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Review

Efficient ML technique in blockchain-based solution in carbon credit for mitigating greenwashing

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Abstract
The rapid growth of carbon credit markets, driven by global efforts to mitigate climate change, highlights the critical need for transparency and accountability—particularly in forest-based carbon offset projects. Forest ecosystems play a vital role in carbon sequestration; however, these projects are increasingly vulnerable to greenwashing, where organizations exaggerate or misrepresent their environmental impact to appear more sustainable than they are. This literature review explores the integration of blockchain technology and machine learning (ML) to enhance verification processes and reduce fraudulent practices in forest carbon credits. Blockchain's decentralized, immutable ledger offers a transparent and tamper-proof system for recording carbon credit transactions, ensuring traceability and reducing the risk of manipulation. Smart contracts embedded within blockchain networks can automate verification and compliance processes, enhancing efficiency while minimizing the need for human oversight. However, while blockchain ensures transparency, it lacks real-time anomaly detection capabilities. ML algorithms, particularly supervised models such as Random Forest, XGBoost, and Neural Networks, are well-suited for detecting fraudulent patterns and verifying the authenticity of forest carbon credit transactions. These algorithms can process large datasets, including satellite imagery and corporate disclosures, to identify discrepancies and improve the accuracy of carbon sequestration claims. This review also examines key performance metrics such as accuracy, precision, recall, and processing time to evaluate the efficiency of various ML algorithms for real-time fraud detection. The findings suggest that integrating ML and blockchain technologies, combined with satellite data, can significantly strengthen transparency and verification in forest carbon credit markets. By enhancing verification mechanisms, this interdisciplinary approach helps mitigate greenwashing and fosters a more credible and transparent carbon credit market. It supports global sustainability efforts by ensuring that carbon sequestration claims from forest-based projects are both accurate and verifiable.

Keywords Blockchain · Carbon credit management · Carbon markets · Carbon offsets · Environmental data analytics · Greenwashing · Machine learning · Smart contracts · Sustainable development goals

1 Introduction

The increasing urgency of addressing climate change has accelerated the development of innovative sustainability solutions, as noted by Saraji et al. [1]. Among these, Kim and Huh [2] highlight carbon credit systems as a vital tool for encouraging businesses and individuals to reduce their carbon footprint. However, Stern [3] identifies greenwashing—where organizations exaggerate or falsely claim environmental benefits—as a significant challenge

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to these systems. This deceptive practice not only misleads consumers but also undermines the integrity of carbon markets. Despite existing regulatory measures, ensuring transparency and accountability in carbon credit markets remains a pressing issue. Many verification processes rely on third-party audits and self-reported data, which are susceptible to manipulation and fraud [4].

The absence of an efficient, automated, and tamper-proof verification system weakens the credibility of carbon credits, limiting their effectiveness as a climate mitigation tool. Chen [5] reinforces this concern, emphasizing that blockchain technology offers a promising solution to enhance accountability in carbon markets through its decentralized and immutable ledger, which helps reduce fraudulent claims. However, while blockchain ensures transparency and traceability, it lacks the ability to analyze, predict, and flag fraudulent transactions in real-time.

This is where machine learning (ML) becomes crucial. ML algorithms can process large datasets, identify patterns, and detect anomalies that may indicate fraudulent or exaggerated carbon credit claims. When combined, blockchain serves as an immutable record-keeping system, while ML enhances its functionality by automating fraud detection and improving credit validation efficiency. Despite this potential, the integration of ML with blockchain for real-time verification and fraud detection remains underexplored. Existing research primarily focuses on blockchain's traceability and immutability but lacks comprehensive models that leverage ML for proactive fraud detection and optimization of credit validation.

There is limited research on how ML algorithms can effectively enhance blockchain-based carbon credit systems to combat greenwashing. This study addresses this gap by exploring the synergy between ML and blockchain in carbon credit verification. By examining efficient ML techniques, this research highlights their potential to enhance fraud detection, improve data integrity, and strengthen market credibility within a blockchain framework. The findings contribute to the development of a more robust, automated, and transparent carbon credit mechanism, ultimately increasing confidence in sustainability claims and supporting global climate goals.

The remainder of this paper is structured as follows: Sect. 2 details the research methodology, including the systematic literature review approach and selection criteria. Section 3 provides an overview of the carbon credit market and the challenges posed by greenwashing. Section 4 examines the role of blockchain technology in enhancing transparency and accountability within carbon credit markets. Section 5 explores various machine learning techniques used for environmental monitoring and fraud detection. Section 6 discusses the integration of machine learning with blockchain, highlighting its potential to strengthen greenwashing detection and verification processes. The final section summarizes the findings from the reviewed articles.

2 Research methodology

This study employs a systematic literature review (SLR) methodology to explore the integration of blockchain and machine learning (ML) in carbon credit verification to mitigate greenwashing. A structured search was conducted across major academic databases, including Springer, IEEE Xplore, Elsevier, and Google Scholar, focusing on publications from 2020 to 2025 to ensure recent advancements were included. The search strategy utilized a combination of Boolean operators and keyword-based filtering, using terms such as "Blockchain and Carbon Credit," "Machine Learning in Carbon Markets," "Smart Contracts and Greenwashing," and "Fraud Detection in Carbon Offsets."

2.1 Research question

In line with the objectives of this research, the following research questions (RQs) have been formulated:

- RQ1: What machine learning techniques have been utilized for detecting greenwashing in carbon credit markets, and how effective are they?
- RQ2: How has blockchain technology been applied to enhance transparency and prevent fraudulent activities in carbon credit trading?
- RQ3: What are the key challenges and existing research gaps in applying machine learning and blockchain technologies for carbon credit verification?

- RQ4: What are the emerging trends and future research directions for improving greenwashing detection and carbon credit transparency using ML and blockchain?

The selection process followed a two-step screening approach: (1) an initial title and abstract review to filter studies that explicitly addressed blockchain and ML applications in carbon credit markets; and (2) a full-text analysis of shortlisted papers to ensure their relevance to fraud detection and greenwashing mitigation. Papers were included based on their focus on blockchain-based carbon markets, ML-driven fraud detection, and smart contracts for transparency enhancement. Excluded studies comprised non-peer-reviewed articles, technical reports, duplicate studies, and those lacking empirical validation.

To ensure a systematic and unbiased synthesis, data from selected studies were categorized into four key research dimensions: (i) blockchain's role in carbon markets, (ii) ML techniques for fraud detection, (iii) hybrid blockchain-ML models, and (iv) challenges and future directions. A comparative evaluation of Random Forest, XGBoost, Neural Networks, and KNN was conducted, focusing on key performance indicators such as accuracy, precision, recall, processing time, and scalability. These models were chosen based on prior literature emphasizing their effectiveness in environmental fraud detection and large-scale anomaly detection.

Despite its comprehensive scope, this study has limitations. The findings rely on secondary data from existing literature, and no empirical testing or real-world implementation was conducted. Additionally, the absence of standard evaluation benchmarks across studies may introduce variability in model comparisons. Future research should validate these findings through experimental testing, real-world blockchain deployment, and comparative benchmarking of ML models on large-scale carbon credit datasets.

3 Overview of carbon credits market and greenwashing

Carbon credit markets play a crucial role in mitigating climate change by enabling organizations to offset their emissions through the purchase of carbon credits. These credits represent verified reductions in greenhouse gas (GHG) emissions, often achieved through initiatives such as renewable energy projects, reforestation, and carbon capture technologies [6]. However, the effectiveness of carbon credit markets is increasingly threatened by greenwashing, a deceptive practice where companies exaggerate or misrepresent their environmental impact to appear more sustainable than they actually are [4].

Carbon markets are generally divided into compliance markets and voluntary markets, each serving distinct purposes and regulatory structures. Abiodun et al. [7] explain that compliance markets function under international regulatory frameworks, such as the European Union Emissions Trading System (EU ETS) and the Kyoto Protocol, which impose legally binding emission caps. Organizations operating within these markets must either implement emission reduction strategies or purchase carbon credits to offset excess emissions and maintain compliance with established regulations.

In contrast, voluntary carbon markets provide corporations and individuals the flexibility to purchase carbon credits without legal mandates. Saraji et al. [1] note that these markets have expanded rapidly as businesses seek to strengthen their sustainability commitments and enhance corporate social responsibility (CSR) initiatives. However, Sipthorpe et al. [8] emphasize that the lack of regulatory oversight in voluntary markets increases the risk of greenwashing and the circulation of low-quality offsets, potentially undermining the credibility of emissions reduction efforts.

Greenwashing is the practice of misleading consumers, investors, and regulators about a company's environmental efforts. In the context of carbon markets, Parhamfar et al. [9] explain that greenwashing often occurs when companies purchase low-quality carbon credits without implementing meaningful emissions reductions.

One common form of greenwashing is double counting, where the same carbon credit is claimed by multiple entities, leading to inflated emissions reduction figures [8]. Another issue arises from overestimated carbon reductions, where certain offset projects fail to deliver their promised emissions savings, effectively rendering the credits worthless [10].

Additionally, Boumaiza and Maher [11] highlight concerns regarding lack of additionality, which refers to carbon credits funding projects that would have occurred regardless of credit financing. For example, some forest conservation initiatives may have taken place even without the sale of credits, making them invalid as legitimate offsets.

In addition to these fraudulent practices, carbon credit markets face broader challenges such as a lack of standardization in credit verification, high transaction costs, and regulatory inconsistencies across different jurisdictions [12]. To enhance transparency and trust, emerging solutions such as blockchain technology and artificial intelligence have been proposed to automate carbon credit verification, reduce fraud, and ensure that offsets genuinely contribute to emissions reductions [11]. However, regulatory gaps and industry-wide adoption challenges remain significant barriers to creating a robust and reliable carbon trading system [7].

Greenwashing has become a significant issue in carbon markets, where companies misrepresent their sustainability efforts. Grewal et al. [13] investigated the impact of mandatory carbon reporting on greenwashing and found that increased transparency reduced selective disclosure of favorable data. Similarly, In and Schumacher [4] coined the term "carbonwashing" to describe misleading carbon reduction claims, emphasizing the need for robust blockchain-based verification systems.

4 Blockchain technology in carbon credit markets

Saraji et al. [1] were among the first to propose a blockchain-based carbon credit ecosystem, emphasizing the tokenization of carbon credits to enhance market liquidity and standardization. Their model introduced smart contracts to automate transactions, reducing reliance on intermediaries. However, they identified key adoption challenges, including regulatory concerns and technological integration issues. Around the same time, Sipthorpe et al. [8] analyzed blockchain projects within carbon markets, identifying 39 organizations developing blockchain-based solutions. While their study highlighted blockchain's potential to improve carbon offset tracking, most initiatives remained in the proof-of-concept stage due to regulatory uncertainty and technical barriers.

Building on these early models, Kotsialou et al. [6] explored blockchain's potential within the REDD+ framework, demonstrating its ability to enhance transparency and reduce transaction costs in forest carbon offset projects. Their findings addressed critical concerns such as additionality, permanence, and leakage but emphasized the need for further pilot studies. Concurrently, Da Silva et al. [14] introduced NetZeroCO2, an AI-integrated blockchain framework leveraging satellite data and machine learning to improve carbon stock estimation and credit allocation accuracy.

As blockchain adoption in carbon markets evolved, researchers expanded its application to peer-to-peer (P2P) carbon trading. Parhamfar et al. [9] examined blockchain-enabled P2P systems, demonstrating how smart contracts and AI-driven decision-making optimize carbon offset transactions. While their findings pointed to significant efficiency gains, challenges related to regulatory compliance and blockchain energy consumption persisted. Similarly, Prapulla et al. [15] introduced a blockchain-powered carbon credit management system that automated verification and trading while preventing double counting, though scalability and regulatory hurdles remained barriers to widespread adoption.

Further innovations incorporated AI-powered blockchain models for decentralized carbon markets. Baklaga [16] proposed an intelligent carbon credit trading system integrating smart contracts and predictive analytics. Afaq et al. [17] explored blockchain-based federated learning techniques for privacy-preserving machine learning applications in carbon trading. Meanwhile, Che et al. [18] developed a blockchain-based carbon emissions verification mechanism using reverse auctions to improve credibility and cost efficiency.

Beyond carbon credit trading, blockchain has been increasingly applied in energy markets for emissions reduction. Danish et al. [19] reviewed blockchain's role in energy credits and certificates, emphasizing its potential in decentralized renewable energy trading. Francisco et al. [20] systematically examined blockchain-based carbon trading systems, identifying key challenges such as regulatory uncertainty and scalability constraints. Basu et al. [21] focused on the sustainable management of blockchain-powered carbon credit supply chains, advocating for IoT and AI integration for more efficient tracking. Similarly, Chakraborty et al. [22] proposed blockchain automation for data management to enhance transparency and mitigate fraud in carbon credit trading.

Despite these advancements, challenges remain. Vilkov and Tian [12] highlight the persistent difficulties in tracing carbon credit transactions due to fragmented registries and inconsistencies in reporting standards, which hinder transparency and accountability. Sipthorpe et al. [8] further emphasize concerns around greenwashing and fraud, where companies may inflate reported emissions reductions or acquire low-quality carbon credits to project a misleading image of sustainability. Illarionova et al. [10] identify double counting as a major issue, where the same credit is claimed by multiple entities, leading to an overestimation of actual emissions reductions. Additionally, Boumaiza and Maher [11] note that regulatory gaps in voluntary carbon markets create challenges in verification and accountability, as the lack of uniform standards makes it difficult to ensure the credibility of carbon credits.

Overall, early research primarily focused on tokenization and smart contract automation, while more recent studies have integrated AI and satellite data to enhance accuracy in carbon credit verification. However, widespread adoption continues to face barriers related to scalability, regulatory frameworks, and data reliability, underscoring the need for further advancements and standardized policies.

5 Machine learning technique for environmental monitoring

Puntumapon et al. [23] explore the use of satellite data and machine learning models to estimate above-ground biomass (AGB) in Thai dry-evergreen forests. Their study highlights the potential of remote sensing as a cost-effective and scalable alternative to traditional field-based carbon credit measurements, which are often labor-intensive and expensive. By analyzing data from Sentinel-1, Sentinel-2, and MODIS, they assess the performance of various machine learning techniques, with the random forest algorithm achieving the highest accuracy in AGB estimation. These findings underscore the critical role of precise biomass assessment in carbon credit monitoring, reinforcing the value of remote sensing in advancing sustainability efforts.

Expanding on the need for accurate forest carbon assessments, Meressa and Rannestad [24] address the broader context of climate change and deforestation, emphasizing global commitments such as the New York Declaration on Forests, which aims to halt deforestation by 2030. Their research underscores the growing demand for reliable data on tropical forests, which play a crucial role in carbon sequestration and climate change mitigation. To enhance predictive accuracy, they focus on optimizing hyperparameters for various regression models, including Random Forest (RF), XGBoost (XGB), and LightGBM, while employing K-fold cross-validation and multiple error metrics to evaluate model performance. However, their study does not explore the limitations of relying solely on satellite data, which may overlook ground-level variations and structural complexities within forests. Additionally, their findings are primarily based on dry forest ecosystems, limiting the generalizability of their approach to other forest types.

While machine learning enhances carbon credit monitoring, its own environmental impact must also be considered. Gutiérrez et al. [25] examine the energy demands associated with ML algorithms, particularly as European companies increasingly integrate AI into their operations. They introduce two frameworks for assessing energy consumption in ML: Green-IN ML, which focuses on improving the energy efficiency of ML models themselves, and Green-BY ML, which leverages ML to optimize sustainability across various domains. Their study establishes a direct relationship between task completion time and energy consumption, highlighting the need for more energy-efficient ML practices.

Similarly, the integration of remote sensing and machine learning has been applied to carbon stock estimation. Illarionova et al. [10] propose a methodology for estimating growing stock volume and stem carbon stock using Sentinel-2 multispectral imagery. Their approach involves an automated machine learning pipeline designed to enhance carbon stock assessment while also providing insights into forest structure. They compare two estimation methods: a direct approach relying solely on remote sensing data and a hierarchical approach that integrates predicted inventory attributes with conversion equations. By reducing dependence on manual field measurements, their study streamlines the carbon stock estimation process, making it more efficient and scalable.

The accuracy and transparency of machine learning applications in carbon markets remain critical concerns. Reiersen et al. [26] investigate the integration of remote sensing and ML to enhance measurement, reporting, and verification (MRV) in forestry carbon offsets. They stress the importance of rigorous auditing of algorithms and data to prevent systematic overestimations in carbon stock calculations. Their study advocates for automated carbon offset certification protocols that combine high-resolution satellite data with field measurements for validation. Additionally, they highlight a significant gap in the systematic evaluation of carbon estimation methodologies, which can lead to inflated offset claims. Strengthening transparency and accountability in MRV processes is identified as crucial to maintaining the credibility of carbon offset initiatives. Furthermore, they emphasize the need for comparative studies between aerial and satellite imagery to establish a standardized global framework for forest carbon measurement.

Together, these studies illustrate the transformative role of machine learning and remote sensing in carbon credit assessment. While advancements in algorithmic accuracy and automation offer promising solutions, challenges remain in ensuring data reliability, addressing energy consumption concerns, and standardizing methodologies for global applicability. Machine learning has demonstrated immense potential in enhancing environmental monitoring through remote sensing, carbon stock assessment, and deforestation tracking. However, challenges related to data reliability, energy consumption, and regulatory oversight must be addressed to fully leverage ML's capabilities. Future research should focus on improving model generalization, developing standardized validation protocols, and expanding ML applications to broader environmental domains. By addressing these gaps, ML can become a cornerstone of transparent and efficient environmental monitoring systems, supporting global sustainability efforts.

5.1 Comparative analysis of machine learning algorithms for fraud detection

Machine learning (ML) has emerged as a powerful tool for detecting fraud and anomalies in carbon credit markets, where ensuring the authenticity of carbon offsets is critical for mitigating greenwashing. The rapid expansion of carbon markets has increased the need for automated systems capable of processing large datasets, identifying irregularities, and verifying the legitimacy of carbon credits. This section presents a comparative analysis of the most commonly applied ML algorithms in existing literature, focusing on their efficiency, accuracy, and scalability.

Table 1 provides a comparative analysis of several supervised machine learning algorithms for fraud detection in carbon credit markets. XGBoost is highlighted for its exceptional scalability, rapid processing, and efficiency in handling large datasets, making it particularly well-suited for real-time fraud detection. Random Forest demonstrates impressive accuracy and resilience against overfitting, proving effective in scenarios like forest biomass estimation and carbon sequestration monitoring, though its heavy computational demands may limit its real-time application on very large datasets. Neural Networks excel at identifying intricate patterns within large, complex datasets, delivering high predictive performance for detecting sophisticated fraud; however, their high resource requirements pose scalability challenges. K-Nearest Neighbors is straightforward and works well with small datasets but becomes computationally burdensome as dataset size increases, reducing its feasibility for real-time verification in expansive carbon credit systems. Overall, the analysis suggests that XGBoost offers the best balance of accuracy, scalability, and processing speed for real-time verification, while Random Forest, Neural Networks, and KNN serve as valuable alternatives depending on specific dataset sizes, resource availability, and verification needs.

5.2 Performance metrics for efficient machine learning models

Performance metrics are critical in evaluating the effectiveness of machine learning (ML) algorithms applied to carbon credit verification. These metrics help assess not only the accuracy of fraud detection systems but also their scalability, processing speed, and energy efficiency—key factors in ensuring robust, real-time fraud detection mechanisms. This section explores the metrics reported across existing studies and highlights gaps in the current evaluation frameworks.

Table 2 outlines the performance metrics critical for evaluating ML algorithms in carbon credit verification. In essence, accuracy, precision, and recall ensure that fraudulent transactions are reliably detected, while the F1-score provides a balanced measure of precision and recall. XGBoost distinguishes itself by achieving high accuracy, superior precision, and a strong F1-score, combined with fast processing times and excellent scalability—qualities that make it ideally suited for real-time fraud detection in large-scale carbon credit markets. Random Forest also delivers robust accuracy and recall, proving effective in applications like forest biomass estimation and carbon sequestration monitoring, though its heavy computational demands can restrict its use in real-time scenarios with very large datasets. Neural Networks, on the other hand, excel at detecting complex fraud patterns through high recall but require significant computational resources, posing challenges for scalability. K-Nearest Neighbors is effective for small datasets but becomes less practical as dataset size increases. Overall, XGBoost emerges as the most efficient algorithm for real-time verification by balancing accuracy, speed, and scalability, while Random Forest, Neural Networks, and KNN provide viable alternatives depending on the dataset size, available computational resources, and specific verification needs.

6 Integration of machine learning and blockchain

The convergence of machine learning (ML) and blockchain technology has emerged as a transformative solution for enhancing transparency, security, and efficiency across a wide array of domains. This integration is particularly impactful in fields such as sustainable development, financial fraud detection, and decentralized carbon trading systems. This section explores the latest contributions from scholarly research, offering a critical evaluation of the methodologies used while highlighting both their strengths and inherent limitations.

A notable example of this integration is presented by Baklaga [16], who proposes a comprehensive framework that leverages AI-driven prediction models within blockchain networks to optimize carbon credit trading in decentralized markets. By incorporating advanced AI algorithms, the study introduces a dynamic pricing mechanism that adjusts in response to real-time market fluctuations. This approach enhances forecasting accuracy and boosts transparency through the use of smart contracts, streamlining carbon credit transactions while promoting sustainable emissions reduction

Table 1 Comparison of commonly used ML algorithms for carbon credit fraud detection

Author	Algorithm	Contributions	Strengths	Weaknesses
Xu et al. [27]	K-Nearest Neighbors (KNN)	Detects patterns based on similarity; useful for identifying vulnerabilities in smart contracts	Simple to implement, effective for small datasets, easy to interpret	Computationally intensive as data size increases; longer training times
Pranto et al. [28]	XGBoost	Detects anomalies in e-commerce transactions applicable to carbon credit fraude-commerce transactions applicable to carbon credit fraud	Fast processing, highly scalable, and effective on large datasets	Prone to overfitting on noisy data; requires careful tuning
Zhao et al. [29]	Neural Networks (NN)	Analyzes complex datasets for environmental monitoring and fraud detection	Excels at complex pattern recognition and handling non-linear relationships	Requires large datasets, high computational costs
Puntumapon et al. [23], Meressa and Rannestad [24]	Random Forest (RF)	Effective in biomass estimation for carbon sequestration and forest monitoring	High accuracy, robust against overfitting, and effective in noisy environments	Demands significant computational resources on large datasets

Table 2 Performance metrics for evaluating ML algorithms in carbon credit verification

Metrics	Importance for carbon credit	Author	Key findings
Accuracy	Measures the overall correctness in detecting fraudulent transactions and verifying carbon claims	Xu et al. [27], Pranto et al. [28], Puntumapon et al. [23]	• Xu et al. report that the KNN-based model achieves over 90% accuracy in detecting smart contract vulnerabilities • Pranto et al. achieved a testing accuracy of 98.93% for fraud detection • Puntumapon et al. report high accuracy for Random Forest in AGB estimation
Precision	Reduces false positives to improve reliability in carbon credit validation	Pranto et al. [28], Xu et al. [27]	• Pranto et al. highlight that the XGBoost-based approach exhibits high precision in identifying fraudulent patterns in financial transactions • Xu et al. note that their KNN model maintains high precision in vulnerability detection
Recall	Ensures fraudulent cases are not missed by minimizing false negatives	Xu et al. [27], Puntumapon et al. [23]	• Xu et al. demonstrate that the KNN model achieves high recall (> 90%), ensuring most vulnerabilities are detected • Puntumapon et al. show that Random Forest maintains high recall, crucial for comprehensive fraud detection
F1-Score	Provides a balanced measure when data is imbalanced, combining precision and recall	Ural and Yoshigoe [30], Pranto et al. [28]	• Ural & Yoshigoe indicate that the XGBoost model achieves a strong F1-score by balancing precision and recall effectively • Pranto et al. report a 98.22% F-beta score (recall-biased) for their incremental ML model
Processing Time	Critical for real-time verification in high-frequency carbon credit markets	Pranto et al. [28]	• Pranto et al. note that the XGBoost-based approach processes data faster than alternatives, making it well-suited for real-time fraud detection in large-scale applications
Scalability	Essential for handling large datasets in widespread carbon markets	Xu et al. [27], Puntumapon et al. [23]	• XGBoost is highlighted for its ability to scale effectively with large datasets • In contrast, models like KNN and Random Forest may face challenges when processing very large datasets, potentially limiting real-time applications

strategies. However, despite the model's theoretical sophistication, Baklaga's framework lacks empirical validation using real-world market data. While the simulations offer valuable insights, they fall short of addressing the practical complexities involved in applying the model to diverse regulatory environments or under volatile market conditions. Additionally, the study does not thoroughly explore scalability challenges, particularly regarding blockchain's ability to process large transaction volumes efficiently. These gaps highlight the need for further empirical research to confirm the model's real-world viability.

Building on the potential of ML and blockchain for sustainability, Lakhanpal et al. [31] developed a system that integrates federated learning with blockchain technology to enable real-time monitoring of energy consumption and carbon footprint tracking. Utilizing Long Short-Term Memory (LSTM) networks, their framework predicts energy demand patterns while ensuring data privacy through blockchain's immutable ledger. This decentralized energy-tracking system fosters more efficient and sustainable energy consumption practices by providing accurate and privacy-preserving data analytics. Nevertheless, the study encounters scalability issues, especially in managing geographically distributed energy networks. Furthermore, the potential energy costs associated with blockchain's mining processes are not sufficiently addressed, posing a challenge to the sustainability benefits that the framework aims to achieve. Addressing these limitations will be essential for deploying such systems on a global scale while maintaining both energy efficiency and operational effectiveness.

In the realm of financial security, Pranto et al. [28] introduce an innovative approach that combines blockchain technology with incremental ML algorithms to improve fraud detection in e-commerce transactions. The model incorporates smart contracts to facilitate automated verification while enabling privacy-preserving data sharing across organizations. An adaptive incentive mechanism is also introduced, rewarding participants based on the complexity of updating the model—an approach designed to encourage collaboration without compromising data security.

Despite its high accuracy (98.93%) in detecting fraud, the model's incentive system may not be universally applicable across financial institutions with varying regulatory frameworks. Moreover, the study overlooks the energy inefficiencies inherent in blockchain mining and the potential vulnerability of the system to adversarial attacks that could undermine the incremental learning process over time. These challenges need to be thoroughly addressed to enable broader adoption in real-world financial ecosystems.

In a broader analysis, Ural and Yoshigoe [30] provide an extensive survey of blockchain-enhanced ML systems, highlighting how blockchain's decentralized and immutable ledger can enhance data security, privacy, and model validation. Their exploration of innovative concepts such as Proof of Learning and federated learning underscores the potential of blockchain to safeguard ML models while fostering transparency and trust in decentralized ecosystems. Despite these valuable contributions, their analysis remains largely theoretical, with limited empirical data to substantiate the claims. Key challenges such as scalability and the high energy consumption associated with blockchain consensus mechanisms are acknowledged but not sufficiently resolved. Additionally, integrating ML models into blockchain networks with limited computational resources remains a significant barrier to real-time applications, restricting practical implementation at scale.

Overall, the integration of ML and blockchain technologies holds significant promise across various applications, from sustainable energy monitoring to fraud detection and secure smart contract deployment. While existing research highlights innovative solutions and theoretical advancements, several limitations persist. Challenges related to scalability, energy efficiency, and real-world validation continue to obstruct the widespread adoption of these technologies.

7 Conclusion

This systematic literature review underscores the substantial potential of integrating machine learning (ML) and blockchain technology to enhance transparency and mitigate greenwashing within carbon credit markets, particularly in forest-based offset projects. By combining blockchain's decentralized and immutable ledger with ML's advanced analytical capabilities, this integration offers a powerful solution to strengthen verification processes and ensure the authenticity of carbon credit transactions. Together, these technologies foster trust among market participants by enabling real-time detection of fraudulent claims, enhancing the accuracy of carbon credit reporting, and improving overall accountability.

While the integration of ML and blockchain presents significant advantages, it alone is insufficient to fully address the complexities of greenwashing. Regulatory frameworks and government policies remain critical in promoting genuine environmental responsibility and preventing deceptive practices. Blockchain can complement these frameworks by automating verification processes and creating a transparent reputation system that encourages organizations to adopt verifiable sustainable practices. However, improper subsidy allocation without adequate verification could inadvertently incentivize greenwashing, highlighting the need for a balanced and well-regulated system. Despite their potential, several challenges must be addressed for effective implementation. These include the necessity of large, labeled datasets to train ML algorithms, the rapid evolution of deceptive practices by organizations, and inherent biases in algorithmic decision-making. Furthermore, concerns regarding the scalability and energy efficiency of blockchain networks must be resolved to ensure practical, long-term applications.

A critical element in improving verification processes lies in the integration of satellite data with blockchain and ML algorithms. Satellite imagery serves as an independent and verifiable data source, enabling accurate tracking of forest conditions, monitoring deforestation, and validating carbon sequestration outcomes. By incorporating diverse datasets ranging from corporate disclosures to satellite-derived environmental observations ML algorithms can more effectively detect inconsistencies and enhance the credibility of carbon credit systems.

Future research should focus on developing scalable and energy-efficient ML models tailored for analyzing large-scale forest-related satellite data. Additionally, exploring the integration of unsupervised learning techniques could provide novel methods for detecting previously unidentified patterns of fraud in carbon markets. Refining regulatory frameworks to support blockchain-based verification processes for forest conservation projects will also be essential. Addressing these challenges will strengthen the legitimacy of forest carbon credits and contribute significantly to achieving global sustainability goals.

Author contributions Bama Raja Segaran played a key role in the conceptualization and design of this systematic review, defining its scope, objectives, and methodology. She was responsible for the identification and selection of relevant literature, ensuring that the sources were comprehensive, up-to-date, and aligned with the research focus. Additionally, she led the drafting and revision of the manuscript, structuring the content and refining its clarity and coherence. Her contributions also included synthesizing the findings and drawing meaningful insights from the reviewed literature. Siti Nurulain, Mohd Izuan, and Teh Noranis contributed by critically reviewing the selected literature, ensuring its relevance, rigor, and alignment with the study objectives. They also provided valuable input in developing the research discussion and refining the conclusions. All authors collaborated in reviewing and approving the final manuscript to ensure its accuracy and integrity before submission.

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