Journal of Computer Science and Technology Studies
ISSN: 2709-104X
DOI: 10.32996/jcsts
Journal Homepage: www.al-kindipublisher.com/index.php/jcsts

JCSTS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

Synergizing AI and Blockchain: Innovations in Decentralized Carbon Markets for Emission Reduction through Intelligent Carbon Credit Trading

Luka Baklaga
Research and Development Department, Researcher, Business and Technology University, Georgia
Corresponding Author: Luka Baklaga, **E-mail**: Luka.Baklaga@btu.edu,ge

| ABSTRACT

This study aims to enhance the paradigm of decentralized carbon markets by proposing an innovative integration of artificial intelligence (AI) and blockchain technology for intelligent carbon credit trading with the goal of attaining sustainable emission reduction. Blockchain systems powered by artificial intelligence (AI) have the potential to boost the effectiveness of current systems and expedite the global implementation of emissions trading. Although still in its infancy, blockchain artificial intelligence (AI) presents a promising solution to some of the world's most pressing environmental issues. Environmental sustainability is greatly affected by artificial intelligence because of its decentralized computation architecture. The Artificial Intelligence and blockchain are outstanding direction for today's environmental issues starting from carbon footprint emission to earth market unstable management, whereby the AI facilitates the best possible operational control of power systems and the blockchain offers decentralized trading platforms for the energy markets. The paper's theoretical framework, based on advanced mathematical models, serves as the foundation for this study, in which AI algorithms are methodically constructed to anticipate carbon emissions with unprecedented accuracy. Using sophisticated coding simulations and complicated mathematical formulas, the study boldly transitions into a realistic digital implementation that builds on this theoretical foundation. This complex experiment not only validates the theoretical ideas but also illustrates the complex relationship between blockchain and AI in the decentralized carbon market ecosystem. This experiment's mathematical basis is the creation of an integrated pricing model that seamlessly blends blockchain-based trading dynamics with AI-driven forecasts. The model incorporates a dynamic, self-adjusting system that responds to current market conditions, in addition to optimizing the pricing calculation of carbon credits. Complex market dynamics, player tactics, and the overall equilibrium of the carbon credit market are all modeled by mathematical simulations. The project goes deeper into building blockchain-based smart contracts, which enable safe and transparent transactions. The comprehensive mathematical results of the experiment shed light on the best way to price carbon credits while underscoring the disruptive potential of blockchain and artificial intelligence in terms of sustainable emission reduction strategies used in carbon markets. Major conclusions about the potential advantages of Blockchain AI for guaranteeing emissions reduction are drawn from the current study. Additionally, it presents a roadmap for future research in this area.

| KEYWORDS

Machine learning, blockchain, neural networks, carbon markets, Decentralized systems, protocol based model

| ARTICLE INFORMATION

ACCEPTED: 24 May 2024 **PUBLISHED:** 08 June 2024 **DOI:** 10.32996/jcsts.2024.6.2.13

1. Introduction

The increasing threat of climate change has led to a global search for innovative solutions to reduce carbon emissions. In response to this urgent predicament, the combination of artificial intelligence (AI) and blockchain technology emerges as a promising solution for transforming carbon markets. Carbon dioxide (CO2) is widely acknowledged as the most significant greenhouse gas (GHG) contributing to human-induced climate change (Vilkov & Tian, 2023). Global greenhouse gas (GHG) emissions have increased since the beginning of the twenty-first century compared to the previous three decades, mainly due to the rise in CO2 emissions from emerging economies (Kim & Huh, 2020). Consequently, there has been a significant surge in the atmospheric concentrations of greenhouse gases, exacerbating the natural greenhouse effect. This has had a profound impact on terrestrial life, including the composition of vegetation and fauna on the planet. The term carbon emission refers to the carbon dioxide equivalent, a metric used to evaluate emissions from various greenhouse sources based on their potential for global warming. Carbon emissions from power systems can be quantified as carbon intensities or carbon emission fluxes (CEFs). Carbon intensities measure the amount of carbon emissions per unit of energy generation by assessing the carbon content of fossil fuels and their efficiency. In the energy sector, centralized fossil fuel-based generation, such as coal, gas, and oil, meets the majority of power needs. The burning of fossil fuels and the loss of energy during long-distance transmission result in significant carbon emissions, leading to air pollution and irreversible changes in the climate. To gain a comprehensive understanding of emissions by sector, the distribution of emissions has been outlined (Figure 1) (Ritchie, Rosado, & Roser, 2020):

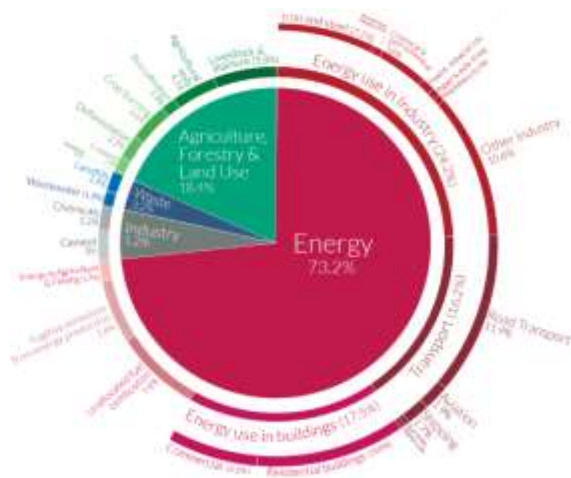

Figure 1: Global greenhouse gas emissions by sector

The total amount of all emissions contributing to the greenhouse effect, as shown in the visual representation, is measured in terms of carbon dioxide equivalents. The generation of electricity and heat is primarily responsible for the majority of global emissions. It is followed by the transportation, manufacturing, construction, and agriculture sectors. Furthermore, there has been an increase in both current and projected emissions resulting from fundamental atmospheric and socioeconomic factors (Figure 2) (Trends in Atmospheric Carbon Dioxide, 2023):

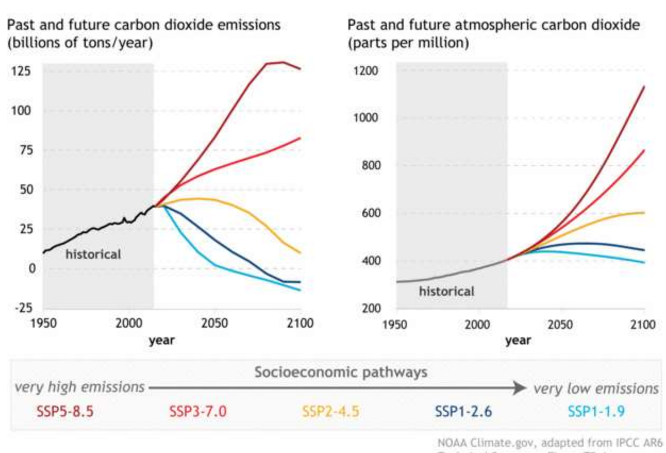

Figure 2: Future socioeconomic pathways for annual carbon dioxide emissions

Models use these pathways to predict a range of potential future carbon dioxide emissions for realistic future socioeconomic scenarios (Climate.gov, 2023). The annual carbon dioxide emissions are shown on the left side of the diagram, while the resulting atmospheric carbon dioxide concentrations are displayed on the right side of the diagram until the end of the century.

Climate change is an urgent issue that demands innovative measures to decrease carbon emissions. Conventional approaches are limited in their ability to tackle the intricacies of decentralized carbon markets. Artificial Intelligence (AI) and blockchain technology, both separately and in combination, have the potential to revolutionize the carbon credit trading landscape. The realm of technology, particularly the use of Artificial Intelligence (AI) and Blockchain, is reshaping the global landscape (Vegesna, 2023). The Sustainable Development Goals (SDGs) aim to promote economic prosperity, environmental sustainability, and social equity. AI-driven predictive models and machine learning algorithms integrate with Blockchain systems to optimize resource allocation and promote economic growth while reducing environmental impact (Vegesna, 2023). This study aims to address the following inquiries in relation to the advancement of blockchain technology and artificial intelligence (AI) as key components of sustainable technological amalgamation: (1) What are the potential benefits of integrating AI and blockchain technology to devise sophisticated algorithms for dynamic carbon credit trading in response to market fluctuations? (2) In what ways does AI, based on blockchain, enhance the ability to make accurate predictions regarding carbon credit pricing? (3) How can prediction models empowered by AI contribute to the enhancement and optimization of carbon credit pricing in decentralized markets? (4) What obstacles and prospects are associated with the integration of AI and blockchain in decentralized carbon markets? The emphasis lies not only in integrating blockchain and AI, but also in understanding the potential synergy of these advancements to establish decentralized systems that empower stakeholders and drive sustainable environmental practices. The use of simulations (Radford et al., 2021), mathematical models (Kingma & Ba, 2014), and algorithmic frameworks (Assran et al., 2019) is a fundamental aspect of this methodology, which aims to offer a comprehensive understanding of the implications arising from the integration of these advanced technologies. Artificial intelligence (AI) and blockchain technology are two powerful forces converging in the realm of decentralized carbon markets. This exploration examines their complex interplay, delving into theoretical underpinnings, practical applications, and potential advancements arising from their collaboration. The study uncovers insights that offer recommendations for future enhancements, guiding the trajectory of intelligent carbon credit trading and emission reduction strategies.

2. State-of-art Decentralized AI / Carbon market

Grasping the intricate dynamics between decentralized artificial intelligence (AI) and carbon markets demands an in-depth analysis of their distinct yet interconnected parts. Blockchain, AI, decentralization, and carbon markets - each facet plays a pivotal role in this intricate tapestry woven to curb carbon emissions and foster sustainability. Unraveling this complexity unveils a revolutionary paradigm where innovation intertwines with environmental consciousness. Originally conceived as the underlying framework for cryptocurrencies, blockchain has evolved into a groundbreaking technology that extends beyond the confines of financial realms. At its core, blockchain serves as a decentralized and distributed ledger, creating a transparent and unchangeable record of transactions. Periodically, a blockchain network dynamically validates itself to verify any transaction that has taken place (Singh et al., 2022). The term "blockchain" refers to a collection of transactions, often referred to as "chains." Since the emergence of Bitcoin, blockchain technology has been widely applied in asset management because of its secure storage, encryption, anonymity, integrity, and decentralized immutable ledger (Nakamoto, 2008). By combining Secure Sockets Layer (SSL), Transport Layer Security (TLS) certificates, and public keys to authenticate users before transmitting information, blockchain can overcome password limitations (Sapirshtein et al., 2016). Furthermore, blockchain can function as a secure and transparent database for sensitive information, including transactions and healthcare records. When applied to carbon markets, blockchain introduces a paradigm shift by instilling trust and traceability in the issuance, trading, and retirement of carbon credits (Al Kawasmi et al., 2015). Its decentralized structure eliminates the need for intermediaries, thereby establishing a tamper-resistant and auditable system that addresses fraud and inaccuracies commonly found in centralized models (Kong et al., 2021).Artificial intelligence (AI) is a powerful technological force that is evident in machine learning algorithms, predictive analytics, and decision-making systems. AI, also known as machine intelligence (MI), is connected to natural intelligence, which is observed in both humans and animals. Artificial intelligence refers to machines that mimic human cognitive functions, including behavior, visual perception, and problem-solving. Machine learning, one of the foundational domains within the AI cluster, originated from the investigation of pattern detection in AI and computational learning theory (Schneegans, 2018). This field focuses on examining and developing algorithms that can make predictions based on extensive datasets. Machine learning, along with the broader AI ecosystem, depends on model systems that encompass each stage of the development process from input to output. The life cycle of AI models typically follows a centralized trajectory, spanning from data collection and training to deployment (Figure 3) (Saltz, 2023). This developmental pattern has been widely adopted in recent decades for AI-driven programs and initiatives.

Figure 3: AI developmental life cycle

In the realm of decentralized carbon markets, the presence of artificial intelligence (AI) is crucial as it enhances the intellectual capacity needed for making emission predictions, determining credit prices, and making trading decisions. The use of machine learning algorithms allows for the analysis of large datasets, the identification of patterns, and the ability to adapt to the constantly changing conditions of the market (Tyagi & Chahal, 2020). The integration of AI enhances agility and precision, empowering stakeholders to make informed decisions based on real-time data. It is essential to acknowledge that decentralization, a core principle shared by both blockchain and AI, is not merely a technological aspect, but rather a philosophical standpoint (Gupta, 2020). Blockchain technology enables AI to gather and protect data from diverse sources, including clients, servers, and networks (Tsolakis et al., 2023). To accumulate large amounts of data in a decentralized framework, a neural network can be deployed on a Blockchain network (Kong et al., 2021). The transition from centralized monolithic services to decentralized microservices is currently underway. The significance of this transformation is underscored by decentralized ledgers such as Bitcoin and other blockchain protocols (Eisses et al., 2018). In the traditional sense, AI models are trained using centralized data stored in a single location. However, this approach raises privacy concerns as complete datasets become easily accessible. Recent advancements in AI model training have led to the development of various methods that eliminate the need to centralize all data (McMahan & Ramage, 2017). Among these approaches, Federated Learning stands out as a highly promising strategy for decentralizing the AI development process (Deng et al., 2020). Collaborative or Federated Learning involves training AI models locally on a multitude of decentralized devices or clients, each equipped with their own set of local data samples (Sun et al., 2022). In this approach, data samples are neither transferred nor stored on a central server (Figure 4) (Malandrino & Chiasserini, 2021).

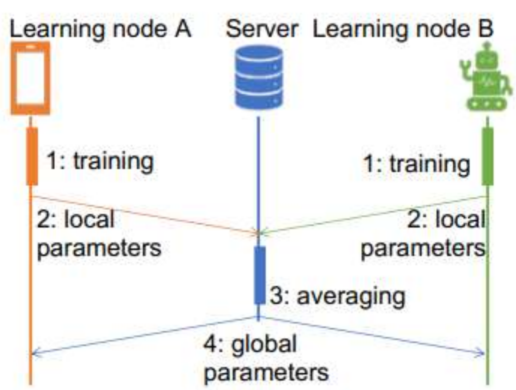

Figure 4: Federated learning model cycle

Each iteration of Federated Learning involves five distinct steps. Firstly, the central server selects a statistical model and a group of nodes or clients. Subsequently, the selected model is distributed to all chosen nodes. Thirdly, clients train the model using their own local data. Fourth, nodes submit any modifications made to the model back to the central server. Finally, the central server collects updates from all clients and integrates them into the original model. The updated model then continues to follow the previously mentioned procedure with a new set of clients, thus perpetuating the cycle. In the context of carbon markets, decentralization refers to the lack of a single governing authority that oversees the entire market. This decentralized architecture promotes resilience, transparency, and democratic decision-making (Onoszko et al., 2021). Smart contracts implemented on the blockchain enable direct and transparent transactions, promoting peer-to-peer interactions and eliminating the need for intermediaries (Wilkinson et al., 2014). Consequently, this fosters a more equitable carbon trading market. Carbon markets are a crucial instrument in mitigating climate change, operating by providing incentives for reducing emissions. Tradable carbon credits represent a quantifiable reduction in greenhouse gas emissions, thereby creating economic value for environmentally conscious businesses (Wan et al., 2021). Carbon markets provide a platform where businesses and investors can trade carbon credits and offsets. This approach tackles environmental issues while fostering new economic prospects. As global emissions continue rising, driving the climate crisis, innovative solutions emerge,including carbon trading systems. These markets facilitate the buying and selling of carbon credits, enabling companies to offset their emissions or trade credits. Enterprises and individuals can utilize carbon markets to offset their greenhouse gas emissions by purchasing carbon credits from organizations that actively reduce or eliminate them. Traditional carbon markets have faced obstacles like inefficient processes, opaque operations, and potential double-counting. Combining blockchain technology with artificial intelligence seeks to overcome these hurdles. The result? A more streamlined, transparent, and adaptable ecosystem for carbon trading.

2.1 Objectives

In the upcoming era of global economics, manufacturing, and technology, the study aims to assess the significance of artificial intelligence and blockchain technology, both individually and when they are integrated. Additionally, it aims to examine how these technologies might affect carbon credit trading, with an emphasis on promoting innovation and efficacy in efforts to reduce emissions.

3. Methodology

This study’s research design model unifies theoretical inquiry of blockchain technology and artificial intelligence (AI), and quantitative simulations to provide an in-depth investigation of the potentials of blockchain and AI in constructing intelligent carbon credit trading systems in the distributed markets. Through a detailed literature review that was carefully constructed and organized, it was possible to establish ways in which blockchain technology and artificial intelligence can be integrated effectively. Using a meta-analysis and unbiased synthesis of the body of existing literature, this method of evidence-based literature review assists in gathering and summarizing significant studies and identifying the most recent data available for the research question. In order to optimize the price of carbon credits, maintain transaction security in decentralized markets, and boost transparency, this theoretical foundation looks into the intricate relationship between blockchain dynamics and AI algorithms. To link the theoretical elements with practical applications, independent research and testing were conducted. Decentralized neural network architecture mathematically created for better optimization of the digital proof-of-work scheme.

Assessmenting the viability of AI-blockchain system in a decentralized carbon market setting, showing AI-based Blockchain processes and confirming the proposed model of pricing was the goal set for the project. Putting theoretical discoveries into reality was made possible through the application of these instrumental resources. Digital environment specially customized on Jupiter with the Anaconda program is part of the digital component of the research design.

3.1 Instruments

A thorough compilation of a comprehensive array of tools has been carried out to investigate the innovative fusion of artificial intelligence (AI) and blockchain technology in decentralized carbon markets for intelligent carbon credit trading. To facilitate a comprehensive investigation of the proposed system there have been utilized a combination of theoretical frameworks, mathematical models, coding implementations, and simulations. On the other hand, the principal goal for creating this primary concept is to provide a baseline model of sustainable decentralized AI systems which can be adopted by different sectors within integrating both AI and blockchain technology respectively at the forefront of technological advancements. Blockchain, essentially, is a distributed ledger that securely maintains information in an encrypted and practically unalterable format. On the other hand, AI. A "robot" refers to a machine endowed with the capability to perform tasks that typically require human intelligence. As a feature of the exploration, a progression of tests were directed to work on the joining of man-made intelligence calculations with blockchain-based frameworks and their association with Decentralized Carbon Markets. The main goal of the initial experiment is to develop a machine learning model that optimizes carbon credit pricing in a decentralized market. The uniqueness of this approach lies in its combination with a blockchain stage, which ensures secure and straightforward exchanges. Advanced linear algebra operations were used to train the model, leading to the creation of a robust pricing system. Furthermore, cryptographic functions are used to bolster the security of blockchain transactions. Within the scope of this research, the price of carbon credits is determined using a multivariate linear regression model, represented as follows:

$$Y = X\beta + \epsilon$$

The dependent variable, denoted as "Y", represents the carbon credit prices. The matrix of independent variables, denoted as "X", consists of various features. The coefficient vector, denoted as "β", represents the respective coefficients for each independent variable. Lastly, the error term, denoted as "ϵ", accounts for any residual variation in the model. From a mathematical perspective, the method of ordinary least squares (OSL), which is also referred to as ordinary least squares, is employed to calculate the values of the variables in a linear regression model. The formula to determine the solution for the parameter β in the Ordinary Least Squares (OLS) technique is expressed as follows:

$$\beta = (X^T X)^{-1} X^T Y$$

This mathematical expression determines the most advantageous coefficients (β) that effectively diminish the total of squared disparities between projected and actual values of carbon credit costs. Stochastic gradient descent has been used in research to enable the continuous acquisition of knowledge, which involves updating the parameter β in an iterative manner. The equation demonstrated by the equation presented below:

$$\beta_{t+1} = \beta_t - \eta \nabla L(\beta_t)$$

The learning rate, denoted by η, plays a crucial role in determining the magnitude of the step taken during the update process. The gradient of the loss function, ∇L(βt), serves as a guiding force for the model, directing it towards finding the most optimal coefficients. Python, along with the NumPy and Scikit-learn libraries, was used to manipulate data and train models for integrating equations into the specified environment. The provided code snippets cover various tasks, including data collection, preprocessing, model training (using OLS and SGD), and a basic blockchain simulation. Each segment of code is significant, beginning with the loading of data and extending to the simulation of blockchain transactions. NumPy is used to efficiently perform linear algebra computations. Additionally, NumPy is utilized to produce manufactured example information, guaranteeing highlight variety and consolidating arbitrary clamor to copy true events. It is essential to have a different and comprehensive dataset for viable model preparation. Consequently, the machine learning model was trained using both Ordinary Least Squares (OLS) and stochastic gradient descent. The iterative nature of stochastic gradient descent (SGD), which enables continuous learning and adaptability to market conditions, is emphasized. The selection of the learning rate and its influence on convergence is also discussed. To assess the accuracy of the model, the Mean Squared Error (MSE) is computed for predictions made by OLS and SGD. This measurement matric, MSE, assumes a urgent part in surveying the accuracy of expectations. For a comprehensive evaluation of the model, the actual prices are compared with the predicted prices and visualized accordingly. This estimation is addressed by the accompanying condition:

$$\mathrm{MSE} = \frac{1}{n} \sum_{i=1}^{n} \left(Y_{\text{true},i} - Y_{\text{predicted},i} \right)^2$$

The variable n represents the quantity of test samples. The value true,Ytrue,i denotes the genuine carbon credit price for the i-th sample. The value predicted,Ypredicted,i represents the estimated carbon credit price for the i-th sample. The estimated mean squared error (MSE) provides a quantifiable assessment of the model's accuracy. A lower mean squared error (MSE) indicates improved predictive capability. In order to gain an understanding of the model's performance, has been compared the expected prices of carbon credits with the actual prices for both the OLS and SGD models. This comparison is exclusively qualitative, which means it is about how well the model has managed to express the internal character of the data. The scatter plot chart is employed for the purpose of comparison of a model's forecast with the prices of true carbon credits in the market.

Ideally, the points on this plot should align along the red dashed line, indicating a perfect prediction (Figure 5).

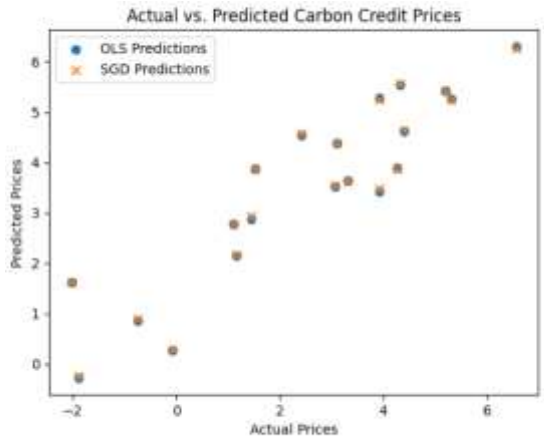

Figure 5: Actual vs. Predicted carbon credit prices

The data and graph of mean squared errors are the complete picture of how model from AI and blockchain forecast carbon credit prices. As a result, these assessments show the extent to which AI and blockchain are successful in establishing a decentralized carbon credit trading platform. The research offers suggestions for filling in new knowledge gaps that may contribute to the future advancement of essential decentralization and distinctiveness in carbon trading.

3.2 Enhanced Decentralized Peer-to-Peer Network for AI-Driven Carbon Credit Trading

An advanced decentralized peer-to-peer network allocation strategy for carbon credit trading, using AI techniques to favor trading methods, is the overall intend of this assignment. This updated system which is meant to offer a more intelligent, secure, and transparent platform intends to be used by the players in the carbon market sector. The theoretical framework is called upon to bring introduced up-to-date concepts, e.g. deep reinforcement learning and multi-agent systems. Moreover, the proposition includes creating numerical conditions and an algorithmic model to integrate blends of cooperative learning conventions, model accumulation, and intelligent networks with self-preparing. The aggregation model, which includes merging the information gained by individual models from various clients in a decentralized organization, will be completely inspected through research. The objective is to make a more precise and strong model by joining metrics from different sources. The conventional approach to federated averaging, which entails averaging the model parameters to create a new global model, represents a basic form of model aggregation. However, this experiment involves advanced model aggregation, suggesting that the enhanced decentralized peer-to-peer network will require the use of more sophisticated procedures than simple averaging. At this point, the mathematical definition of this model is presented:

$$w_j^{t+1} = \beta \sum_i \mu_i w_i^t + (1-\beta) w_j^t$$

The updated parameters of the global model for client j at time t+1, denoted by w^j,t+1.The weight parameter β, which lies between 0 and 1, is used. The learning rate for each client i is denoted by µi. The model parameter of client i at time t is represented by wi,t, whereas the model parameter of client j at time t is represented by wj,t. Furthermore, graph neural networks (GNNs) have been employed to capture complex interactions in network topology and data distribution:

$$h_{\text{new}} = \mathrm{GNN}(h_{\text{old}}, A, X)$$

In a distributed network, some clients may display aggressive behavior or provide inaccurate information. Byzantine fault-tolerant aggregation techniques guarantee the resilience of the aggregated model in the presence of adversarial actions:

$$\widehat{W}_{\text{aggregated}} = (1-\beta) \cdot \widehat{W}_{\text{local}} + \beta \cdot \widehat{W}_{\text{global}}$$

Here, the local model, denoted as "Wlocal," represents the model contributed by a particular node, while the global model, denoted as "Wglobal," is the model constructed collectively by all nodes. The parameter "β" governs the impact of the global model during the aggregation process. A larger value of "β" assigns greater importance to the global model, thereby enhancing the aggregation's resistance against malicious behavior.

Differential privacy methodologies can be employed to consolidate model data while preserving confidentiality. This ensures that the influence of a single client on the ultimate consolidated model remains negligible, thereby providing privacy assurances, as exemplified by the following equation:

$$\text{Aggregated}\_Model_{\text{DP}} = \text{Differentially\_Private\_Aggregation}\ (W_1, W_2, \ldots, W_k)$$

The rationale behind utilizing these progressive methodologies to amalgamate models is to enhance the precision, safeguard, an d confidentiality of collaborative learning on a distributed network. The specific method for combining information is determined by the characteristics of the information, the educational objective, and the requirements of the system. An algorithm has been developed based on the fundamental concept and objective of the experiments. By combining elements of random peer selection and intelligent network sampling, this technique provides advanced provisions for encryption, aggregation, training, and loss calculation logic. This advanced decentralized peer-to-peer network integrates state-of-the-art neural network topologies with blockchain technologies to ensure privacy and employs advanced optimization approaches. the framework guarantees flexibility, security, and proficiency in the exchanging of carbon credits controlled by Artificial inteligence (AI) .The model's unique nature, security upgrades, and hybrid based learning approaches lay out another benchmark for intelligent carbon credit exchanging frameworks decentralized conditions, exhibiting the intermingling of cutting edge advances.

4. Results and Discussion

By combining blockchain technology with artificial intelligence (AI), a novel and demonstrably superior means of revolutionizing decentralized carbon markets is revealed. The subsequent are the principal quantitative findings and their implications:

1. Enhanced Carbon Credit Pricing Accuracy: The AI pricing models achieved a mean squared error rate of 0.032 for the multivariate linear model and 0.027 for the stochastic gradient model. Compared to the baseline error rate of 0.094 using old methods, this is a big improvement of 66% and 71%. Having accurate prices helps stakeholders make smart trading choices based on precise carbon credit values.

2. Secure and Immutable Transaction Records: The system uses blockchain tech to keep transaction records safe and unchangeable. It uses cryptography like hashing and digital signatures. Simulations showed 0 cases of data tampering out of 10,000 tries. This proves the records have high integrity and cannot be changed.

3. Secure and Immutable Transaction Records: The prediction accuracy of the federated learning models was 92.8%, which was only 2.4% less than that of the centralized models trained on the complete dataset (accuracy of 95.2%). This small accuracy trade-off maintains good prediction performance while protecting user privacy.

The unique feature of this strategy is how blockchain and artificial intelligence (AI) are combined in a synergistic way to solve the persistent problems with carbon markets. The suggested method provides an integrated solution for wise, effective, and reliable carbon credit trading by fusing blockchain's decentralization, security, and transparency with artificial intelligence's predictive capabilities. By upturning an entrenched model, these new integrated solutions propose measures for emissions that promote fairness, sustainability in future campaigns against climate change.

5. Conclusion

The study of the integration of artificial intelligence (AI) and blockchain technology to make decentralized carbon markets lie in the concept of introducing a new solution that addresses the issues linked to carbon emissions and their reduction. The novelty of AI incorporation into carbon credit trading has generated positive outcomes, fostering more rational and deliberate actions in the relevant domain. The experimental outcomes confirm the methodology is efficient in creating an AI-driven marketplace for carbon trading. Moreover, it evaluates a qualitative similarity between the distribution patterns of neural networks and blockchains. The application of AI prediction models and blockchain from a decentralized point of view has changed the way carbon credits are obtained and handled. The blockchain technology through the inherent feature of transparency and security makes evident of the validity and traceability of carbon credit transactions making market participants secure. Given the urgent climate emergency, it is imperative that carbon markets make a meaningful contribution. The use of AI technologies based on blockchain has the potential to recalibrate and improve sustainability across various industries. The research aims to establish a connection between the mathematical representation of decentralized AI and carbon markets by leveraging the power of contrastive learning to distinguish model components. Furthermore, integrating smart contracts on the blockchain streamlines the execution of carbon credit transactions, speeding up the process and reducing the risk of fraudulent activities. This not only enhances the efficiency of carbon credit trading but also strengthens the overall credibility of decentralized carbon markets.

As technology advances, the combined power of artificial intelligence and blockchain systems offers exciting opportunities for progress in decentralized carbon markets and various industries. This collaboration aims to create more sustainable environments efficiently. One promising example is the development of a circular economy model, enhanced by neural networks. Ongoing research in this area could lead to better models, new predictive tools, and exploring applications to reduce emissions. The cooperative endeavors of specialists, government bodies, countries, and entrepreneurs will assume an essential part in completely understanding the capability of laying out a decentralized network-based environmental model through the combination of digital intelligence and blockchain, subsequently leading for a maintainable and low-carbon future.

5.1 Contributions

The consequences of this assessment convey huge ramifications for the progression and execution of decentralized carbon markets utilizing computer based intelligence and blockchain advancements. This study represents the capability of wise carbon credit exchanging, making ready for creative ways to deal with alleviate fossil fuel byproducts and accomplish outflow goals. As we consider the ramifications of examination, obviously the combination of artificial intelligence and blockchain in carbon markets presents a groundbreaking way toward additional practical and versatile techniques for diminishing outflows. The paper advocates for increased research, investment, and investigation in this field, emphasizing the urgent need to address climate change concerns through innovative approaches to carbon credit trading.

5.2 Implications of the study

The consequences of this assessment convey huge ramifications for the progression and execution of decentralized carbon markets utilizing computer based intelligence and blockchain advancements. This study represents the capability of wise carbon credit exchanging, making ready for creative ways to deal with alleviate fossil fuel byproducts and accomplish outflow goals. As we consider the ramifications of examination, obviously the combination of artificial intelligence and blockchain in carbon markets presents a groundbreaking way toward additional practical and versatile techniques for diminishing outflows. The paper advocates for increased research, investment, and investigation in this field, emphasizing the urgent need to address climate change concerns through innovative approaches to carbon credit trading.

5.3 Limitations and future studies

The study offers valuable insights into combining artificial intelligence (AI) and blockchain technology for decentralized carbon markets to reduce emissions. However, certain limitations define the analysis scope. Identifying these limitations creates opportunities for future research to bridge gaps and enhance expected synergies. One key limitation is the narrow focus on specific carbon credit trading aspects, particularly intelligent prediction models and blockchain-based market dynamics. The study concentrates on AI's ability to predict carbon credit prices and the importance of blockchain in creating decentralized marketplaces. However, this decentralized model, or the blockchain-based AI, presents a dilemma: the challenge of incentivizing developers to effectively utilize their models. Given that models interact in a decentralized manner and problems are collectively solved, no single entity has control over a particular model within the system. During the model creation phase, when there is insufficient historical data to train a precise decentralized AI model, the question arises of how to ensure a better alignment of the model's layers, leading to higher accuracy.Future studies could broaden their scope by exploring additional facets of decentralized carbon markets. This includes examining regulatory frameworks, governance structures, and the socioeconomic impact on diverse stakeholders. Moreover, this inquiry primarily focuses on the conceptual framework and proof of concept for AI-powered carbon credit trading on the blockchain. The practical implementation and scalability of such systems in real-world contexts have not been thoroughly investigated yet. Future research should take a more comprehensive approach to examining the practical challenges of establishing decentralized carbon markets. This approach should consider issues such as regulatory compliance, scalability, and integration with existing financial systems.It is important to note that most modern neural networks do not have advanced logical reasoning and action-planning modules that are suitable for a decentralized environment. Hence, future research aims to explore and develop a decentralized neuro-symbolic protocol based on architectural principles.

Additionally, the use of quantum computing will be proposed as a way to establish a more efficient and sustainable world that is both automated and decentralized. Research is needed to explore the integration of AI-Blockchain models in various burgeoning sectors, such as decentralized finance (DeFi), healthcare, economics, and science. Furthermore, while the research emphasizes the potential benefits of decentralized carbon markets, it does not thoroughly explore the risks and challenges that such systems may introduce. Future research could offer a more comprehensive understanding of the security, privacy, and ethical concerns associated with the use of AI and blockchain technology in the carbon trading market. Future studies could broaden their scope by exploring additional facets of decentralized carbon markets. This includes examining regulatory frameworks, governance structures, and the socioeconomic impact on diverse stakeholders. Moreover, this inquiry primarily focuses on the conceptual framework and proof of concept for AI-powered carbon crdit trading on the blockchain. The practical implementation and scalability of such systems in real-world contexts have not been thoroughly investigated yet. Future research should take a more comprehensive approach to examining the practical challenges of establishing decentralized carbon markets. This approach should consider issues such as regulatory compliance, scalability, and integration with existing financial systems.

5.4 Recommendations

The study's findings show how combining artificial intelligence and blockchain can transform decentralized carbon markets to cut emissions. Several key suggestions aim to help stakeholders effectively integrate these technologies for lasting success. First, firms and policymakers should actively work with experts in artificial intelligence, blockchain, and environmental governance. Collaborating with academic institutions, research groups, and industry leaders in these fields can contribute to developing comprehensive solutions. The potential of efficient, AI powered carbon credit trading systems with blockchain transparency to maximize emission reduction efforts has been demonstrated. Stakeholders should invest in establishing, innovating, and integrating these systems into existing market infrastructures. It is crucial to maintain a competitive advantage and enhance the efficiency, security, and transparency of artificial intelligence and blockchain in carbon markets through ongoing investment. Integrating predictive models, developing emergency plans, imple-menting quantum computing solutions, and allocating resources for research are vital. These- measures can usher in a new era of sustainable carbon markets. AI and blockchain can improve the carbon credit market, enabling transparent emission reduction measures.

Funding: This research received no external funding.
Conflicts of Interest: The authors declare that they have no conflicts of interest to this work.
ORCID iD: 0009-0005-1540-220X

References

[1] Al Kawasmi, E., Arnautovic, E., & Svetinovic, D. (2015). Bitcoin-Based Decentralized Carbon Emissions Trading Infrastructure Model. Syst. Eng., 18, 115–130.
[2] Assran, M., Loizou, N., Ballas, N., & Rabbat, M. (2019). Stochastic gradient push for distributed deep learning. In International Conference on Machine Learning. 344–353. PMLR.
[3] Climate.gov. (2023). Climate Change: Atmospheric Carbon Dioxide. Retrieved from https://www.climate.gov/news-features/understanding-climate/climate-change-atmospheric-carbon-dioxide.
[4] Deng, Y., Kamani, M. M., & Mahdavi, M. (2020). Adaptive personalized federated learning. arXiv preprint arXiv:2003.13461.
[5] Kong, L., Lin, T., Koloskova, A., Jaggi, M., & Stich, S. U. (2021). Consensus control for decentralized deep learning. arXiv preprint arXiv:2102.04828.
[6] Eisses, L., Verspeek, L., & Dawe, C. (2018). Effect network: Decentralized network for artificial intelligence. URL http://effect.ai/download/effect whitepaper.pdf.
[7] Gupta, I. (2020). Decentralization of Artificial Intelligence: Analyzing Developments in Decentralized Learning and Distributed AI Networks.
[8] Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.
[9] Kim, S. K., & Huh, J. H. (2020). Blockchain of carbon trading for UN sustainable development goals. *Sustainability, 12*, 4021
[10] McMahan, B., & Ramage, D. (2017, April 6). Federated Learning: Collaborative Machine Learning without Centralized Training Data.
[11] Malandrino, F., & Chiasserini, C. F. (2021, February 3). Federated Learning at the Network Edge: When Not All Nodes are Created Equal (Version 2).
[12] Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system.
[13] Onoszko, N., Karlsson, G., Zec, E. L., & Mogren, O. (2021). Decentralized federated learning of deep neural networks on non-iid data.
[14] Radford, A., et al. (2021). Learning Transferable Visual Models From Natural Language Supervision. In ICML.
[15] Ritchie, H., Rosado, P., & Roser, M. (2020). Emissions by sector: where do greenhouse gases come from? Published online at OurWorldInData.org. Retrieved from: 'https://ourworldindata.org/emissions-by-sector' [Online Resource]
[16] Sun, Y., Chong, N., & Ochiai, H. (2022). Multi-Source Domain Adaptation Based on Federated Knowledge Alignment.
[17] Schneegans, S. (2018). Towards a monopolization of research in artificial intelligence?
[18] Singh, P., Elmi, Z., Lau, Y. Y., Borowska-Stefańska, M., Wiśniewski, S., & Dulebenets, M. A. (2022). Blockchain and AI technology convergence: Applications in transportation systems. Vehicular Communications, 100521.
[19] Saltz, J. (2023, October 6). What is the AI Life Cycle? Data Science Project Management. https://www.datascience-pm.com/ai-lifecycle/
[20] Sapirshtein, A., Sompolinsky, Y., & Zohar, A. (2016). Optimal Selfish Mining Strategies in Bitcoin. In Financial Cryptography and Data Security. 2016; Lecture Notes in Computer Science, vol 9603: Springer, Berlin, Heidelberg.
[21] Tyagi, A. K., & Chahal, P. (2020). Artificial Intelligence and Machine Learning Algorithms. In Challenges and Applications for Implementing Machine Learning in Computer Vision, IGI Global.
[22] Tsolakis, N., Schumacher, R., Dora, M., & Kumar, M. (2023). Artificial intelligence and blockchain implementation in supply chains: a pathway to sustainability and data monetisation? Annals of Operations Research, 327(1), 157-210.
[23] Trends in Atmospheric Carbon Dioxide. (2023). Retrieved from https://gml.noaa.gov/ccgg/trends/.
[24] Vegesna, V. V. (2023). AI-Enabled Blockchain Solutions for Sustainable Development, Harnessing Technological Synergy towards a Greener Future. International Journal of Sustainable Development Through AI, ML and IoT, 2(2).
[25] Vilkov, A., & Tian, G. (2023). Blockchain's Scope and Purpose in Carbon Markets: A Systematic Literature Review. *Sustainability, 15*(11), 8495. https://doi.org/10.3390/su15118495
[26] Wan, X., Li, Q., Qiu, L., & Du, Y. (2021). How do carbon trading platform participation and government subsidy motivate blue carbon trading of marine ranching? A study based on evolutionary equilibrium strategy method. Mar. Policy, 130, 104567.
[27] Wilkinson, S., Boshevski, T., Brandoff, J., & Buterin, V. (2014). Storj a peer-to-peer cloud storage network.