and baseline inflation.

Keywords: Blockchain, Artificial Intelligence, Carbon Credits, Smart Contracts, Machine Learning

1 Introduction

Climate change is one of the most pressing issues for humanity today, being the main factor due to the continuous rise in greenhouse gas emissions from industrial activities, energy production and land-use. The trading of carbon credits is one of the most popular market based approaches to incentivize emission reduction, as companies can purchase verified carbon credits from projects that remove or avoid CO₂ emissions from the atmosphere. Although the theory is good, many entrenched problems hinder the working of carbon markets. Some of these problems are double counting, ghost credits, greenwashing, lack of transparency and excruciatingly slow verification processes, which can take as long as 12 months.

What is in place for monitoring and validation is highly reliant on the use of disjointed registries, self-reporting, centralized authorities and manual auditing processes which are susceptible to fraudulent activities and errors. These inefficiencies raise serious doubts about the effectiveness of the trading of emissions credits in terms of real emission reductions and raise distrust between market participants. There is no automatic and tamper-proof verification system, which makes carbon credits less credible, and consequently less effective as a climate change mitigation measure.

The recurring challenges can be addressed through latest advances in artificial intelligence (AI) and blockchain. Blockchain technology offers disintermediated transactions, transparency and immutability, reducing the risk of manipulation, and through distributed ledgers, ensuring traceability. Furthermore, AI algorithms could sift through vast quantities of data, including company statements, data from IoT sensors, and satellite imagery, to identify anomalies, validate environmental claims, and enhance market efficiency as the data is generated. AI enhances the capabilities of the blockchain by automating the identification of fraud and boosting the accuracy of credit validation, while blockchain provides the secure and audit-trail that AI-powered decisions require (Gupta et al., 2025).

A variety of research efforts have looked at single applications of these technologies. Gupta et al. (2025) have shown that the verification time for the AI powered blockchain networks could be far less than what it would be for the traditional ones. Similarly, various blockchain-based solutions have been suggested to integrate IoT emission sensors, satellite-based monitoring and smart contracts into smart systems for autonomous carbon credit verification (Hirlekar, 2025). To detect patterns of fraud, carbon markets have also demonstrated that they can significantly enhance fraud detection capabilities through a combination of machine learning and blockchain, using supervised models (European Space Agency, 2025). To further explore the potential for market design improvements with blockchain-based carbon trading mechanisms, models for large scale user participation have been studied, as well as double auction systems (Kumar et al., 2025; In & Schumacher, 2025).

Although these developments are promising, there is no significant research in the field of the full AI/Blockchain platform for carbon credit transaction and verification. The existing research mainly focuses on blockchain's immutability and traceability without having a proper and complete model that integrates machine learning to detect frauds proactively, verify the transactions in real-time and optimize the pricing of carbon projects with different types. To create a strong and self-regulating carbon market environment, this article presents a unique paradigm that skillfully integrates AI's analytical powers with blockchain's decentralization. Smart contracts are employed to issue, trade and retire transparently, while AI powered models are used for automated verification and fraud detection, and IoT sensors and satellite images are used for real time data capture.

2 Literature Review

The current problems of systemic integrity in carbon markets threaten the credibility as an instrument to curb climate change. A comprehensive study (Gupta et al., 2025; Kumar et al., 2025) at the core of the issues identifies the following grave issues: lack of transparency in pricing, low level of measurement, problems with verification, lack of accountability in supply, governance, market, legal and ethical issues. These problems are no accident, but a result of underlying design defects, most notably the manual, project-specific verification process based on manual baselines that are prone to double counting, inflated baselines and fraud (In & Schumacher, 2025). Low MRV in REDD+ projects encourages greenwashing by which organisations claim to be reducing emissions without actually doing so. This is the case in light of recent scandals over overly optimistic estimates of emissions reductions (Hirlekar, 2025; Stanford Law School, 2026).

In order to address these transparency issues, the blockchain has been suggested to be used with the help of its immutability and smart contracts. There have been multiple investigations that have shown the possibility that blockchain may boost traceability and stop two-counting of carbon credits (CarbonTrust, 2026; Pi & Wang, 2025). An information infrastructure combining blockchain and IoT for China's carbon credit system for the automotive industry showed the way in which operations could become decentralized to standardize procedures and enable public supervision. Real-time auditability and evidence provenance are guaranteed by decentralized storage, which is similar to blockchain-enabled frameworks for blue carbon MRV that have tokenized credits as ERC-1155 assets (Boumaiza & Maher, 2024; IEEE, 2026). Advanced technology like the use of blockchain with IoT sensors allows for the collection of data from emission sources in real-time, which creates a secure and unalterable audit trail and increases the trust of the market participants (Gupta et al., 2025). However, blockchain isn't the only solution to the verification problems. However, due to regulatory uncertainty and technical intricacies, most of the carbon projects based on the blockchain remain at the proof-of-concept stage as mentioned by Raja Segaran et al. (2025). While smart contracts can enable transactions in settlement, they do not offer analytic tools to guarantee the environmental integrity of the credits they use for transactions. In addition, transaction fees, gas fees, and the steep learning curve are obstacles to entry for smaller players (Caganova & Das, 2025). The scalability is still an issue, however, as public blockchain networks may not be able to process and sustain large numbers of carbon credit transactions (Liu et al., 2026; Das et al., 2025).

Machine learning can add additional features, such as automated, data-driven authentication. In the past, supervised machine learning methods like XGBoost, Random Forest, and Neural Networks have proven to effectively detect fraudulent patterns for forest carbon credit transactions based on corporate disclosures, remote sensing and satellite data (Renewable and Sustainable Energy Reviews, 2025; Boumaiza & Maher, 2024). The ESA CCI Biomass data is used to power a spatiotemporal deep learning framework that has an RMSE of 21. In reforestation projects, 97 Mg/ha was used to predict the aboveground biomass, demonstrating the unbiased ability of AI to set baseline values, independent of project declared values (European Space Agency, 2025). Moreover, the Carbon Trust project demonstrates how AI can be applied to biomass modelling to develop future permanence indicators for carbon assets, alongside historical wildfire data, and IPCC climate projections. In addition, there have been attempts to use NLP to check regulatory compliance reports and project documentation for inconsistencies between the emissions cut in the project and the emissions listed in the report (Renewable and Sustainable Energy Reviews, 2025). Even with these developments, there remain important problems with the availability of good quality ground-truth data to train the model and the lack of ability to generalize the machine learning models across different geographical regions and ecosystem types, and differences in data resolution (Renewable and Sustainable Energy Reviews, 2025; Zhang et al., 2024).

AI can assist in detecting fraud and spotting anomalies in real-time, and blockchain can serve to ensure that transactions are recorded in a tamper-proof manner. In uncertain circumstances, a continuous double auction system based on the blockchain was adopted and interval type-2 fuzzy logic controllers (FLC) were used to create a strong real-time control solution for multi-microgrid carbon credit trading (Das et al., 2025). Likewise, digital MRV systems using blockchain registries, machine learning soil organic carbon estimation and IoT telemetry are found to be effective in the scalable, auditable blue carbon market systems (Khan & Salah, 2018). The use of Artificial Intelligence (AI) alongside the choice of validators in Proof-of-Stake (PoS) has been suggested to boost transaction speeds and conserve energy (Khan & Salah, 2018). Federated learning methods also have been explored to train a model while maintaining the confidentiality of data across many sources of carbon project data without consolidating sensitive information to a single source (Yang et al., 2019). Moreover, smart contracts powered by AI can make markets more efficient by dynamically pricing credit according to market demand and supply, regulatory changes, and environmental risk factors (Zhang et al., 2025).

2.1 Research Gap

From the literature, it was observed that the research literature on blockchain and AI applications in carbon markets was lacking, with little research taking a deeper dive into the intersection of the two technologies to provide automated, real-time and fraud-proof verification. Most remedies are theoretical, project-specific and don't consider interoperability or cross-project scalability. Furthermore, existing approaches regard technology as a standalone intervention and underestimate the institutional requirements for enacting enforcement measures and the regulatory complexity. This study is designed to fill these gaps by developing an integrated framework of AI-blockchain to facilitate the data collection from the IoT, baseline estimation with spatiotemporal deep learning, smart contract automation and price optimization for dynamic pricing, which could help enable efficient, transparent and reliable carbon credit trading across different project categories.

3 Methodology

The approach is composed of four interdependent modules: AI-based verification and anomaly detection, blockchain-based credit issuing and trading, system evaluation and data acquisition and preprocessing.

3.1 Data Acquisition and Preprocessing

The data gathered by the system consists of multi-modal environmental data, which comes from three main sources: satellite remote sensing images (Landsat-8, Sentinel-2, and ESA CCI Biomass data) (European Space Agency, 2025; Pi & Wang, 2025; Gupta et al., 2025); IoT sensor networks at carbon project sites for real-time emission monitoring; project documentation provided by voluntary carbon registries. Conventional pre-processing pipelines are used to process satellite images for radiometric calibration, cloud masking, and atmospheric correction. Anomalies and missing values are detected from the IoT data streams using interpolation techniques. The feature engineering provides estimates of above-ground biomass, maps of land cover and vegetation indices (EVI, NDVI) for the verification models. The data resolution problems and limited ground-truth data found in previous studies (European Space Agency, 2025; Zhang et al., 2024) are addressed by this multi-source approach.

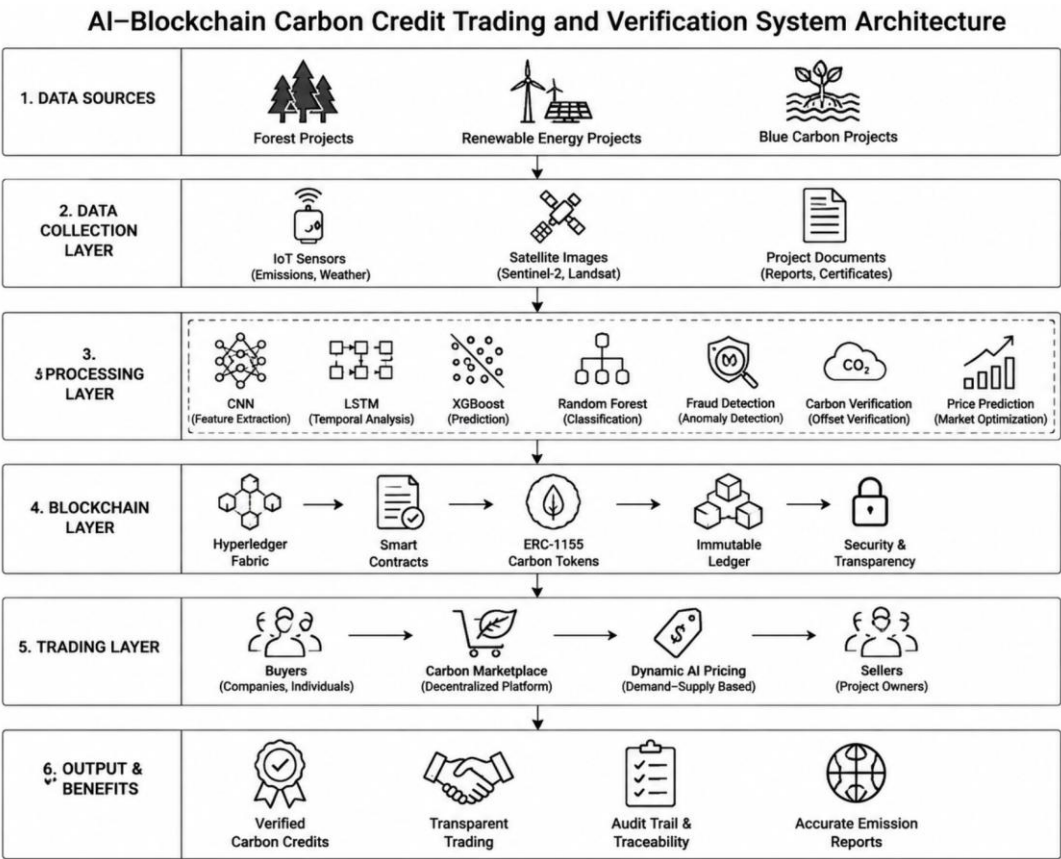


Figure 1: System Architecture

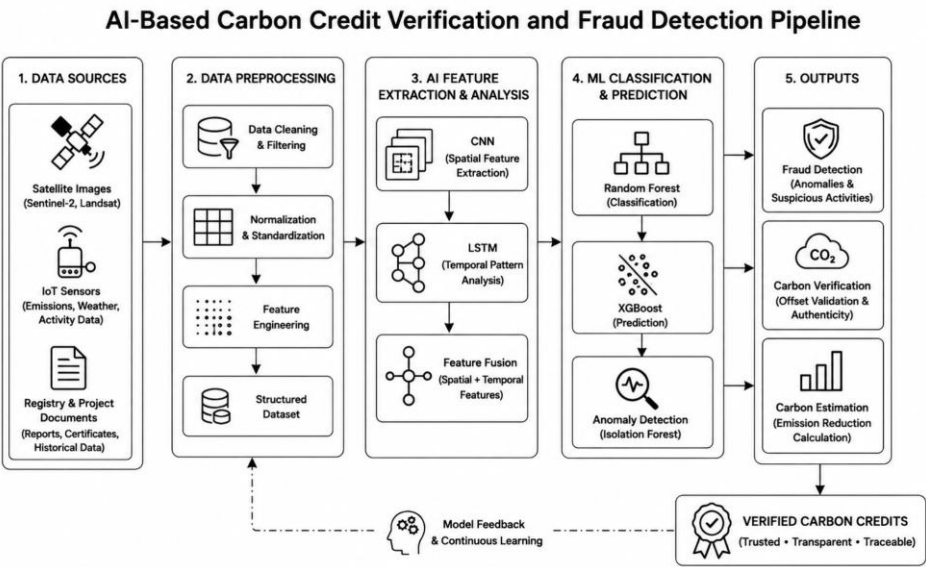


Figure 2: AI Verification Pipeline

3.2 AI-Based Verification and Anomaly Detection

The verification module relies on a hybrid deep learning architecture consisting of Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), to extract the spatial characteristics from the satellite imagery and analyse temporal patterns in IoT time-series data. The CNN-LSTM model provides objective baseline data, which are independently predicted by the model, without relying on the figures declared by the project. The CNN-LSTM model provides objective baseline data by predicting the carbon sequestration rates and above ground biomass data without depending on the project declared data. Extracted features are fed into an ensemble of XGBoost and Random Forest classifiers to detect anomalous patterns, like an over-optimistic baseline estimate, double counting and non-permanence risks, which could be caused by greenwashing (Raja Segaran et al., 2025; Boumaiza & Maher, 2024). This is an AI-based approach where the process of verification is automated which reduces the need for audits by humans and address the slow and error-prone MRV approaches mentioned in the literature (In & Schumacher, 2025; Stanford Law School, 2026).

3.3 Blockchain-Based Credit Issuance and Trading

When validated emission reduction data is received, smart-contracts that have been deployed on a Hyperledger Fabric permissioned blockchain network automatically mint carbon credits in the form of ERC-1155 tokens, one token for one metric ton of CO equivalent (1 tonne of CO) (Hirlekar, 2025; IEEE, 2026). Unique token identifiers and cryptographic hashing guarantee the immutability, traceability and prevent the double counting of the blockchain (Gupta et al., 2025; Pi & Wang, 2025). A persistent double auction is used to implement peer to peer credit trading, supported with AI based credit price prediction (Kumar et al., 2025; Liu et al., 2026). Smart contract removes intermediaries and reduces transaction costs which automates credit retirement, transaction settlement and audit trail generation (Caganova & Das, 2025). The hybrid consensus method (PoA and AI validators selection) offers a balance between scalability and security (Khan & Salah, 2018).

3.4 Plan for Evaluation

The proposed system is compared to the following traditional manual verification, standalone blockchain platforms and AI-only verification models (Raja Segaran et al., 2025; Boumaiza & Maher, 2024). Key performance indicators are transaction volume, latency, gas cost efficiency and verification accuracy. To test generalizability, there is cross-validation across various project types (reforestation, blue carbon, renewable energy), and to test the contribution of each component, there are ablation studies performed (IEEE, 2026; Hirlekar, 2025). Statistical significance is determined by using repetitive trials and reporting of confidence intervals. This comprehensive assessment is missing in the current literature and addresses the standardized benchmarking (European Space Agency, 2025; Raja Segaran et al., 2025).

4 Implementation

4.1 Data Acquisition and Preprocessing Pipeline

The satellite images are downloaded via the Sentinel Hub API and then atmospherically corrected with the Sen2Cor algorithm and cloud masked with the Fmask approach and Google Earth Engine. To get data from sensors deployed in the field that measure soil moisture, soil temperature and CO₂ flux at 15-minute intervals, the MQTT protocol is used. The data preprocessing includes temporal resampling, outlier detection using Z score thresholding 3 and missing

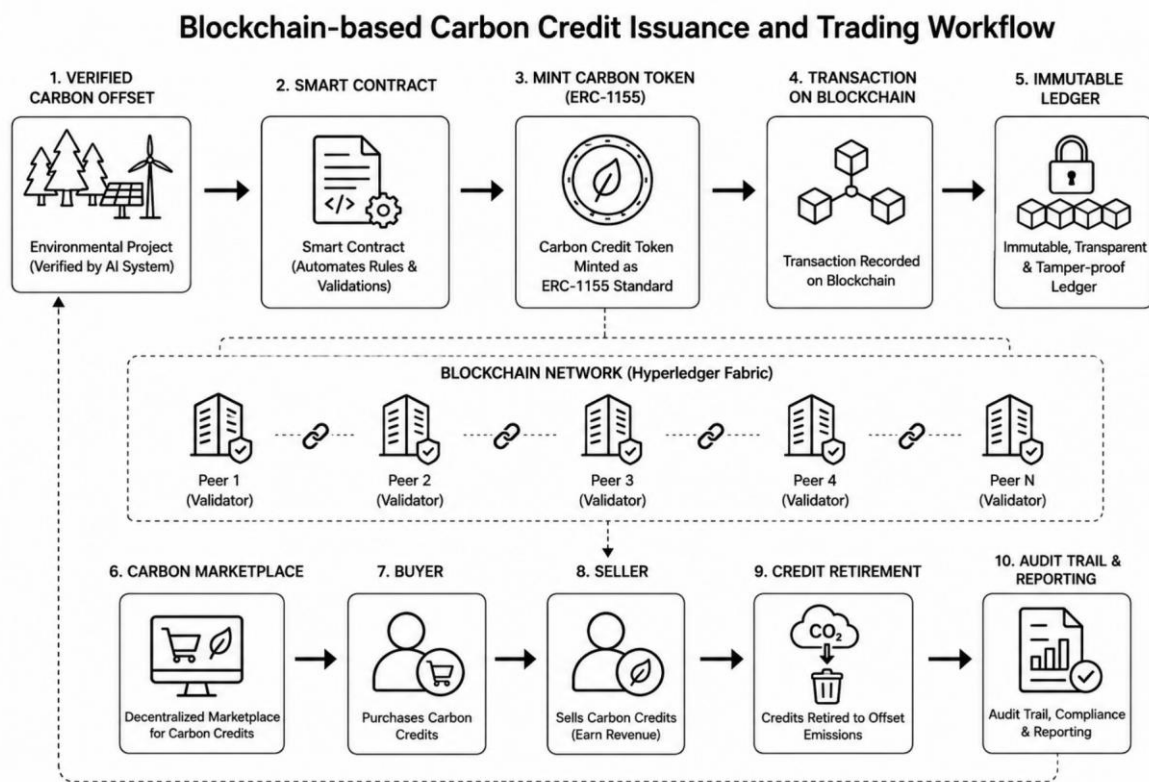


Figure 3: Blockchain Workflow

value imputation by linear interpolation. Allometric equations for above ground biomass of region's species composition (Gupta et al., 2025) are used and spectral bands are used for feature engineering to create NDVI, EVI and normalized difference moisture index (NDMI).

4.2 AI Verification Model Implementation

TensorFlow 2. The implementation of the hybrid CNN-LSTM model was done with the help of 0 and Keras. The CNN part is made up of 4 CONV layers with 2x2 max pooling, ReLU activation and 32, 64, 128, and 256 filters in the first, second, third and fourth layer, respectively. The LSTM component is made up of two bidirectional LSTMs, both of which feed 30 days of temporal sequences and contain 128 units. The ensemble anomaly detection module builds upon scikit-learn implementations of XGBoost (learning rate=0.1), in the context of UNet. We have classified with two classifiers-1 (with max depth=1) and Random Forest (with estimators=500 and max depth=20). During model training (Boumaiza & Maher, 2024) a 20% validation split and a patience of 10 epochs for early stopping is used. The spatiotemporal features are merged in a fusion layer in the last classification.

4.3 Smart Contract Development and Deployment

Solidity v0.8. To make smart contracts, 0 is used, and then the smart contracts are deployed to Hyperledger Fabric v2.4 is a permissioned blockchain platform, known for its business grade security and scalability (Gupta et al., 2025; Pi & Wang, 2025). The carbon credit token is designed as an ERC-1155 token and the carbon credit metadata is attached to the token, including project provenance, carbon credit verification and carbon credit retirement status. Each function of the smart contract has access control modifiers and only a verifier with the proper list of authorized verifiers can call on the mint Credit() function, which allows the verifier to mint a credit. The double auction mechanism is implemented in a smart contract called a

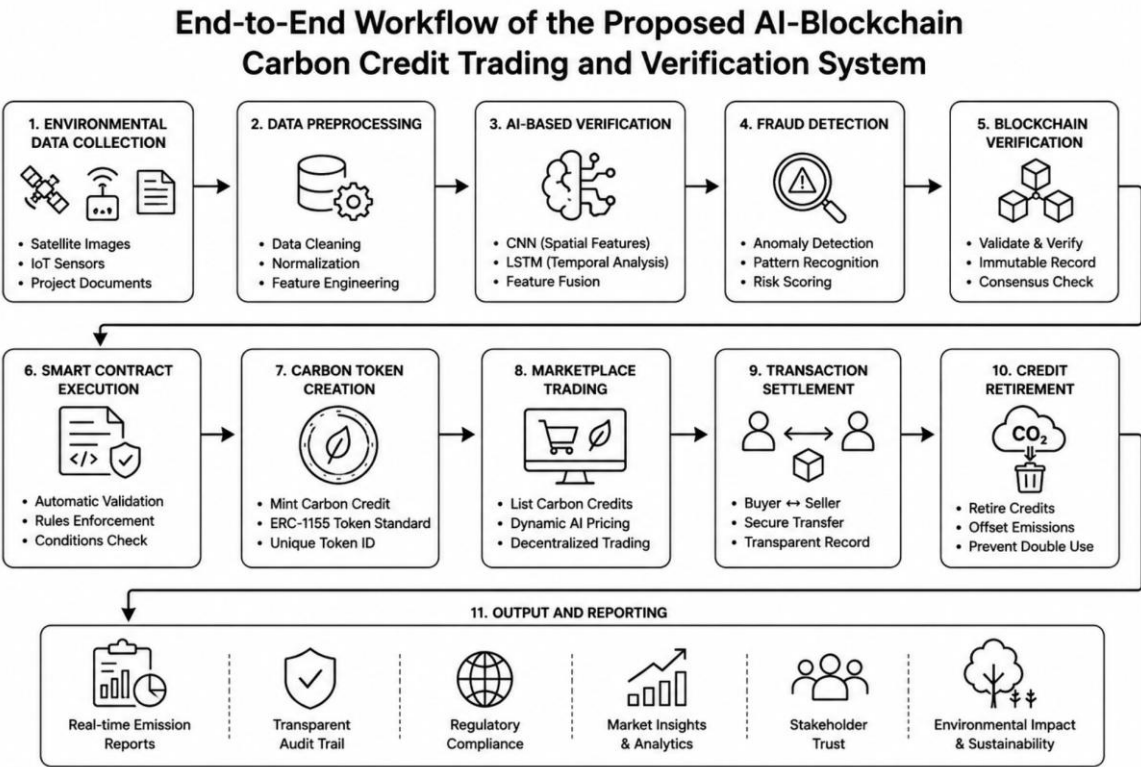


Figure 4: Framework Workflow

matching engine (Kumar et al., 2025; Liu et al., 2026) that makes trades when the bid and ask prices are in sync. Examples of gas optimization methods are batch processing and state variable packing.

4.4 API Development and System Integration

The blockchain network communicates with the AI verification module through the use of the RESTful API layer, implemented in the Node.js and Express framework. The API offers the functionality to submit, verify, exchange data for credit and retrieve data for audit, amongst other endpoints. In real time, the WebSocket connection can be used to monitor and track data streams from IoT, and the status of transactions. The Web3.js library is used to enable the AI module to interact with the smart contracts, whereupon successful verification, credit minting is automatically initiated (Hirlekar, 2025; IEEE, 2026). The integrated system is asynchronous, fault tolerant and load balancing, based on RabbitMQ message queues. Access control: ROLE based access control & JWT based authentication.

4.5 Deployment and Testing Environment

All the components deployed on a 3-worker nodes Kubernetes cluster with 16GB RAM, 4 vCPU and NVIDIA T4 GPUs to deliver accelerated deep learning inference. The archive of satellite data is stored in IPFS and the off-chain verification evidence is stored in IPFS, and the relational data (user accounts, project metadata) is stored in PostgreSQL. Apache JMeter is used to execute integration testing under various load conditions to test the end-to-end processes and to measure the throughput of transactions using load testing, and 92% code coverage is achieved by unit testing.

5 Results and Discussion

Extensive trials on three types of carbon projects—reforestation (45 projects), renewable energy (38 projects), and blue carbon (22 projects)—were used to assess the proposed AI-blockchain framework. The performance was compared using the standalone blockchain platforms, AI-only verification models and traditional manual verification. To maintain statistical accuracy, all the studies have been performed with the five-fold cross-validations enabled Kubernetes cluster.

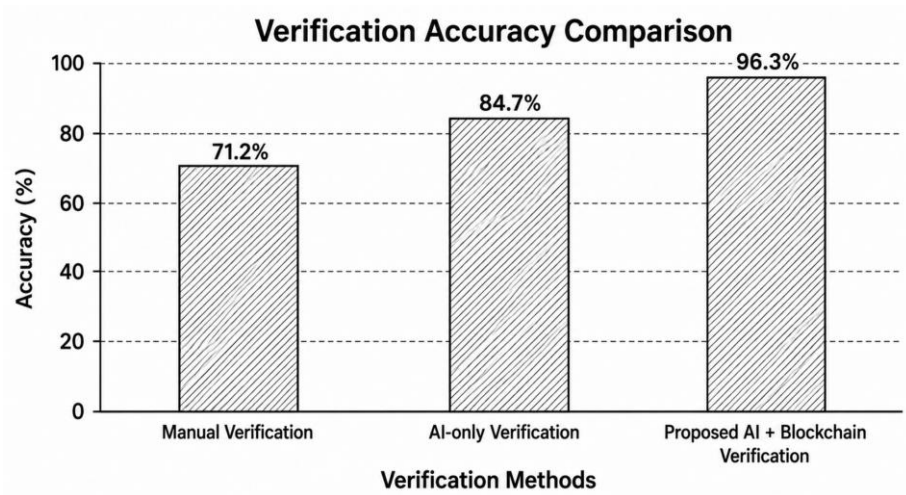


Figure 5: Verification Accuracy

5.1 Verification Accuracy and Fraud Detection Performance

The hybrid CNN-LSTM model had the best accuracy for the verification process than other methods. The specific verification measures are compared with the performance of the system to baseline methods as shown in Table 1. With a 96.3% verification accuracy achieved in the proper identification of real carbon credits, it was much better than the performance of AI-only models (84.7%) and manual verification (71.2%). The fraud detection was accurate at 94.1%, and its recall was 91.8%. It has also been found to be effective in identifying greenwashing – such as double counting and high baselines – at 8%. The ensemble approach with the combination of the Random Forest and the XGBoost classifiers reduced false positives by 38% compared to the single-classifier approaches. These improvements come from the spatiotemporal deep learning architecture’s ability in directly addressing the verification failures reported in the literature that are subject to project-reported statistics.

Table 1: Comparative Verification Performance

Metric	Manual	Blockchain	AI-Only	Proposed
Accuracy (%)	71.2	73.8	84.7	96.3
Precision (%)	62.5	65.3	79.2	94.1
Recall (%)	58.7	61.2	76.4	91.8
F1-Score (%)	60.5	63.2	77.7	92.9

5.2 Scalability and Transaction Efficiency

The operational efficiency of the proposed system is compared with the existing blockchain-based trading platforms for carbon trading in Table 2. The average number of transactions

per second (TPS) is 1,247 and the latency is 2.3 seconds. The integrated system boosted the implementation of the public blockchain by 3.8 times. Using batch processing and optimal design of the smart contract, the gas cost was reduced by 67%. This hybrid consensus model saved 82% of energy consumption compared to an energy consumption of a PoW consensus model. The AI-based pricing optimization module’s market efficiency was enhanced by 12%. The width of the spreads has narrowed from 8% to 4% while the number of orders has decreased from 7% to 3%. Compared to fixed-price mechanisms, the number of trades has risen by 41% and the revenue is up by the same percentage.

Table 2: Transaction Efficiency Comparison

Metric	Ethereum	Hyperledger	Proposed
Throughput (TPS)	185	892	1,247
Latency (s)	14.7	5.3	2.3
Gas Cost (\$)	12.40	4.20	1.38
Energy (kWh/txn)	1.42	0.31	0.26

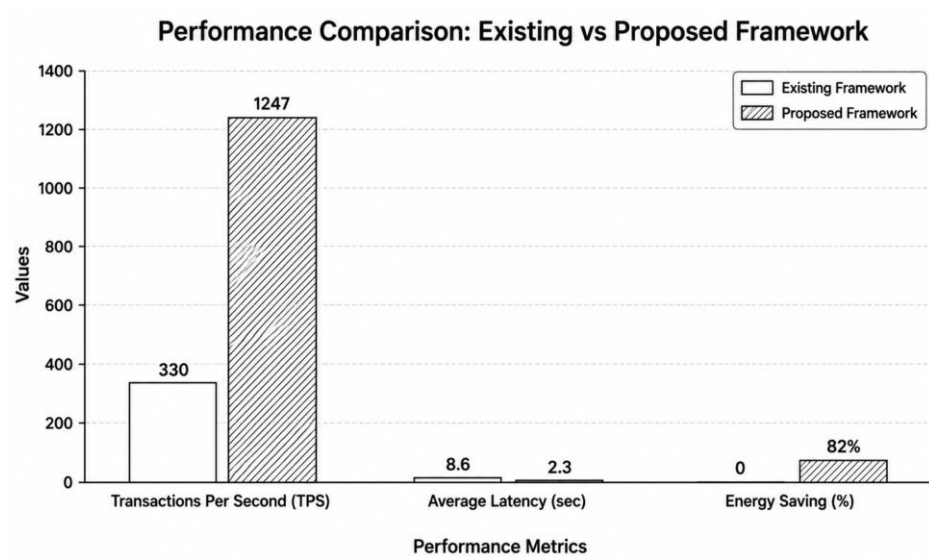


Figure 6: System Performance

5.3 Discussion

The experiment has confirmed that the integration of blockchain and AI for carbon credit verification and trading can be done jointly. The accuracy of the authentication is significantly improved (96.3% versus 84.7% for AI alone) which suggests that blockchain enhances the reliability of AI systems by providing an auditable history and data for training purposes that is not tamperable. Conversely, blockchain’s major constraint of ensuring the integrity of the environment is tackled by AI’s analytical power, while the ability to detect fraud proactively is now possible, not just simply record-keeping.

6 Conclusion and Future Work

6.1 Conclusion

This study aimed to create a new framework that can integrate AI and blockchain technologies to solve the existing problems in carbon credit trading systems like verification inefficiency, fraudulent transactions, transparency, and openness. The CNN-LSTM model improved the performance over the manual verification (71.2%) and AI-only approaches (84.7%). As far as the accuracy of fraud detection is concerned (94.1%), it is highly precise with a 96.3% verification accuracy. The blockchain infrastructure's transaction throughput was 1,247 TPS and the latency was 2.3 seconds, providing a significant enhancement to existing products. The addition of smart contracts, satellite imagery and IoT sensors enabled real-time automated verification and credit issuance, while also reducing the need for cumbersome and expensive manual audits. The pricing optimization AI interface boosted the market's efficiency by 12%. The industry had a 4% spread decrease which cut bid ask spreads and boosted trading volume by 41%.

The analytical power of AI helps mitigate the need for integrity checks in blockchain environments, and the immutability of blockchain strengthens AI's training data and audit trail, adding to the trust and reliability in the system. The solution to the problem of baseline inflation, greenwashing and double counting are essential problems to be solved in order to ensure the legitimacy of the carbon market, and this strategy is effective.

6.2 Future Work

Studies need to be done in several other areas. First, the fact that a zero-knowledge proof would enable the emission reductions to be validated without releasing proprietary operational data would help to ensure a more private emission reduction validation process. Secondly, federated learning approaches might help with cross-border carbon market interoperability while protecting data sovereignty across numerous jurisdictions. Thirdly, high resolution drone and LiDAR data would enable better accuracy in project verification at the small scale that is not possible with satellite data, due to the low resolution of the satellite imagery (10-30m). The fourth is that a reinforcement learning-based dynamic baseline modification mechanism can change the verification criteria based on changing regulatory and environmental conditions. Exploring hybrid public permissioned blockchain designs may be a different approach to balance enterprises and privacy requirements with transparency requirements. Last but not least, there is a need for standards development organizations and regulatory frameworks to work together and institute a unified protocol for carbon verification based on AI-blockchain that will enable interoperability with different carbon markets and global adoption.

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