AI and Carbon Capture Technologies: A Survey

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Abstract

This survey examines the intersection of artificial intelligence (AI) and carbon capture technologies, highlighting their pivotal role in climate change mitigation. Structured to provide a comprehensive overview, the survey begins by introducing the significance of AI-enhanced carbon capture in reducing greenhouse gas emissions. It explores the application of AI and machine learning in optimizing carbon capture processes, focusing on advancements in post-combustion technology, and the integration of AI-driven optimization strategies. Key findings demonstrate that AI models significantly enhance the efficiency of carbon capture technologies, reduce carbon footprints, and improve resource management. Moreover, the survey addresses challenges such as data privacy and communication efficiency, particularly within federated learning frameworks, emphasizing the need for robust privacy-preserving techniques. The survey also highlights the importance of interdisciplinary collaboration in advancing AI-driven carbon capture solutions, advocating for sustainable AI development that aligns with environmental goals. By fostering innovation and integrating advanced optimization techniques, AI-driven carbon capture technologies offer scalable solutions to reduce greenhouse gas emissions, ultimately supporting global efforts to combat climate change. The survey concludes by emphasizing the critical role of AI in enhancing the effectiveness of carbon capture technologies and its potential to contribute to a sustainable future.

1 Introduction

1.1 Structure of the Survey

This survey provides a detailed examination of the intersection between artificial intelligence (AI) and carbon capture technologies, highlighting their essential role in mitigating climate change. It begins with an **Introduction** that underscores the importance of AI and carbon capture technologies in reducing greenhouse gas emissions. The subsequent section, **Background and Definitions**, defines key concepts such as AI, machine learning, carbon capture, post-combustion technology, carbon capture and storage, and AI-driven optimization.

The third section, **AI and Machine Learning in Carbon Capture**, explores the application of AI and machine learning in enhancing the efficiency and accuracy of carbon capture processes. It discusses specific machine learning models and their impact on minimizing carbon footprints, alongside AI's role in earth system and climate modeling.

In the **Post-Combustion Technology** section, the focus shifts to the challenges and advancements in this area, addressing the contribution of dynamic simulation-based soft sensors (DSSS) and the challenges posed by federated learning in these systems.

The survey further investigates **Carbon Capture and Storage (CCS)**, emphasizing AI's integration in optimizing CCS operations while addressing data privacy and communication efficiency concerns within AI-enhanced CCS frameworks.

An in-depth analysis of highlights advanced optimization techniques and algorithms that combine large language models (LLMs) with traditional methods, improving decision-making in dynamic

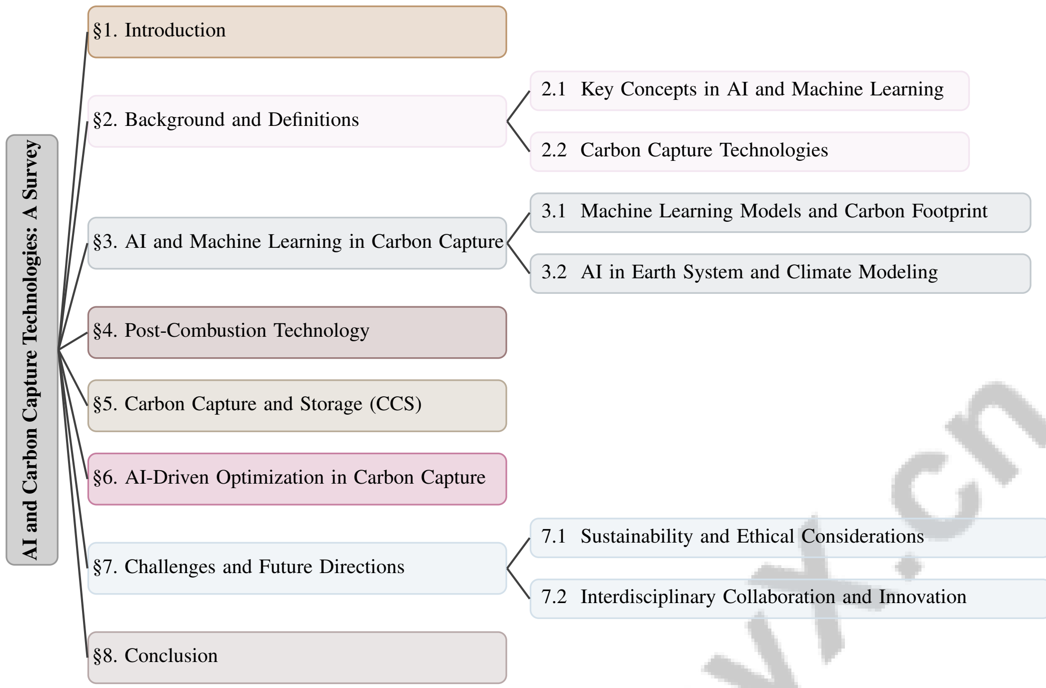

Figure 1: chapter structure

environments. It also examines AI-optimized resource management strategies that prioritize sustainability, addressing the ecological impacts of AI and advocating for a holistic approach that balances innovation with environmental integrity and social justice [1, 2, 3, 4, 5].

The penultimate section, **Challenges and Future Directions**, identifies current challenges in integrating AI with carbon capture technologies and proposes potential avenues for future research. It emphasizes sustainability, ethical considerations, and the importance of interdisciplinary collaboration for fostering innovation.

The synthesizes the survey's key findings, reaffirming AI's critical role in enhancing carbon capture technologies and its significant contribution to climate change mitigation efforts. It advocates for sustainable AI practices that encompass ecological and social implications throughout the lifecycle of AI development. By addressing the interconnectedness of AI innovation with sustainable resource management and equitable societal values, the findings promote a comprehensive approach to leveraging AI in the fight against climate change [4, 6, 3].The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Key Concepts in AI and Machine Learning

Artificial intelligence (AI) and machine learning (ML) are instrumental in enhancing carbon capture technologies by improving efficiency and precision through extensive data analysis. The evolution of ML methodologies aims to develop universal algorithms capable of learning from diverse experiences, crucial for advancing carbon capture technologies [7]. Deep neural networks (DNNs) have transformed traditional Earth system models into interpretable hybrids, essential for understanding Earth's systems and supporting effective carbon capture strategies [2]. Optimizing tensor configurations via ML aligns with fundamental AI concepts, enhancing carbon capture technology performance [8].

Large Language Models (LLMs) serve as search operators or generators of optimization algorithms, vital for AI-driven carbon capture optimization [1]. Heuristic search methods are crucial for discovering new catalysts, enhancing chemical processes for sustainable carbon capture [9]. AI integration in carbon capture must prioritize sustainability, aligning with sustainable development goals to minimize environmental impact [3]. This includes evaluating operational and embodied energy trade-offs in

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AI applications, relevant to carbon capture deployment [10]. Innovative approaches to measuring carbon emissions in data science tasks provide benchmarks for assessing AI's environmental impact in carbon capture [4].

Advanced methodologies like Spline Continued Fraction Regression (Spln-CFR) elucidate relationships between chemical structures and critical temperatures, enabling AI to refine carbon capture methodologies [11]. Benchmarks evaluating lossy compression across ML/AI applications offer insights into performance and resource usage trade-offs, crucial for optimizing carbon capture technologies [12]. Dynamic Data Reduction (DDR), which adjusts input data during neural network training, further optimizes performance and resource utilization, underscoring AI's potential in enhancing carbon capture processes [13].

A comprehensive understanding of AI and ML concepts is vital for advancing innovative carbon capture technologies, fostering Sustainable AI practices that consider the entire lifecycle of AI systems. This integration enhances climate change mitigation strategies while ensuring alignment with ecological integrity and social justice, promoting equitable resource distribution and addressing pressing environmental challenges [6, 2, 3].

2.2 Carbon Capture Technologies

Carbon capture technologies are essential in the global strategy to combat climate change, effectively reducing atmospheric CO_2 levels. These technologies integrate AI advancements and sustainable practices to lower greenhouse gas emissions while supporting broader sustainability goals [4, 6, 3]. They encompass methods designed to capture CO_2 emissions from industrial and energy sources before atmospheric release, allowing for underground storage or industrial utilization.

A significant challenge in carbon capture is identifying optimal catalysts from a vast combinatorial space of chemical descriptors, often not fully understood empirically [9]. This complexity necessitates advanced AI-driven heuristic search methods to discover catalysts that enhance carbon capture efficiency, improving reaction kinetics and contributing to sustainable, cost-effective technologies.

Energy consumption and carbon emissions associated with data processing in carbon capture are critical factors. Datasets containing energy metrics, throughput rates, and carbon emissions data for various CNN acceleration technologies, such as GPUs, FPGAs, and Racetrack memory, provide insights into the sustainability of AI applications in carbon capture [10]. These metrics facilitate evaluations of trade-offs between computational efficiency and environmental impact, informing the design of energy-efficient carbon capture systems.

Benchmarks for compressing large volumes of floating-point training data for ML/AI applications tackle the challenge of maintaining model performance while reducing data storage and transmission costs [12]. Effective data compression techniques are vital for optimizing resource usage in AI models deployed in carbon capture systems, ensuring economic and environmental viability.

Measurements of power consumption across various data science tasks offer a comparative framework for assessing the energy efficiency of carbon capture technologies [4]. Understanding these power dynamics allows researchers to identify opportunities for improvement in carbon capture system design and implementation, ultimately enhancing their effectiveness in reducing greenhouse gas emissions.

In recent years, the intersection of artificial intelligence (AI) and climate science has garnered significant attention, particularly in the context of carbon capture technologies. The integration of machine learning methodologies into these domains presents both opportunities and challenges that necessitate careful examination. As shown in Figure 2, this figure illustrates the hierarchical structure of AI and machine learning applications in carbon capture and climate modeling. It categorizes the advancements and challenges in machine learning models, environmental implications, optimization methods, transformative approaches in Earth system modeling, and practical innovations to enhance climate strategies. This comprehensive framework not only highlights the current state of research but also serves as a roadmap for future developments in the field, emphasizing the critical role of AI in addressing climate-related issues.

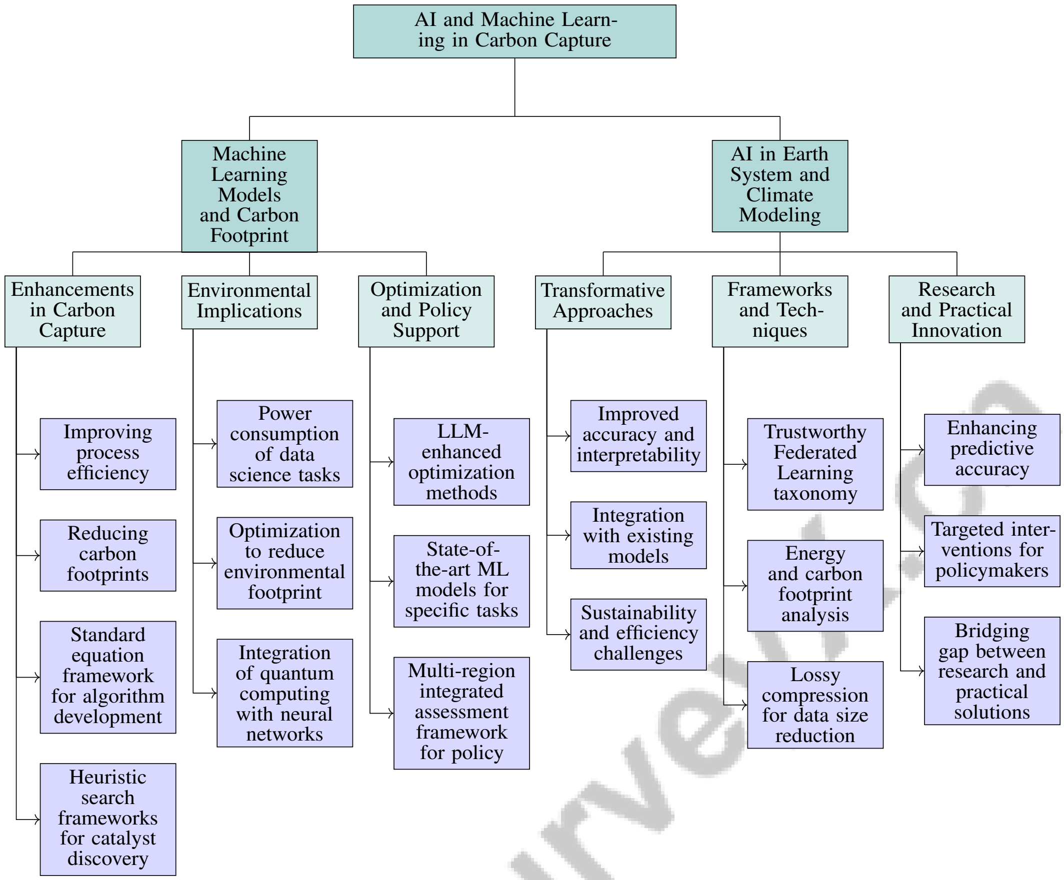

Figure 2: This figure illustrates the hierarchical structure of AI and machine learning applications in carbon capture and climate modeling. It categorizes the advancements and challenges in machine learning models, environmental implications, optimization methods, transformative approaches in Earth system modeling, and practical innovations to enhance climate strategies.

3 AI and Machine Learning in Carbon Capture

3.1 Machine Learning Models and Carbon Footprint

Machine learning models play a crucial role in enhancing carbon capture technologies by improving process efficiency and reducing carbon footprints. A significant challenge is the limited extrapolation capability of existing soft sensors, which rely heavily on historical data, limiting their accuracy in novel scenarios [14]. To overcome this, a 'standard equation' framework has been proposed to guide the development of new machine learning algorithms, enhancing the adaptability and robustness of models used in carbon capture [7]. The integration of heuristic search frameworks, such as CHEMREASONER, which combines LLM-driven hypothesis generation with quantum-chemical feedback, aids in discovering effective catalysts and improving sustainability [9]. Additionally, TGraph, a graph neural network configuration, has demonstrated significant improvements in runtime prediction accuracy, thereby reducing CO_2 emissions from data centers [8].

The environmental implications of machine learning models are underscored by the substantial power consumption associated with data science tasks, necessitating optimization to reduce their environmental footprint [4]. AQ-PINNs, which integrate quantum computing principles with physics-informed neural networks, offer a promising solution by enhancing climate modeling while minimizing computational resource use and associated carbon emissions [15]. The AiBEDO model, leveraging principles from the Fluctuation-Dissipation Theorem, exemplifies the use of machine learning in generating rapid climate response scenarios, thus supporting effective carbon capture strategies

[16]. The Spln-CFR method further illustrates the potential of machine learning in material science, achieving superior performance in predicting critical temperatures and optimizing processes [11].

Optimization methods, particularly those enhanced by LLMs, often surpass traditional approaches, providing adaptable and efficient solutions for carbon capture applications [1]. State-of-the-art ML models designed for specific tasks, such as data compression, highlight the importance of optimizing resource use to sustain model performance while minimizing environmental impact [12]. These advancements are essential for reducing the carbon footprint of carbon capture technologies, significantly contributing to global climate change mitigation efforts. The RICE-N model, a multi-region integrated assessment framework, supports these initiatives by simulating climate negotiations and evaluating various agreements and protocols, thus informing policy and decision-making processes [17].

3.2 AI in Earth System and Climate Modeling

The integration of AI into Earth system and climate modeling offers a transformative approach to understanding and mitigating climate change effects. As illustrated in Figure 3, this figure highlights key challenges, techniques, and impacts associated with the integration of AI in this field. The challenges focus on maintaining physical consistency and sustainability, while AI techniques such as lossy compression and network science enhance predictive accuracy. AI enhances ESMs through improved accuracy and interpretability via advanced data processing and pattern recognition techniques, though successful application requires careful integration with existing models to maintain physical consistency and ensure reliable outputs [2]. A key challenge is ensuring sustainability and efficiency, with the sustainability pillar within the trustworthy Federated Learning (FL) taxonomy providing a framework for assessing carbon intensity and hardware efficiency, vital for evaluating AI-driven climate models' environmental impact [18]. Frameworks analyzing energy and carbon footprints throughout the AI product life cycle, including cross-silo FL applications, broaden the focus beyond model training to encompass the broader implications of AI deployment in climate modeling [5].

Advanced techniques like lossy compression significantly reduce data size with minimal impact on model accuracy, enhancing the feasibility of AI workflows in climate modeling [12]. This is crucial for managing the vast data generated in Earth system modeling, ensuring AI applications remain efficient and environmentally responsible. By leveraging AI's capabilities to process and analyze complex datasets, researchers can enhance the predictive accuracy of climate models, facilitating more effective carbon capture strategies. This integration deepens our understanding of climate dynamics through advanced methodologies like AI and network science, enabling targeted interventions that empower policymakers to devise effective strategies against climate change. The impact of AI in this domain includes improved accuracy, informed policymaking, and the development of actionable solutions that consider economic incentives and the unique challenges of various sectors, ultimately enhancing our capacity to adapt to and address climate change complexities [6, 2, 3, 17, 16]. As AI evolves, its role in Earth system and climate modeling is expected to expand, presenting new opportunities for innovation and collaboration in pursuing sustainable climate solutions.

4 Post-Combustion Technology

4.1 Dynamic Simulation-based Soft Sensor (DSSS) in Post-Combustion

The Dynamic Simulation-based Soft Sensor (DSSS) significantly enhances post-combustion carbon capture by integrating artificial intelligence with dynamic simulation and reinforcement learning to estimate unobservable internal states in real-time. This approach improves the accuracy and efficiency of post-combustion processes by providing insights into internal dynamics that are difficult to measure directly [14]. Complementing DSSS, the AiBEDO model addresses the complex, multi-timescale effects of radiation perturbations on climate systems, elucidating the broader environmental impacts of post-combustion technologies [16].

Dynamic data management techniques, such as Data Step, Data Increment, and Data Cut, optimize resource allocation during AI model training in post-combustion applications [13]. These methods dynamically adjust data volumes, ensuring efficient computational resource use while maintaining model performance, crucial for the economic and environmental viability of carbon capture systems.

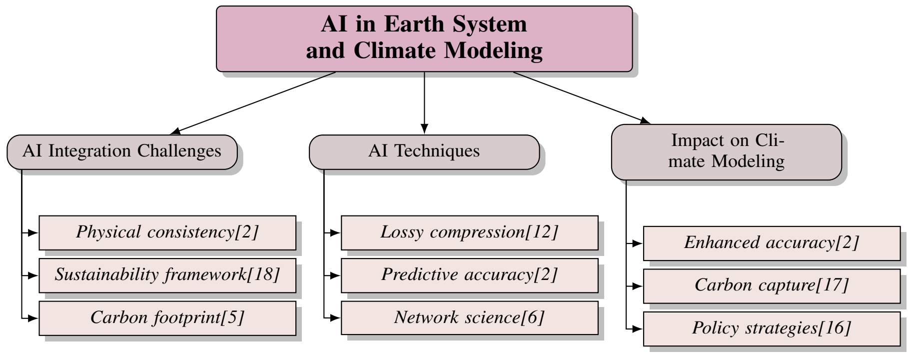

Figure 3: This figure illustrates the integration of AI in Earth system and climate modeling, highlighting key challenges, techniques, and impacts on climate modeling. The challenges focus on maintaining physical consistency and sustainability, while AI techniques like lossy compression and network science enhance predictive accuracy. The impact includes improved accuracy, carbon capture strategies, and informed policymaking.

The integration of Data-Driven Soft Sensors with advanced AI methodologies represents a significant advancement in carbon capture, enhancing real-time monitoring and optimization capabilities. By accurately estimating internal process variables and minimizing carbon emissions, this approach aligns with sustainability goals and supports effective, environmentally responsible carbon capture strategies [14, 3, 5].

4.2 Federated Learning Challenges in Post-Combustion Systems

Federated Learning (FL) provides a decentralized framework for enhancing post-combustion carbon capture systems through distributed data processing and model training. However, challenges such as the absence of metrics that incorporate sustainability aspects, like carbon intensity and hardware efficiency, complicate assessments of FL's environmental impact [18]. High communication costs and potential data leakage during gradient updates between clients and servers further complicate FL's application, leading to inefficiencies and privacy risks, particularly in sensitive post-combustion environments [19]. Additionally, the lack of comprehensive methodologies to evaluate carbon emissions associated with cross-silo FL compared to centralized methods limits informed decision-making regarding environmental trade-offs in post-combustion systems [5].

As illustrated in Figure 4, the primary challenges of Federated Learning in post-combustion systems can be categorized into three main areas: sustainability metrics, communication and privacy issues, and evaluation methodologies. This figure highlights the pressing need for comprehensive frameworks that address both environmental impacts and operational efficiency. Addressing these challenges requires developing metrics and methodologies that encompass environmental sustainability and operational efficiency, considering factors such as carbon emissions, hardware efficiency, and energy consumption throughout the AI product lifecycle. This holistic approach aligns with emerging legal data privacy requirements and fosters a more sustainable AI ecosystem by integrating sustainability into FL model evaluations [6, 18, 5, 3]. Enhancing the sustainability and efficiency of FL in post-combustion systems can advance carbon capture technologies while reducing their environmental footprint.

5 Carbon Capture and Storage (CCS)

5.1 Data Privacy and Communication Efficiency in CCS

Incorporating artificial intelligence (AI) into Carbon Capture and Storage (CCS) systems demands stringent data privacy measures and efficient communication protocols, given the extensive processing of sensitive data involved. To enhance privacy, the Compressed Differentially Private Aggregation (CDPA) method employs a unique random bit-flipping technique, introducing noise into data aggregation to protect sensitive information while maintaining model effectiveness [19]. This approach ensures data security and fosters trust in AI-driven CCS applications.

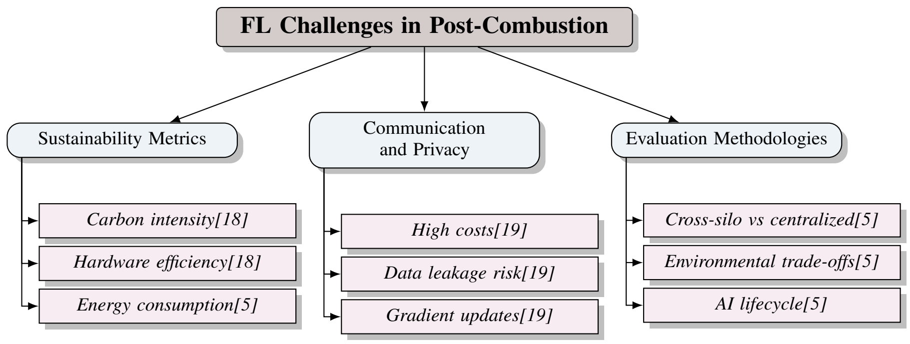

Figure 4: This figure illustrates the primary challenges of Federated Learning in post-combustion systems, categorized into sustainability metrics, communication and privacy issues, and evaluation methodologies, highlighting the need for comprehensive frameworks that address environmental impacts and operational efficiency.

Efficient communication is equally critical, particularly within federated learning frameworks. The Cross-silo Federated Learning and Analytics (CSFLA) method effectively reduces data transfer and storage needs, thereby curbing the carbon emissions linked to AI processes [5]. By streamlining communication, CSFLA not only enhances the sustainability of CCS systems but also improves their economic feasibility through lowered operational costs.

The integration of advanced privacy-preserving techniques like CDPA with efficient communication strategies in AI-driven CCS strengthens data security against potential breaches and promotes sustainability by significantly reducing communication costs and carbon emissions [18, 19, 5]. These innovations are pivotal for the widespread adoption of CCS technologies, addressing critical challenges related to data security and environmental impact, and thereby contributing to global climate change mitigation efforts.

6 AI-Driven Optimization in Carbon Capture

6.1 Advanced Optimization Techniques

Advanced optimization techniques are pivotal in enhancing the efficacy of AI-driven carbon capture systems, particularly through the integration of large language models (LLMs) that refine decision-making in dynamic settings. Leveraging extensive domain knowledge, these techniques address the computational complexities of carbon capture by aligning optimization algorithms with AI, which not only improves output quality but also promotes sustainable practices. This comprehensive strategy ensures AI applications contribute to sustainability objectives, such as reducing carbon emissions in carbon capture technologies [13, 1, 3, 12, 5]. These methodologies encompass a range of machine learning and AI strategies to optimize data processing and operational strategies in carbon capture systems.

A notable method is Compressed Differentially Private Aggregation (CDPA), which merges differential privacy with gradient quantization to enhance privacy while minimizing communication overhead [19]. This approach is particularly applicable in federated learning frameworks used in carbon capture, as it reduces communication loads and preserves data privacy, thereby enhancing the sustainability and security of AI-driven carbon capture technologies.

Moreover, integrating generative models, reinforcement learning, and advanced parameter tuning algorithms offers a comprehensive approach to optimizing solver performance in carbon capture applications [20]. Generative models produce synthetic data for robust AI training, while reinforcement learning develops adaptive policies that improve decision-making processes. Advanced parameter tuning ensures peak operational efficiency by refining model parameters.

Implementing these advanced optimization techniques significantly enhances the operational efficiency of carbon capture technologies, promoting both environmental and economic sustainability by reducing carbon emissions and resource consumption throughout their lifecycle. This aligns with Sustainable AI principles, emphasizing ecological integrity and social justice in technology development [3, 5]. By harnessing AI and machine learning, these methods facilitate more effective and scalable carbon capture solutions, supporting global efforts to mitigate greenhouse gas emissions and combat climate change.

6.2 Optimization and Resource Management

Optimization and resource management are essential for deploying AI-driven carbon capture technologies, focusing on enhancing operational efficiency while minimizing environmental impact. Machine learning models optimize resource allocation in carbon capture processes by employing sophisticated algorithms, including LLMs and various optimization techniques, to analyze extensive datasets. This integration allows for optimal resource distribution strategies that maximize efficiency and minimize waste. Advanced data reduction methods achieve substantial compression ratios while maintaining high quality, reducing training costs and the environmental impact of AI processes [13, 1, 12].

A crucial aspect of resource management involves applying AI-driven optimization techniques for adaptive resource allocation through real-time data analysis, boosting operational efficiency and sustainability throughout AI systems' lifecycle. This approach addresses the immediate needs of carbon capture while promoting ecological integrity and social justice by aligning AI development with sustainable practices and equitable resource distribution [1, 3, 5]. These techniques leverage machine learning models to predict system behavior and adjust resource allocation, ensuring peak operational efficiency and reducing energy consumption and carbon emissions.

Federated learning frameworks in resource management offer significant advantages for data privacy and communication efficiency. Federated learning enables decentralized data processing and model training, allowing multiple clients to collaboratively develop a global model without sharing sensitive data. This significantly reduces data transmission volumes, lowering communication costs and minimizing the carbon footprint of data transfers. Studies indicate that federated learning can substantially reduce carbon emissions compared to traditional centralized methods. Techniques like CDPA have demonstrated the potential to halve communication costs while enhancing model privacy and utility, contributing to sustainable AI practices in critical infrastructure settings [18, 19, 5]. This approach is beneficial in scenarios where data security and privacy are paramount, enabling secure information sharing across multiple sites without compromising sensitive data.

Advanced parameter tuning algorithms further optimize resource management by enhancing AI model performance in carbon capture processes. These algorithms systematically adjust model parameters for optimal performance, ensuring AI systems remain efficient and effective in resource management. By enhancing AI model performance through innovative algorithms and data reduction techniques, these advancements are crucial for developing more sustainable and cost-effective carbon capture technologies, ultimately reducing AI systems' environmental impact while maintaining operational accuracy and efficiency [13, 1, 3, 5].

7 Challenges and Future Directions

7.1 Sustainability and Ethical Considerations

The integration of artificial intelligence (AI) into carbon capture technologies demands careful consideration of sustainability and ethical issues to meet environmental and societal goals. Incorporating sustainability within the Federated Learning (FL) framework is crucial, addressing both the environmental impact and carbon footprint of these systems to ensure responsible AI deployment [18]. Explainability in AI is vital, especially in carbon capture and climate science, where AI-driven decisions have significant implications. Explainable AI (XAI) enhances trust by making AI predictions transparent and understandable, fostering broader stakeholder acceptance [2]. This transparency is key to the reliability and accountability of AI-enhanced carbon capture systems.

Data privacy and communication efficiency are critical in AI-driven carbon capture, exemplified by the Compressed Differentially Private Aggregation (CDPA) method, which enhances data security while minimizing carbon emissions and maintaining model utility [19]. However, deploying large language models (LLMs) in optimization tasks poses challenges such as high computational costs and interpretability issues, necessitating a careful assessment of the trade-offs between computational demands and environmental benefits [1]. Additionally, the limitations of AI models like AiBEDO in specific regions, such as high latitude areas, raise ethical concerns regarding the fairness and applicability of AI-driven climate interventions [16].

Methods like Spln-CFR rely heavily on dataset quality, highlighting the ethical responsibility to ensure data integrity and accuracy in AI applications. Incomplete data can hinder prediction accuracy, leading to suboptimal decisions in carbon capture processes [11]. Addressing these challenges requires a commitment to ethical data management practices. Advancements in integrated assessment models (IAMs) can enhance climate agreements and policies, promoting better outcomes for AI-driven carbon capture technologies [17]. However, a research-action gap in areas like bioproducts and risk assessment indicates a need for interdisciplinary collaboration to strengthen AI applications in carbon capture [6].

Prioritizing sustainability and ethical considerations in AI applications for carbon capture is essential for effective climate change mitigation. By emphasizing transparency, data privacy, and equitable access, AI-driven carbon capture technologies can align with broader environmental and social goals, enhancing ecological integrity and social justice throughout the AI product lifecycle. Utilizing decentralized methods like federated learning can reduce carbon emissions while protecting sensitive data, aligning technological advancements with sustainability objectives [19, 6, 3, 4, 5].

7.2 Interdisciplinary Collaboration and Innovation

Interdisciplinary collaboration is vital for fostering innovation in AI and carbon capture technologies. The convergence of expertise from fields such as Earth science, data analytics, and AI is essential to address the complexities of climate change and develop effective carbon capture solutions. This collaboration integrates domain-specific knowledge with advanced AI methodologies, enhancing the overall impact of carbon capture technologies [2].

The RICE-N model exemplifies the benefits of interdisciplinary collaboration by bringing together researchers from machine learning, economics, and climate science to simulate climate negotiations and evaluate various agreements and negotiation protocols [17]. This model underscores the necessity of interdisciplinary insights to inform policy and decision-making processes, leading to more effective climate interventions.

Future advancements in AI-driven carbon capture technologies will benefit from incorporating additional metrics and adjusting metric weights to enhance algorithmic compatibility across diverse frameworks [18]. This strategy will facilitate the development of more adaptable and sustainable solutions that align with broader environmental goals. The adaptability of the Compressed Differentially Private Aggregation (CDPA) method to heterogeneous client environments and its potential enhancements in communication efficiency highlight the importance of collaborative efforts in refining AI methodologies for carbon capture [19]. By leveraging interdisciplinary insights, researchers can improve the scalability and efficiency of AI-driven carbon capture systems.

In data processing, exploring non-IID datasets and incorporating Federated Analytics can enhance the sustainability of collaborative learning frameworks [5]. This exploration will lead to the development of more resilient AI models capable of addressing the diverse challenges associated with carbon capture. The integration of additional molecular descriptors and ensemble methods within the Spln-CFR approach offers another avenue for interdisciplinary innovation, promising to improve the predictive capabilities of AI models in carbon capture applications [11]. Similarly, exploring additional compression methods and their application to emerging ML/AI domains can yield valuable insights for optimizing resource usage and enhancing the sustainability of AI-driven carbon capture technologies [12].

8 Conclusion

This survey delves into the pivotal role of artificial intelligence (AI) in revolutionizing carbon capture technologies, underscoring its potential to enhance system efficiency and effectiveness. AI and machine learning models are instrumental in optimizing carbon capture processes, reducing carbon footprints, and refining resource management strategies. Their integration into Earth system and climate modeling showcases AI's ability to generate more accurate and interpretable models, necessitating a collaborative approach to overcome the inherent challenges and limitations of both AI and traditional modeling techniques.

The survey also stresses the importance of sustainable AI development to prevent adverse environmental impacts, advocating for policy and funding decisions that align AI advancements with sustainability goals. AI-driven optimization techniques in carbon capture, such as advanced parameter tuning and federated learning frameworks, have demonstrated substantial improvements in operational efficiency and sustainability, thus contributing significantly to global climate change mitigation efforts.

By fostering interdisciplinary collaboration and innovation, AI-driven carbon capture technologies hold the promise of advancing further, offering scalable and effective solutions for reducing greenhouse gas emissions. As the field progresses, the integration of AI in carbon capture will be essential in tackling the pressing challenges of climate change, paving the way for a sustainable and environmentally responsible future.

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