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Artificial Intelligence in Carbon Trading: Enhancing Market Efficiency and Risk Management

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ABSTRACT

Carbon trading is a market-based technique to decrease greenhouse gas (GHG) emissions through the sale and purchase of carbon offsets. Incorporating artificial intelligence (AI) into carbon trading can alter the industry by improving information processing, statistical modeling, and trade automation. This paper presents an extensive structure for AI-driven carbon trading that considers critical aspects such as carbon trading volume and pricing to maximize productivity and sustainability. The study assesses numerous AI and machine learning (ML) theories, including their use in cost prediction, real-time market forecasting, and financial risk assessment. The main results show that AI integration increases market transparency, lowers fraud, and promotes informed decision-making, all of which helps to establish an environmentally friendly, effective, and adaptable carbon market. Furthermore, this work underscores the role of AI in advancing carbon-neutral economies by fostering innovation in emissions monitoring and reporting. These advancements highlight AI's critical contribution to achieving global climate objectives and addressing the urgent challenges posed by climate change.

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1. INTRODUCTION

The carbon trading sector has been significantly influenced by the incorporation of AI, which has brought forth innovative solutions to the pressing issues of climate change and the degradation of the environment. Trading carbon creates lower emissions with a market-based strategy of greenhouse gases by buying and selling authorizations to produce carbon dioxide. AI technologies are crucial for making the process more cost-effective, accurate, and transparent [1]-[3]. An essential part of incorporating AI into carbon trading is predictive analytics that use ML techniques. Through the analysis of market patterns, historical information, and environmental variables, these algorithms can forecast future carbon prices. Market participants can use the predictive ability to limit risks, make educated choices, and strategically organize their carbon trading activity. To help governments and businesses set realistic and achievable carbon reduction goals, AI-driven analytics can also provide useful information on emission patterns [4]-[7]. AI has also significantly contributed to establishing a market for carbon trading. To reduce the likelihood of fraud and preserve the validity of environmental credits, AI collaborates to ensure safe and transparent operations. The verification and validation process can be automated and accelerated with the use of AI-powered smart contracts, which can increase the accessibility and efficiency of participants [8], [9].

The accuracy of carbon counting is enhanced when credits are distributed or withdrawn according to verified emissions data from this real-time monitoring. Algorithms powered by AI that can detect potential non-compliance may further bolster the legitimacy of carbon exchange. By integrating AI into carbon trading, new financial products can be easier to create. AI algorithms create new investment opportunities by assessing the financial risks associated with carbon expenditures. Carbon trading has attracted more investors, resulting in a lively and ever-changing market [10]-[14]. A new era of efficiency, transparency, and innovation could be dawning due to the adoption of AI, which is reshaping the carbon trading industry. As the world steps up its efforts to combat climate change, AI will keep playing a critical role in maximizing carbon markets, promoting moral behavior, and, in the long run, contributing to a future that is both resilient and ecologically benign [15]– [17]. Carbon and carbon emissions trading systems are the focus of this review study, which examines several models for AI integration with the goals of improving cost prediction and optimizing price. It explores the use of several ML and deep learning (DL) algorithms to predict the behavior of real-time carbon markets across different regions.

AI and ML are significant in carbon trading and markets as they enhance data analysis, predict market patterns, and detect inefficiency. They can manage vast volumes of data from ecological indicators, economic trends, and legislative regulations, leading to more accurate carbon pricing and risk assessment. AI-powered systems also enhance precision and transparency, reducing fraud and boosting trust in carbon credit authentication. These developments can help close the research gap by improving decision-making, strengthening trading procedures, and encouraging the development of more ever-changing, effective, and scalable climate change markets. Figure 1 illustrates the methodology employed in this study. The figure is divided into key stages that demonstrate the flow of processes and their interconnections. Initially, data acquisition is emphasized, where real-time and historical data on carbon emissions, trading volumes, and prices are collected from diverse sources, including IoT sensors, satellite imagery, and market databases. This data is then processed and fed into the AI-driven analytics stage, where machine learning models analyze trends, predict market behaviors, and optimize trading strategies. The framework also highlights a decision-making layer, where predictive insights from the analytics stage guide policymakers, traders, and other stakeholders in making informed decisions about pricing, risk assessment, and emissions reduction goals. Finally, the execution phase integrates these decisions into actionable steps, such as automated transactions, carbon credit allocation, and system monitoring for compliance and transparency. This comprehensive structure underscores how AI technologies streamline each stage, fostering efficiency, accuracy, and scalability in carbon trading systems.

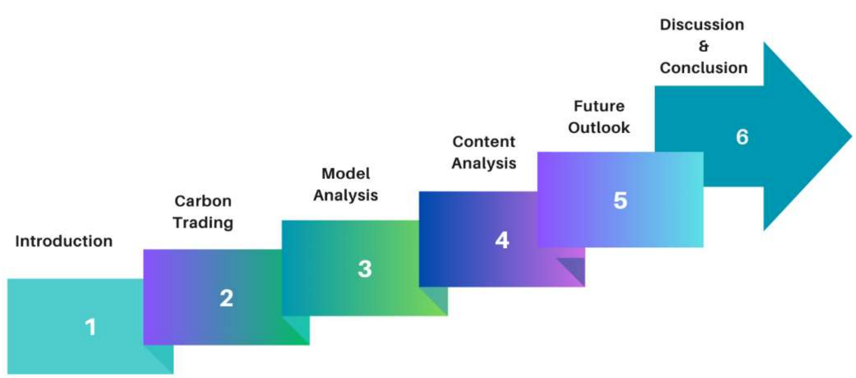

Figure 1. Strategy used in this work.

2. CARBON TRADING

Carbon trading, also known as emission trading, is a market-based strategy aimed at reducing greenhouse gas emissions. In this system, businesses are granted permits allowing them to emit a specific amount of CO_2. Companies that exceed their emissions quota must purchase additional credits from others with surplus allowances. This mechanism incentivizes emission reductions and promotes environmentally friendly practices [18]– [20].

Reference [89], which focuses on smart contracts, green energy operations, and carbon trading, explores blockchain-based solutions for carbon markets. It also discusses the relevance of game theory, artificial intelligence (AI), and cryptocurrencies in improving the transparency and efficiency of these systems.

The expansion of carbon trading markets emphasizes support for companies and investors involved in carbon-reduction technologies and green innovations such as renewable energy projects, energy-efficient infrastructures, and emission reduction initiatives. This growth opens new avenues for sustainable financial investments and technological advancement.

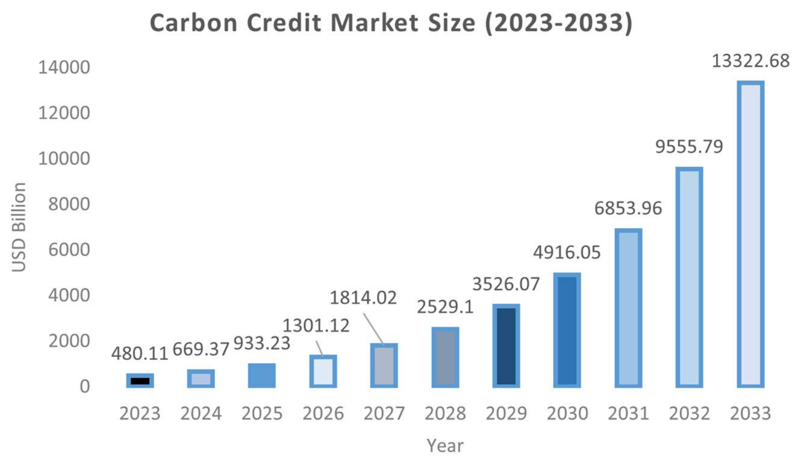

Figure 2. Estimated market size for carbon credits (2023-2033).

Figure 2 presents the projected growth of the carbon credit market between 2023 to 2033. Starting at USD 480.11 billion in 2023, the market is expected to experience significant growth, reaching USD 13,322.68 billion by 2033. This rapid increase underscores the rising importance of carbon credits as a tool for mitigating climate change, driven by global efforts to reduce emissions and the growing adoption of carbon trading mechanisms [21]. To enhance the analysis presented in Figure 2, it is essential to include statistical significance metrics, such as confidence intervals or p-values, to validate the projected growth data for carbon credits from 2023 to 2033. It would add validity to the results while offering a better grasp of the trends presented.

2. 1. Carbon trading market

A climate change mitigation strategy and the carbon trading market facilitate the price of carbon emissions. It is also referred to as cap-and-trade emissions trading, or trading in emissions. In this system, which limits total emissions of GHG to a level set by a regulatory body, businesses are allotted a certain number of emissions credits or permits according to their permitted emissions. By reducing emissions below a certain level, a firm might provide more credits to customers who are consuming more than their allocated amount. Consequently, companies have an economic incentive to implement eco-friendly procedures and technology, which lowers emissions [22]–[25]. Two international agreements that significantly impacted the carbon trading market are the Kyoto Protocol and the Paris Agreement. By establishing a clean development mechanism (CDM) and mandating that developed nations cut their emissions, the Kyoto Protocol broke new ground and allowed developed nations to finance poor nations' carbon reduction programs. Carbon trading schemes were emphasized as crucial market-driven strategies in the battle against climate change in the Paris Agreement, which backs their continuance and expansion [26]-[30]. Carbon trading, a process involving the sale of carbon credits, is a strategy aimed at reducing GHG emissions through programs such as energy efficiency, afforestation, and renewable energy installations. These credits can be traded on carbon markets or through bilateral agreements to create a flexible, affordable system that accelerates the transition to a low-carbon economy and promotes global economic equity [31]-[36]. The author of ref [95] investigated the impact of blockchain methods, such as smart contract technology, cryptocurrencies, and decentralized platforms, in improving carbon trading networks and accelerating the transition to low-carbon energy sources, as well as the incorporation of AI and game theory into energy exchanges.

Table 1. Utilization of AI and ML in carbon trading markets.

Ref	Summary	Main Findings
[95]	The paper suggests a new way to combine AI and blockchain to improve decentralized carbon markets and facilitate sustainable reduction of emissions.	AI-driven pricing models greatly enhanced the precision of carbon credit pricing in comparison to conventional approaches.
[96]	The article suggests an online algorithm that uses carbon spot and future markets to enable carbon-conscious ML task offloading for sustainable edge AI.	The paper suggests a collaborative optimization task to reduce the loss of accuracy and remain within a limited budget for acquiring Carbon Emission Reduction (CERs) to accomplish environmentally friendly edge AI.
[97]	The article explores how Earth observation data and AI algorithms can be used to monitor, report, and verify carbon projects in voluntary carbon markets.	The feasibility of utilizing Earth observation data and AI algorithms to oversee, document, and authenticate carbon projects in voluntary carbon markets is investigated.
[98]	The article talks about how AI and ML are used in the automotive sector to decrease carbon emissions, though it does not focus on carbon markets.	AI and ML are instrumental in driving a shift towards sustainability and environmental awareness in the automotive sector.
[99]	ML algorithms play a significant role in carbon capture and storage by forecasting physical characteristics, assessing stability, and tracking CO2 movement and release.	Various applications of carbon capture and storage extensively utilize ML algorithms such as ANN, CNN, SVM, as well as LSTM for tasks such as predicting physical properties, assessing mechanical stability, and monitoring CO_2 migration and leakage.
[100]	This book utilizes AI and ML methods for predicting prices and trends in carbon markets.	Utilizing data-based algorithms, it provides understanding of market dynamics, enabling accurate predictions of carbon credit prices, recognition of new trends, and evaluation of market instability.

3. MODEL ANALYSIS

Various investigations have presented certain theories, like [37] -[38], because legislation and regulations have had various impacts over the years. The framework of [37] considers pre- and post-treatment phases for an evolving evaluation of the treatment effect, which is important in carbon trading. Total resources, revenue development, revenue to overall assets ratio, payout policy indicator, long-term debt to total properties ratio, and cash reserves to the overall assets ratio are all combined to form the capital restriction indicator WW refers to in equation (1) [38]. The logarithm of total assets (SIZE, negative), the three-digit industry sales growth (ISG) industry sales growth of the firm (ISG, positive), the ratio of cash flow to total assets (CFA, negative), a dividend policy indicator (DIV, negative), the ratio of long-term debt to total assets (LD, positive), and the ratio of cash holdings to total assets (CH, negative) [37,38]. Initially, the SA index is provided [38] as a substitute assessment of the funding restrictions by equation (2).

$$WW = -0.044 * SIZE + 0.102 * ISG - 0.091 * CFA - 0.062 * DIV + 0.021 * LD - 0.035 * CH \quad (1)$$

$$SA = -0.737 * SIZE + 0.043 * SIZE^2 - 0.040 * AGE \quad (2)$$

When AGE is the natural log of the number of periods that a company has been publicly traded, and SIZE is the natural log of the company's overall assets, adjusted for inflation. In [39], Shen and his colleagues compared their model with their models in detail, so their model could complete previous models because it includes the environmental consciousness of clients, reduction of emissions, and variable carbon prices. Thus, the framework is shown in Figure 3 and was modeled in [39].

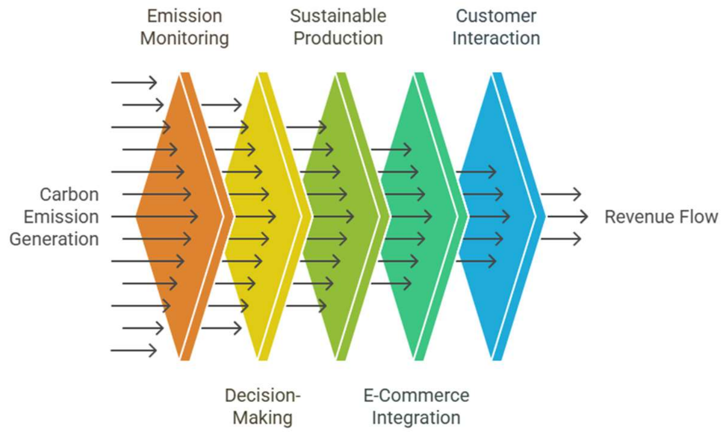

Figure 3. Sustainable business flow.

Figure 3 illustrates a supply chain model where carbon emissions from a manufacturer are influenced by other enterprises, with costs being exchanged between them. The manufacturer supplies products to an e-commerce platform at a price. p, which are then sold to customers at a price q, while the platform may receive a revenue share ρP From the manufacturer. The model captures the interactions between enterprises, manufacturers, e-commerce platforms, and customers, emphasizing the role of carbon emissions in the supply chain. The model heavily relies on the assumption of consumers' low-carbon preferences without accounting for potential variations across different demographics and regions. The findings may have limited generalizability, as consumer preferences can vary based on economic conditions, cultural factors, and market trends. AI can be used to develop predictive models that forecast carbon emissions based on production levels, supply chain activities, and market demand. Another research gap is the lack of integration of real, up-to-date carbon prices in the decision-making model. Ref [40] utilized a city-level dataset from 2001-2015 and a Difference-in-Differences (DID) assessment design to evaluate the impact of the NAAQMN program on local PM2.5 emissions in China. He and Song [41] utilized mathematical aspects in carbon trading and carbon emissions. Different models were presented in this work, such as DID and the Slack-Based Measure (SBM). The DID technique is used to assess how well the carbon trading program has performed in the test zones in terms of lowering carbon emissions and increasing the effectiveness of carbon emissions. The model includes two stages, which are indicated by equations (3) and (4):

$$\text{In } CO2_{it} = \alpha_0 + \alpha_1 p_t + \alpha_2 treat_i + \alpha_3(p_t * treat_i) + \sum_i^h \alpha_i X_i + \mathcal{E}_{it} \quad (3)$$

$$\delta_{it}^* = \beta_0 + \beta_1 p_t + \beta_2 treat_i + \beta_3(p_t * treat_i) + \sum_i^h \beta_i X_i + \mathcal{E}_{it} \quad (4)$$

In (3) and (4), i stands for provinces, and t Stands for years. In $CO2_{it}$ Is the natural log of carbon dioxide emissions, and δ_{it}^* It Is carbon emission efficiency. $treat_i$ Is a dummy variable indicating whether a province is in the treatment group (1 for pilot areas, 0 for non-pilot areas). $p_t It$ is a time variable (1 after 2013, 0 before). $p_t * treat_i$ Is the interaction term, showing when the carbon trading policy was applied in a specific region. α3 and β3 represent the net effect of the carbon trading policy. Xi includes other control variables that might influence the results, and$\mathcal{E}_{it}$ It is a random error term.

The second model is used to minimize the efficiency of the score. δ_{it}^*, which represents the carbon emission efficiency of a decision-making unit. Integrating ML models such as time-series forecasting or reinforcement learning can help in conducting dynamic efficiency analysis. This allows the model to account for changes over time and adapt to new data, improving the relevance and accuracy of efficiency scores.

Another study explored a model in the Carbon Emissions Trading System (CETS) [42] on regional green technology innovation. The analysis was conducted using a DID approach. So, the basic model is presented by equation (5).

$$invent_{ct} = \beta_0 + \beta_1 DID_{ct} + \beta_2 control_{ct} + \Upsilon_t + \eta_t + \mathcal{E}_{ct} \quad (5)$$

The reference mentioned that the model expands the emissions trading policy, which varies across different contexts and under different conditions. These extensions allow researchers to understand the nuanced effects of the policy, going beyond the average impact estimated in the basic model. Here's why the model is extended by certain factors, such as Human Capital (HC), Intellectual Property Rights (IPR) protection, marketization, and spillover Effects.

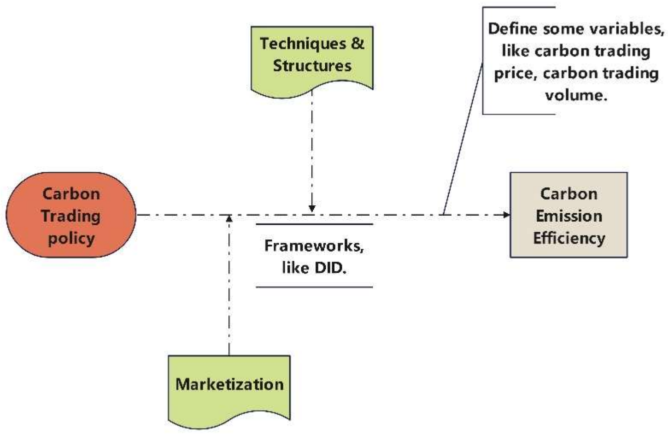

Figure 4. Application of frameworks, variables to reach carbon emission efficiency.

Figure 4 illustrates the relationship between carbon trading policy and carbon emission efficiency, highlighting key factors and frameworks involved. Carbon trading policy influences both marketization and the development of techniques and structures, which are analyzed using frameworks like DID. The techniques and structures define variables such as carbon trading price and volume, which ultimately impact carbon emission efficiency.

3. 1. Carbon trading volume

The whole quantity of carbon credits or permits that are exchanged during a period is called the carbon trading volume. These amounts have been affected by changes in regulatory frameworks, market dynamics, and goals for reducing emissions [43],[44]. The market for the trading of carbon has expanded recently, mostly due to the adoption and spread of emissions trading schemes across different areas and a heightened emphasis on environmentally friendly practices. The commitment of nations and businesses to cut emissions and achieve their goals is another factor that determines the efficacy and success of carbon trading [44]-[49].

The carbon industry can suffer greatly from a resurgence of interest in the carbon market. The price of carbon has increased to a level that coal is being removed from the electrical system in favor of less polluting natural gas or carbon-free renewable energy sources, with a ton costing around €25. Traders believe that the price of carbon will increase to a point where other industries are compelled to invest in cleaner technologies and fuels. This will be beneficial for the environment but will also cause a significant shift in an industry that is yet unclear in its full effects. For financial institutions, increasing the amount of carbon trading makes sense since it can lower price shortages, mitigate the costs of low-carbon change, and provide a variety of monetary futures [50].

3.2. Carbon trading price

Prices for carbon trading vary according to international climate targets, laws and regulations, and the dynamics of the market. Prices for carbon allowances are impacted by a variety of variables in established sectors, policy changes, and adjustments to emission reduction targets. Prices in the optional carbon markets, where companies and people voluntarily reduce their carbon footprint, are decided by the demand overall and the quality of the offset initiatives. Furthermore, many nations and areas have adopted their carbon pricing schemes, resulting in a variety of pricing arrangements worldwide. The general trend has been higher carbon prices as countries and organizations join forces to pursue more aggressive climate goals [51]- [55]. As the economy becomes more decarbonized, the demand for carbon credits will likely increase further. The yearly worldwide demand for carbon credits is expected to increase from 1.5 to 2.0 GtCO2e by 2030 to 7 to 13 GtCO2e by 2050. Governments will probably raise their efforts toward reaching net-zero timeframes, which would probably result in an even easier contraction of the credit supply. In actuality, it actually was a 1.7% annual decrease in the quantity of European union (EU)permits granted between 2013 and 2020. There is expected to be a 2.2% drop in certificates between the present and the year 2030. In 2012, an excess of credit supply resulted in a decrease in prices. If the present trend continues, the cost of emissions per ton by 2024 might range from $50 to $80. The carbon price as updated by the EU's emission trading scheme for the years 2019 through 2024 is shown in Figure 5, this reference [56] can be used to update each framework. Figure 6 shows carbon trading, where traditional resources produce emissions, can be used to purchase carbon offsets, resulting in a certificate of carbon neutrality, and businesses can invest in carbon-reducing projects by new technologies, and renewable energy systems (RESs) in industry. Table 2 presents outcomes, and summary of trending research.

Table 2. Summary of AI-Carbon research.

Ref	Main findings	Limitation
[55]	AI presents prospects for enhancing comprehension of global warming and efficiently tackling the climate emergency.	One challenge in using AI to address global warming is ensuring the accuracy and reliability of climate models, which can be impacted by incomplete data and complex environmental interactions.
[56]	In order to improve decentralized carbon markets and accomplish sustainable emission reduction, the research suggests a novel fusion of blockchain technology with AI.	Pay limited attention to particular characteristics of decentralized carbon markets, such as blockchain-based trade dynamics and AI-based price forecasting, while investigating a larger range of issues.
[57]	AI and blockchain technology can help in managing renewable energy sources and carbon trading.	The high energy consumption of blockchain technology can work against the environmental aims of programs such as carbon trading and renewable energy management. This is a restriction of combining blockchain and AI in these areas.
[58]	Diversity advantages can be obtained from AI as a hedge against carbon costs; nevertheless, the relationship between AI and carbon prices is adversely affected by policy unpredictability and the COVID-19 pandemic.	The volatility of carbon sectors, which is fueled by erratic policy shifts and outside shocks such as the COVID-19, presents a barrier to using AI as a hedge against carbon prices and can impede future investment and strategy.
[59]	In order to accomplish carbon-aware ML task off - loading for green edge AI, the article suggests an online approach that takes use of carbon spots and potential markets.	Determining the best course of action in real-time is difficult due to fluctuations in resource costs, CER purchasing prices, location-specific carbon intensity, and the emergence of Tasks
[60]	The study suggests using AI methods, such as a hybrid neuro-fuzzy controller, to predict carbon pricing and control related expenses.	Due to the complexity of the models, there is a risk of overfitting when employing computational intelligence approaches, such as a hybrid neuro-fuzzy controller for carbon pricing prediction. This can decrease the models' usefulness in practical cases.
[61]	AI can help with the energy revolution and the lowering of carbon emissions, but the effect is dependent on how free commerce is.	Diverse trade policies among nations pose an obstacle to the efficient implementation of AI for energy transition and carbon emission reduction. These policies can impede the exchange of technology, best practices, and data that are essential for effective collaboration and AI deployment

The DID model assumes uniform treatment effects across provinces and relies on historical data, which may limit its adaptability to real-time changes in market dynamics or policy shifts. Similarly, the SBM framework provides efficiency scores but does not account for dynamic variables such as fluctuating carbon prices or external market shocks, which could impact its applicability. The DID model effectively quantifies the regional impact of carbon trading policies, offering a clear evaluation of treatment effects. However, it is limited by its static nature and reliance on pre-determined variables. In contrast, the SBM model's ability to incorporate multiple inputs and outputs provides a more holistic view of carbon emission efficiency but may suffer from reduced accuracy when applied to regions with incomplete or inconsistent data [62]-[63]. To enhance these models, future research should focus on integrating real-time data streams and hybrid approaches. For instance, combining DID with machine learning techniques, such as time-series forecasting, could improve the model's adaptability to evolving market conditions.

Additionally, expanding the scope of these models to consider external factors, such as global carbon pricing trends, geopolitical events, and technological advancements in carbon capture, could provide a more comprehensive and scalable framework. By addressing these limitations, the models can be refined to better align with the dynamic and interconnected nature of global carbon markets.

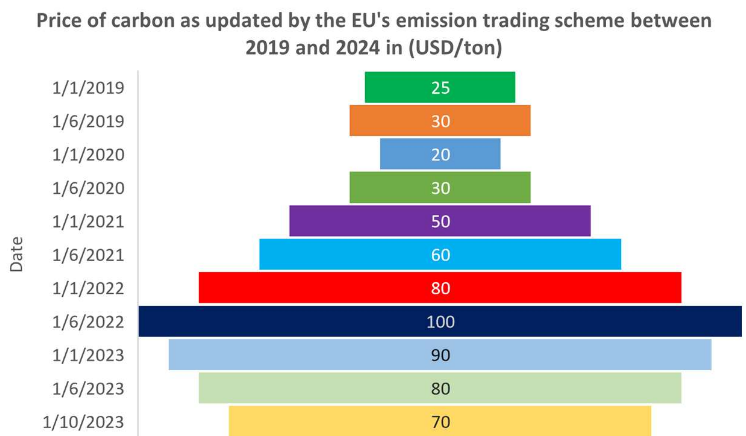

Figure 5. EU Carbon Price Trends between 2019 and 2024.

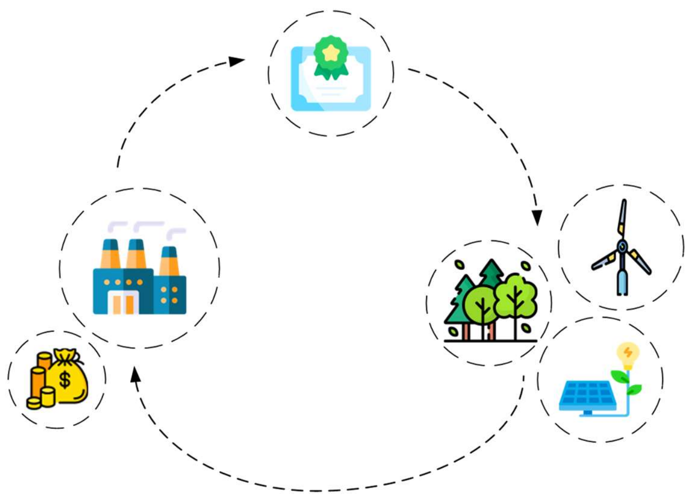

Figure 6. Carbon market dynamic.

4. CONTENT ANALYSIS

AI technologies play a crucial role in enhancing the precision and effectiveness of monitoring emissions and reporting within carbon trading systems. ML-driven automated systems can analyze large datasets to track emissions in real-time, guaranteeing accountability and transparency for involved parties [64]-[66]. AI-driven data analytics assist participants make wise decisions by offering insightful information about market patterns.

Market participants can predict price variations, evaluate threats, and improve their carbon trading tactics for improved economic and ecological results by using forecasting models and historical data analysis [67]- [69]. It improves the accuracy and openness of carbon markets and is frequently combined with AI. It ensures the dependability of carbon credits and reduces the likelihood of fraud. By providing automatic trade execution when predefined conditions are satisfied, smart contracts streamline transactions and reduce administrative expenses. AI-powered algorithms streamline trading processes, allowing for more efficient and rapid transaction execution. These algorithms optimize the purchase and sale of carbon credits by market participants in a way that complies with all applicable regulations by using AI to adapt to changing market circumstances [70]-[75]. AI is being used to assess the effectiveness of carbon offset programs by analyzing various datasets, evaluating environmentally impacting enterprises, verifying emission reductions, and observing established protocols. AI-powered solutions make carbon credits more marketable and of higher quality. It also simplifies scenario simulation to evaluate potential policy changes on carbon markets, helping governments and organizations create effective climate policies [76]-[79]. Figure 7 indicates ML and AI applications in carbon trading.

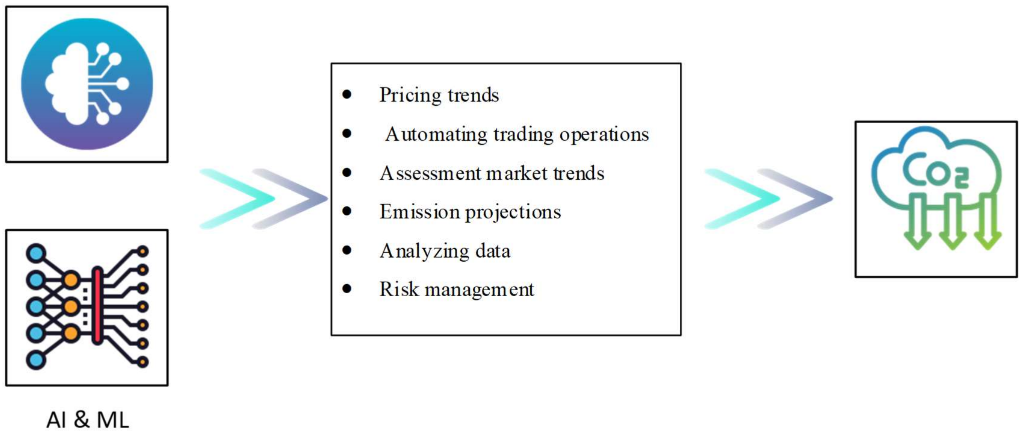

Figure 7. Application of ML and AI in Carbon trading.

The carbon trading sector is being radically transformed by ML, which is enhancing emission forecasts, predicting pricing trends, and automating trading operations. Machine learning algorithms improve real-time trading decisions by analyzing market trends and historical data to provide accurate emission projections. By responding to new information, automated systems keep operations running smoothly by regulations. In addition, ML aids in risk management by allowing traders to optimize carbon trading methods with knowledge by analyzing factors such as economic circumstances and regulatory changes. ML, SVM [80], random forest (RF) [81], and linear regression (LR) [82] can be employed for this purpose. One potential issue with AI- and ML-based automated trading systems is the difficulty in assessing the risk of a deal. The algorithms may fail if traditional risk management approaches are used, as they will override the algorithm's output. Before making a trade selection, an ML approach can evaluate hundreds of factors. The ML and DL methods are shown in Figure 8. ML revolutionizes carbon trading by enhancing emission forecasts and predicting pricing trends. Key factors that can be considered in this process include market trends, historical data, economic conditions, and regulatory changes, which help optimize trading strategies. Algorithms, such as SVM, RF, and LR, would analyze these variables to provide accurate insights. Additionally, ML can aid in real-time decision-making, allowing automated systems to adapt to new information and maintain compliance with regulations. However, assessing the risk of trade remains.

Integrating AI and ML techniques into the framework depicted in Figure 9 can be applied in several areas to achieve specific goals related to carbon trading policy, marketization, techniques & structures, and carbon emission efficiency. Use ML models to predict the impact of various carbon trading policies on market behavior and carbon emission levels, trading prices to achieve the desired environmental outcomes while maintaining economic efficiency, facilitating the market's evolution towards efficient carbon trading. Figure 6 shows the ML, and the AI integrated with the framework is shown in Figure 9.

SVMs are crucial in carbon trading for better risk management and forecasting. Market players can make better, more informed decisions with the help of SVM [80], which effectively predicts carbon credit values using historical data. Due to the algorithm's data classification capabilities, trend analysis is made less difficult, which in effect helps traders to identify patterns and anticipate changes in the market. Additional applications of SVM include evaluating potential outcomes of various scenarios, such as regulatory changes impacting the carbon credit market. Traders are provided with useful information to assist them in navigating the ever-changing carbon credit market, and the SVM-driven application and risk management procedures are enhanced. Through the integration of past data, current trends, and risk evaluation, SVM helps in developing a more adaptable and robust approach within the intricate realm of carbon trading. For better risk management and carbon trading forecasts, SVM is an indispensable tool. With the use of historical data, SVM can accurately forecast the prices of carbon credits in a carbon market context. Because of this, market participants can make better decisions by learning from the industry's historical trends. Due to the algorithm's data-categorization capabilities, trend analysis becomes less difficult, letting traders see patterns and anticipate market shifts. Changes in legislation impacting the carbon credit market are only one example of how SVM can be used to evaluate risks associated with various scenarios.

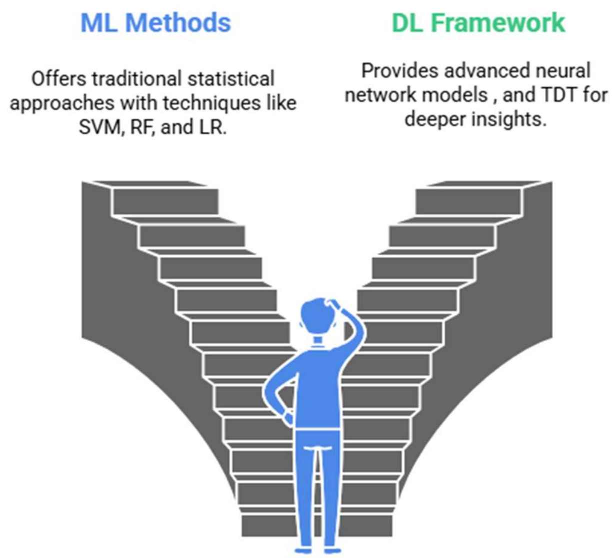

Figure 8. ML and DL methods.

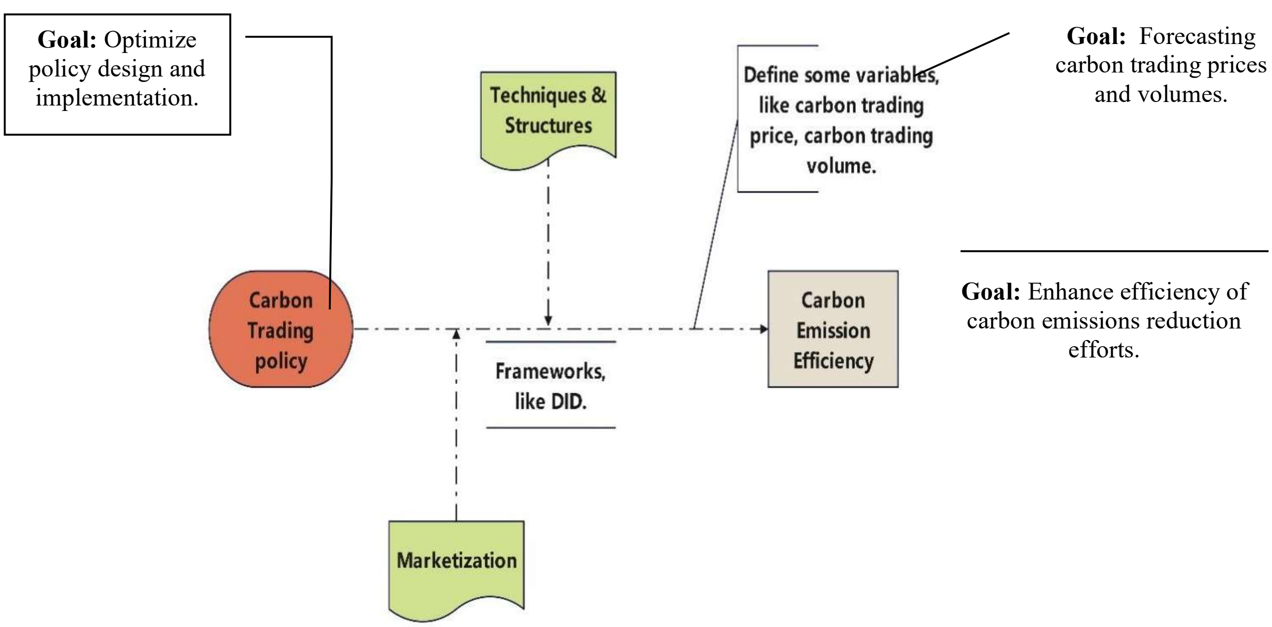

Figure 9. Application of ML, and AI into the framework.

Traders get valuable insight into the complexities of the volatile carbon credit market when they use SVM-driven approaches to enhance risk management. Through the integration of historical research, trend detection, and risk assessment, SVM contributes to the development of a more versatile and long-lasting strategy within the intricate domain of carbon trading. Carbon trading uses the RF method [81], a robust ML tool, for decision-making in complex datasets. It aids in cost estimations, market analysis, and strategy optimization. The RF algorithm's feature identification and prediction capabilities simplify risk assessment and optimize portfolios. LR models help carbon traders predict potential connections between factors affecting carbon credit costs. This improves forecasting accuracy and helps stakeholders respond to market challenges more effectively [82]. DL models analyze historical market data, emissions developments, and policy changes, identifying complex patterns and correlations. These models also enhance predictive analytics, leading to more accurate projections of carbon credit prices and market volatility. Moreover, DL can help with the optimization of portfolios by identifying the best trading approaches based on the analysis of complex data. The incorporation of DL models into carbon trading highlights the potential for enhanced processes for making decisions, more effective risk management, and innovation in environmentally friendly financial markets. Recurrent Neural Network (RNN) [83], ANN [84], Deep Neural Network (DNN) [85], and Traditional Decision Tree (TDT) [86] are different approaches that are reported in the literatures. In the ever-changing field of carbon trading, RNNs are quite helpful [83], particularly when it comes to examining temporal trends in time-series data. By utilizing knowledge from past data, their capacity to identify sequential relationships and patterns improves the forecasting of future emission levels and the cost of carbon credits. With the help of this tool, market players may more effectively forecast future prices, make well-informed judgments, and strengthen risk management plans. Due to their ability to identify complicated associations in historical data, RNNs help to provide a more thorough picture of the dynamic carbon trading landscape. This is because they provide stakeholders with a useful tool for navigating the complexity of the market and precisely and foreseeably optimizing trading strategies.

The carbon trading industry is commencing to experience a rise in the use of ANNs. ANNs [84] are essential for predicting the cost of carbon credits because they are skilled at sifting through large datasets and identifying complex patterns. ANNs improve prediction accuracy by utilizing their ability to find non-linear correlations in past market data and emission patterns. With the use of this technology, market players may maximize their risk management tactics and make educated decisions in the ever-changing carbon trading market. Through the help of ANNs, participants may effectively handle uncertainties, improve trading strategies, and eventually increase the effectiveness and efficacy of ecologically friendly financial practices in the carbon trading space. ANNs offer an advanced tool for adjusting to the intricacies of the business.

DNNs are becoming more and more used in carbon trading because of their amazing ability to evaluate large and complex datasets. DNNs [85] are extremely useful in this situation because they can quickly and accurately spot intricate patterns in past market data, emission trends, and regulatory changes. Their capacity to identify irregular patterns in data is very useful, leading to more precise forecasts and insights. This quality is essential for effectively handling risks, fine-tuning trading tactics, and negotiating the complex and ever-changing carbon trading market. The adaptability and learning capacities of DNNs place them as valuable assets in the pursuit of sustainability and profitability in carbon trading, as stakeholders look for trustworthy instruments to make informed decisions and maintain their competitiveness in the market.

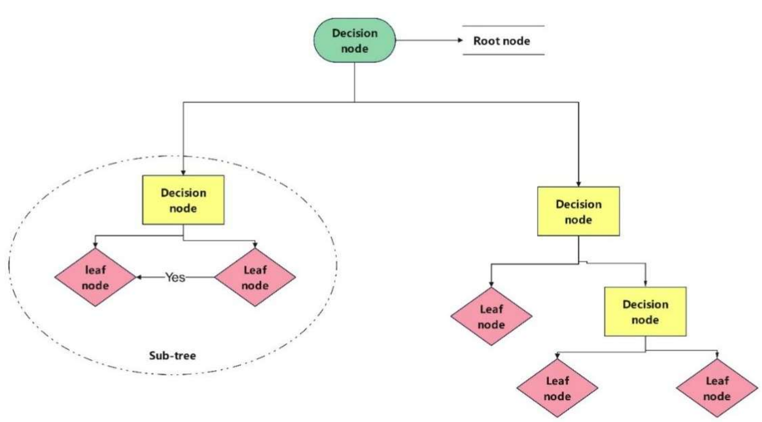

Figure 10. Structure layout of TDT.

In the carbon trading industry, traditional decision trees [86] are useful instruments for making strategic choices based on past performance and other influencing factors. In this situation, decision tree models are used to forecast outcomes like pricing for carbon credits or emission levels by analyzing input variables, including economic indicators, modifications to regulations, and data related to the project. Decision points and possible results are marked by the tree structure, which makes the decision-making process easier to see and understand. Decision trees can help comprehend market dynamics by recursively splitting data based on pertinent features and identifying patterns and connections [87]-[89]. Figure 10 depicts a TDT's structural layout. Three different types of nodes structure a TDT, subtrees, leaves and root nodes. While a leaf node presents a category target label and represents a classification or forecast outcome, root and sub-tree nodes indicate a binary split test on an attribute. The two fundamental phases of the TDT technique are classification and learning. Data is collected throughout the learning process and divided into testing and training sets. The development of testing and training sets is a crucial component in the assessment of big data models, which is accomplished by randomly selecting a sizable portion of the database's data to be utilized as the remaining information as test data and the training data. The incorporation of AI and ML is indicated in Figure 11.

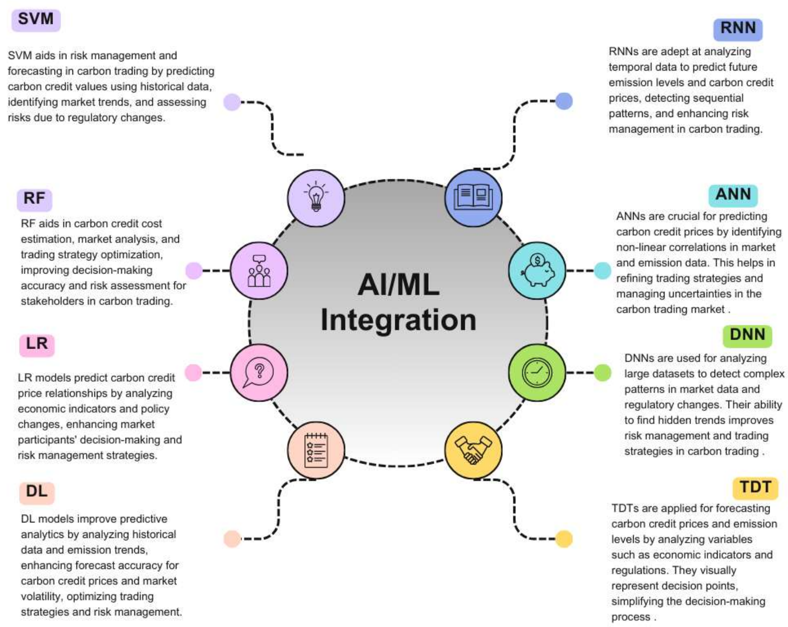

Figure 11. ML and AI techniques for different goals.

5. PROSPECTIVE DIRECTION

The future scope of ML and AI in carbon trading lies in transforming it into a more intelligent, efficient, and transparent system, thus enabling smart trading. By leveraging large datasets, ML techniques such as SVM, RF, and deep learning models can anticipate trends, analyze risks, and optimize trading strategies. For instance, SVM and RF models can be employed to predict market fluctuations based on various environmental and economic indicators, while deep learning can be used to model complex, non-linear relationships within the data [90]-[92].

AI can significantly improve decision-making by analyzing market trends, ensuring legal compliance, and applying advanced statistical analysis to forecast market behavior. For real-world applications, AI could also be used to automate the optimization of trading portfolios, adjust strategies dynamically to external factors such as policy changes or market disruptions, and enhance the effectiveness of carbon market instruments.

Blockchain innovation, along with AI, improves the effectiveness and privacy of emissions trading. Blockchain enables decentralized verification, which increases transparency and reduces the likelihood of fraud. AI models can also simulate probable market reactions to modifications to policies, giving stakeholders data-driven insights to help them make informed tactical decisions. AI can be used to optimize carbon credit price models by taking into consideration factors such as lowering emissions, future potential price volatility and policy impacts. Future research

could focus on developing AI models capable of integrating with blockchain platforms to fully automate carbon credit transactions. A critical area for future investigation is the integration of IoT with carbon trading systems. IoT may facilitate the immediate gathering of data and ongoing monitoring of emissions in a variety of sectors, including industry, transportation, and power plants. IoT devices can collect exact, real-time emissions of carbon data and promptly transmit it to decentralized systems, assuring data reliability and openness in carbon markets. This integration offers significant opportunities for reducing transaction costs and increasing market efficiency.
In the real world, merging IoT with blockchain-based technology enables automatic verification of carbon credit transactions after emission data is authenticated, which speeds up the trading process. AI and ML models can evaluate real-time data to forecast market moves, allowing traders to make selections based on current data rather than trends from the past. Additional studies should focus on developing computations incapable of making real-time forecasts in turbulent markets and examining the financial feasibility of such technology under various market circumstances. Furthermore, automated IoT systems can assist organizations in optimizing their carbon footprints, enabling smarter compliance with carbon trading regulations. This can also lead to more dynamic participation in carbon markets, as companies gain insights into their emissions profiles and adjust strategies accordingly. By enhancing the tracking of renewable energy usage, IoT could allow companies to optimize their energy consumption and emissions reductions, thereby improving their position in the carbon market.
Despite the tremendous potential, there are several challenges to be addressed. Implementing AI, ML, and IoT in carbon trading requires overcoming technical barriers related to data standardization, integration, and privacy concerns. Moreover, there is a need for international collaboration to establish regulations and standards for AI-based carbon trading solutions. The complicated nature of policy frameworks, as well as the varying pace of regulation acceptance between regions, may hinder general implementation. On the other side, the integration of these innovations creates enormous opportunities, such as increased market availability, shorter settlement times, greater transparency, and a lower chance of fraud. There is also a need for further field tests and pilot programs to show that these technologies have practical advantages and can scale.

In conclusion, combining AI, ML, IoT, and decentralized platforms could lead to a smarter, more resilient carbon trading market that accelerates the global transition to low-carbon energy. This collaboration can not only improve market efficiency but also enhance ecological responsibility and boost economic productivity in carbon markets. Future research should continue to explore the interoperability of these technologies, the development of predictive models that integrate real-time data, and the establishment of standards for ensuring the security and scalability of these solutions. This integration would result in an end-to-end smart trading ecosystem, combining real-time IoT insights, AI-powered analytics, and secure blockchain transactions [95], [100]. Furthermore, IoT can improve the tracking of renewable energy usage, enabling companies to trade more efficiently by linking emissions data directly with energy consumption [96],[101]-[102].

6. DISCUSSION

Carbon trading encourages companies to reduce emissions by offering financial incentives for carbon credits. The integration of ML and AI improves emissions tracking accuracy, trading strategies, and market trends, enhancing carbon management efficiency and regulatory compliance. In this paper, the authors provide a framework including the DID model, carbon trading policy, carbon emission efficiency, and market variables such as carbon trading volume and carbon trading price, which are presented in Figure 4. Figure 5 shows the price of carbon as updated by the EU's emission trading scheme between 2019 and 2024. Moreover, Figure 6 displays carbon trading, while the traditional resources are producing emissions, which are represented. This money can be used to purchase carbon offsets, such as RESs, such as wind turbines (WTs), and photovoltaics (PVs) [103]. In return for their investment in these offsets, the factory receives a certificate that verifies their carbon neutrality. Corporations can offset their emission levels by investing in carbon-reducing projects. This can contribute to meeting the goal of lowering carbon dioxide emissions and minimizing climate change. The remainder of this study focuses on the incorporation of AI and ML into carbon trading.

So, Figure 7 to Figure 9 describe the application of these techniques, the structure of AI and ML techniques, and the application of ML, and AI in the framework. Table 3 illustrates the application of ML and DL in carbon trading. Table 3 highlights the application of various ML and DL algorithms in carbon trading and related environmental tasks. It showcases their predictive capabilities in areas like carbon disclosure trends, atmospheric CO2 limits, biomass estimation, carbon cost forecasting, and emissions system predictions. The results emphasize the accuracy and efficiency of models such as RF, SVM, and DNN, underscoring their potential to enhance decision-making and sustainability efforts in carbon trading. Table 4 represents the comparison with previous work. For future research, researchers can bridge some research gaps in this work:

1. Consider other environmental metrics for future work.
2. Apply and simulate ML techniques to the framework presented in Figure 2.
3. Investigate emerging technologies, such as carbon capture.

Table 3. ML and DL algorithms and results in carbon trading.

Ref	Description	Algorithm	Findings
[79]	To employ ML algorithms to investigate the trend of optional disclosure of carbon in the Korean financial sector.	Logistic, RF, and GBDT	Logistics have 89%, RF has 94% and GBDT has 92% accuracy.
[80]	An estimate of when the world would reach a particular upper limit of atmospheric carbon dioxide concentration was made using historical data.	SVM and Linear regression	SVM (Root Mean Square Error (RMSE)= 0.255) and (RMSE= 0.405)
[78]	Recent developments in data science and GIS technologies have made it possible to anticipate aboveground biomass (AGB) and evaluate ecosystem services in agroforestry, and this capacity is growing quickly.	SVM, RF and ANN	SVM (RMSE = 21.97, R^2 = 0.54), RF(R^2 = 0.69 and RMSE = 17.07) and ANN (R^2 = 0.63 and RMSE = 19.35)
[84]	To construct a prediction model that ascertains future carbon costs given a collection of real-world facts. To develop a model for forecasting future carbon pricing.	Conditional Decision Tree (CDT), Traditional Random Forest (TRF), Conditional Random Forest (CRF), and TDT	CDT (Mean Absolute Error (MAE)= 0.6608, MSE= 1.3007), TRF (MAE= 0.2500, Mean Square Error (MSE)= 0.1413), CRF (MAE= 0.5258, MSE= 0.5444) and TDT (MAE= 0.8398, MSE= 1.3991)
[83]	A new and effective forecasting technique helps to properly anticipate the carbon emissions of the electricity system.	Particle Swarm Optimization (PSO)-DNN, Improved Particle Swarm Optimization (IPSO)-DNN, and Spearman Correlation Analysis (SCA)-IPSO-DNN.	PSO DNN (MAE= 0.2016, MSE= 22.6872), IPSO DNN (MAE= 0.1578, MSE= 21.7883) and SCA IPSO DNN (MAE= 0.0867, MSE= 3.7572)

Table 4. Comparison with previous.

Ref	Objective of the study	Algorithm	Findings
[85]	To forecast the solubility of CO_2 in ionic liquids. Evaluating diverse ionic liquid kinds under varied pressure and temperature ranges.	ANN and SVM	The CO_2 solubilities were well-fitting and forecast by both models. But the ANN model managed to identify better results.
[86]	To determine how surface functionalization affects graphene oxide-amine nanofluid CO_2 performance.	MLPNN, Adaptive Neuro-fuzzy Inference Systems (ANFIS), LSSVM, RBF, Gradient Reinforcement) (GR), and Cascade Feedforward (CFF).	The CFF neural network produces accurate predictions because of its minimal root mean square and mean square mistakes.
[87]	To use a genetic algorithm in ML to forecast Metal–organic Frameworks (MOF) efficiency in swing adsorption in vacuum.	Genetic algorithm (GA) method	Establishing greater CO_2 recovery (90%) and purity (95%) is only possible with 482 MOFs materials. Up to 91% of predictions made by the ML model are accurate.
[88]	In the Permian Basin, using ANN to anticipate CO_2 storage and oil recovery.	ANN strategy	The findings show that the ANN technique can accurately forecast CO_2 storage and oil recovery in real-world scenarios.
[89]	To identify irregularities in the monitoring well pressure data sources for the purpose of storing and collecting carbon.	LSTM, CNN, and Conv - LSTM	The Conv-LSTM outperforms other models in terms of accuracy, according to the data.

[90]	By creating standardized CO_2 adsorption models on Porous Carbon Materials (PCMs) and performing a comprehensive examination into the effects of different parameters on CO_2 capture capability within the same framework, this study filled in gaps in knowledge.	RF technique	The findings show that the RF technique has a greater accuracy in predicting the chemical and physical characteristics of materials made of carbon with pores (useful prediction: $R2 > 0.9$).
[91]	Six distinct AI techniques are used to estimate the solubility of CO_2 in 1-n-butyl-3-methylimidazolium tetrafluoroborate ([Bmim][BF4]). These techniques include four ANN, LS-SVM, and ANFIS. The optimal model for the examined issue has been determined to be the feed-forward neural network in cascade.	AI methods, such as ANFIS, SVM, cascade feed-forward neural NN, and ANN.	The findings show that the feed-forward neural network in cascade was very effective in predicting the absorption of CO_2 in liquids with ions.
[92]	It emphasized different strategies that combine using molecular simulations and ML approaches to accurately evaluate the capabilities and characteristics of MOFs for several applications, such as gas storage, segregation, and catalysis, and to forecast the reliability, guest accessibility, and synthesizability of MOFs. The enormous potential of integrating ML strategies into mathematical modeling of MOFs.	ANN and the decision tree model with GB.	Using complete process simulation, ML models were used to forecast the performance of Vacuum-swing Adsorption (VSA) technique uses thirty materials. 91% of the predictions were made with total accuracy.

While it would be true that AI systems require significant energy resources, recent advancements in energy-efficient AI algorithms and hardware offer promising solutions to mitigate these concerns. For instance, edge computing and green AI models have been developed to optimize resource usage, significantly reducing the carbon footprint of AI operations [93]-[96]. Furthermore, in the context of carbon trading, the potential environmental benefits of AI can outweigh its energy demands. AI-driven systems enhance the accuracy of emissions monitoring, automate fraud detection, and enable predictive analytics for market behaviors, which collectively contribute to substantial reductions in GHG. These capabilities create a net-positive impact by promoting efficient trading systems that directly support carbon neutrality goals.

To address the concern more holistically, AI applications in carbon trading can be coupled with renewable energy sources and carbon-offset mechanisms to neutralize their operational emissions. For example, leveraging decentralized platforms powered by blockchain can improve transparency, while using renewable-powered data centers ensures alignment with sustainability objectives. By integrating such approaches, AI-driven carbon trading not only remains a viable tool but also becomes a critical enabler in achieving a balanced and sustainable pathway toward global carbon reduction goals.

This study highlights the transformative role of AI in enhancing efficiency, transparency, and scalability in carbon trading systems. However, the study is limited by the absence of practical implementation data and the reliance on simulated environments for validating AI models. These limitations underscore the need for future research to incorporate real-world datasets and explore region-specific dynamics to ensure the robustness and adaptability of proposed AI frameworks. Addressing these gaps could significantly enhance the reliability of AI applications in achieving global climate objectives.

7. CONCLUSION

The study explores the use of AI in carbon trading to reduce greenhouse gas emissions. It reveals that AI can improve the precision and efficacy of carbon trading systems by analyzing datasets, automating transactions, and forecasting market trends. The study also investigates how artificial intelligence might help reduce carbon emissions in industrial and sustainable systems. However, it emphasizes possible downsides, such as biased algorithms, interpretability concerns, and the necessity for data of superior quality. This study’s strategy is presented in Figure 1. Moreover, this study provides a comparison in previous research including details, limitations, and model analysis as shown in Tables 2 to 4, and ML/AI integration in different goals in carbon trading which is indicated in Figure 11. The findings reveal that AI enhances the precision and efficiency of carbon trading systems by enabling real-time emissions tracking, automating transactions, and providing robust market trend forecasts. This work provides a comprehensive framework that builds on prior research, offering new perspectives on the role of AI in driving global climate objectives. While the study highlights the potential of AI, it also acknowledges limitations, including the need for real-world application and validation of the proposed models. Addressing these limitations in future research could further solidify AI's transformative impact, making carbon markets more effective in combating climate change. This contribution is vital for policymakers, businesses, and researchers aiming to achieve a carbon-neutral economy.

DECLARATIONS

Conflict of interest

All authors declared that there is no conflict of interest in any form.

Data availability interest

The data supporting this study's findings are available from the corresponding author upon reasonable request.

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