AI-Powered Computer Vision for Remote Sensing and Carbon Emission Detection in Industrial and Urban Environments

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Abstract- The rapid industrialization and urbanization of modern societies have led to a significant increase in carbon emissions, contributing to climate change and environmental degradation. Traditional monitoring methods often face limitations in spatial coverage, accuracy, and real-time detection. AI-powered computer vision, combined with remote sensing technologies, offers a transformative approach to monitoring and analyzing carbon emissions from industrial and urban sources. By leveraging machine learning and deep learning techniques, computer vision enables automated detection, classification, and quantification of emissions from satellite imagery, UAV-based sensors, and ground-level monitoring systems. This explores the integration of AI-driven computer vision in remote sensing for carbon emission detection. It examines key techniques such as convolutional neural networks (CNNs), generative adversarial networks (GANs), and transformer-based models, which enhance the analysis of multispectral and hyperspectral imaging data. The application of these models allows for precise identification of emission hotspots, trend forecasting, and environmental impact assessments. Furthermore, the fusion of AI with Internet of Things (IoT) sensors and edge computing provides a real-time, scalable solution for continuous emission monitoring. Despite its advantages, AI-powered carbon emission detection faces challenges, including data availability, model interpretability, and ethical concerns regarding surveillance and data privacy. Addressing these issues through improved data integration, regulatory frameworks, and transparency in AI models is crucial for effective implementation. As AI technology advances, the potential for real-time, high-resolution carbon monitoring will improve, facilitating better regulatory compliance and supporting global sustainability efforts. This highlights the growing role of AI-powered computer vision in environmental monitoring and emphasizes the need for further research and policy development to harness its full potential in combating climate change.

Indexed Terms- AI-powered computer vision. Remote sensing, Carbon emission detection, Urban environments

I. INTRODUCTION

The rapid advancement of artificial intelligence (AI) and computer vision has significantly transformed the field of remote sensing, enabling more efficient and accurate environmental monitoring (Folorunso *et al*., 2024; Ishola *et al*., 2024). AI-powered computer vision refers to the application of machine learning (ML) and deep learning (DL) techniques to analyze and interpret remotely sensed data from various sources, including satellite imagery, aerial photography, and unmanned aerial vehicles (UAVs). These technologies facilitate the automated identification, classification, and quantification of environmental parameters, making them indispensable in addressing critical global challenges such as climate change and air pollution (Afolabi *et al*., 2024). Remote sensing, when enhanced by AI, enables continuous and large-scale monitoring of environmental changes, providing real-time insights that support decision-making and policy formulation (Ewim *et al*., 2024; Alozie, 2024).

One of the most pressing concerns in environmental science today is the detection and management of carbon emissions in industrial and urban environments (Sam-Bulya *et al*., 2024). Carbon dioxide (CO_2) and other greenhouse gases (GHGs), such as methane (CH_4) and nitrous oxide (N_2O), are major contributors to global warming and climate change. Industrial activities, including manufacturing, power generation, and transportation, account for a significant portion of these emissions (Joel *et al*., 2024). Urban environments, characterized by high population density and extensive energy consumption, also contribute heavily to air pollution and carbon emissions. Traditional methods of emission monitoring rely on in-situ sensors and manual inspections, which are often limited in scope and accuracy. AI-powered computer vision, integrated with remote sensing technologies, offers a more scalable, automated, and precise approach to detecting and quantifying carbon emissions. By analyzing thermal infrared imaging, hyperspectral data, and satellite-based gas spectrometry, AI models can identify emission hotspots, track pollution dispersion patterns, and predict future emission trends (Odunaiya *et al*., 2024; Alozie *et al*., 2024).

The primary objective of this review is to explore the integration of AI-powered computer vision with remote sensing technologies for carbon emission detection. The study aims to analyze the capabilities of different AI models, such as convolutional neural networks (CNNs), generative adversarial networks (GANs), and transformers, in processing remote sensing data for emission detection. Additionally, the review will assess the effectiveness of various data sources, including satellite imagery from NASA's OCO-2 and Sentinel-5P missions, UAV-based thermal imaging, and ground-based monitoring stations. Furthermore, this review seeks to evaluate the real-world applications of AI-powered remote sensing in industrial emission monitoring, urban air quality assessment, and policy-driven environmental management.

The significance of this review lies in its potential contributions to environmental sustainability, climate change mitigation, and smart city development. By providing a comprehensive analysis of AI-driven remote sensing methodologies, this study will highlight innovative approaches to emission monitoring that can enhance regulatory compliance, improve industrial sustainability practices, and support evidence-based policymaking. Furthermore, integrating AI-powered remote sensing into urban planning can help cities optimize traffic management, energy distribution, and green infrastructure development, ultimately reducing their carbon footprint. As industries and governments worldwide strive to meet carbon neutrality targets, AI-powered remote sensing technologies present a transformative opportunity to achieve more efficient and cost-effective emission reduction strategies. AI-powered computer vision has the potential to revolutionize remote sensing and carbon emission detection in industrial and urban environments (Collins *et al*., 2024). The integration of AI and remote sensing technologies enables real-time, large-scale monitoring of emissions, providing critical data for mitigating climate change and improving air quality (Ewim *et al*., 2024). This review will offer insights into the latest advancements, challenges, and future prospects of AI-powered emission detection, contributing to the ongoing global efforts to achieve a sustainable and low-carbon future.

II. METHODOLOGY

The PRISMA methodology is used to systematically review existing literature on AI-powered computer vision for remote sensing and carbon emission detection in industrial and urban environments. The study follows four key phases: identification, screening, eligibility, and inclusion.

In the identification phase, a comprehensive search is conducted across databases such as Scopus, Web of Science, IEEE Xplore, PubMed, and Google Scholar to retrieve relevant peer-reviewed articles, conference proceedings, and reports. Keywords and Boolean operators include terms such as "AI-powered computer vision," "deep learning in remote sensing," "machine learning for emission detection," "carbon emission monitoring," "industrial emissions," "urban air quality," "satellite imagery," "UAV-based monitoring," "hyperspectral imaging," and "thermal imaging." Additional sources include grey literature, government reports, and institutional white papers to ensure a comprehensive dataset.

During screening, all retrieved records are imported into reference management tools like Rayyan, EndNote, or Zotero for duplicate removal. Title and abstract screening is performed based on predefined inclusion and exclusion criteria. Inclusion criteria consist of studies published in peer-reviewed journals or conferences, research discussing AI-based computer vision techniques for remote sensing and carbon detection, applications in industrial and urban emission monitoring, and publications in English from the last 10 years (2014–2024). Exclusion criteria include non-English publications, studies unrelated to AI-based methodologies, research not focused on remote sensing or emissions, and review papers without empirical results.

In the eligibility phase, full-text articles that pass the screening phase are reviewed for methodological rigor, data quality, and relevance to AI-driven emission detection. The Critical Appraisal Skills Programme (CASP) checklist is used to evaluate the validity and reliability of selected studies. Key aspects assessed include AI models used (CNNs, GANs, Transformers), remote sensing platforms (satellites, UAVs, IoT sensors), and performance metrics such as accuracy, precision, recall, and F1-score.

Finally, in the inclusion phase, only high-quality and relevant studies are incorporated into the qualitative and quantitative synthesis. A PRISMA flow diagram is constructed to visually represent the study selection process, including the number of records identified, screened, and included in the final review, along with reasons for exclusion at different stages. This systematic approach ensures transparency, reproducibility, and rigor in synthesizing research on AI-powered computer vision for carbon emission detection, contributing to advancements in environmental monitoring and policy development.

2.1 Fundamentals of AI-Powered Computer Vision in Remote Sensing

The integration of artificial intelligence (AI) with computer vision has revolutionized remote sensing, enabling automated, accurate, and large-scale environmental monitoring (Ajayi *et al*., 2024). AI-powered computer vision refers to the application of advanced algorithms that allow machines to interpret and analyze visual data with human-like perception. In remote sensing, these technologies process vast amounts of imagery from satellites, unmanned aerial vehicles (UAVs), and ground-based sensors, extracting critical insights for applications such as climate change monitoring, land-use analysis, and carbon emission detection (Elete *et al*., 2024; Abiola *et al*., 2024). By leveraging machine learning (ML) and deep learning (DL), computer vision enhances the ability to detect, classify, and predict environmental changes in industrial and urban environments.

Computer vision is a subfield of AI that focuses on enabling machines to interpret and understand visual information from digital images and videos (Oluokun *et al*., 2024). It mimics human vision by detecting patterns, identifying objects, and analyzing spatial relationships within an image. The core principles of computer vision in AI involves as shown in figure 1;

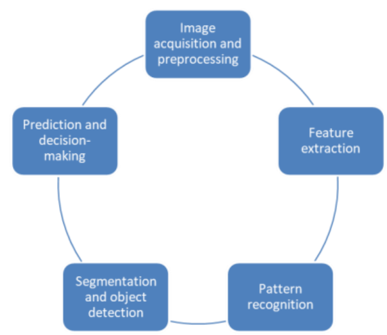

Figure 1: The core principles of computer vision in AI

Image acquisition and preprocessing, capturing and preparing images for analysis through denoising, contrast adjustment, and normalization. Feature extraction, identifying important visual characteristics such as edges, textures, colors, and shapes (Onukwulu *et al*., 2024). Pattern recognition, classifying and detecting objects or anomalies using AI models trained on large datasets. Segmentation and object detection, dividing images into meaningful regions and locating specific objects of interest, such as emission sources or pollution hotspots. Prediction and decision-making, using AI-driven analysis to predict trends, detect changes, and support decision-making processes in environmental monitoring (Alozie *et al*., 2024).

Machine learning and deep learning play a crucial role in advancing computer vision for remote sensing applications. Machine learning involves training algorithms to recognize patterns in data and make predictions without explicit programming (Abiola *et al*., 2024). Supervised learning, unsupervised learning, and reinforcement learning are the primary ML techniques used in computer vision applications. Deep learning, a subset of ML, utilizes artificial neural networks (ANNs) with multiple layers to analyze complex image data. Some of the most widely used DL techniques in remote sensing include; Convolutional neural networks (CNNS) are specialized for image processing and feature extraction (Oluokun *et al*., 2024). They excel in tasks such as object detection, classification, and semantic segmentation of satellite and aerial imagery. Generative adversarial networks (GANs), generate high-resolution synthetic images for training AI models, improving the accuracy of remote sensing applications. Recurrent neural networks (RNNs) and transformers, these architectures analyze temporal and sequential data, making them useful for tracking emission patterns over time (Onukwulu *et al*., 2024; Odunaiya *et al*., 2024). AI-driven image analysis enables automated detection of carbon emissions, land degradation, and urban expansion, significantly improving the efficiency and scalability of remote sensing applications.

Remote sensing technologies provide the foundation for AI-powered computer vision in environmental monitoring (Elete *et al*., 2024). These technologies collect vast amounts of geospatial data, which AI models process to extract meaningful insights. Satellites play a critical role in large-scale environmental monitoring by capturing high-resolution imagery and spectral data. Various types of satellites contribute to AI-powered carbon emission detection; Optical satellites, capture visible and near-infrared images, useful for land cover classification and urban heat mapping (Ewim *et al*., 2024; Joel *et al*., 2024). Examples include NASA's Landsat and the European Space Agency's (ESA) Sentinel series. Thermal imaging satellites, detect temperature variations to identify industrial emissions and thermal pollution. NASA's ECOSTRESS and Landsat Thermal Infrared Sensor (TIRS) are key examples. Hyperspectral imaging satellites, provide detailed spectral data for gas detection and emission monitoring. The Sentinel-5P satellite, equipped with the Tropospheric Monitoring Instrument (TROPOMI), detects CO_2, CH_4, and other pollutants. Satellites enable continuous global monitoring, making them essential for detecting emission trends, pollution hotspots, and climate change impacts (Alozie, 2024).

Unmanned aerial vehicles (UAVs), commonly known as drones, provide high-resolution, localized monitoring of emissions and environmental changes. Equipped with AI-powered cameras and sensors, UAVs offer several advantages; UAVs can capture real-time data from difficult-to-reach industrial zones, urban centers, and hazardous areas (Nwulu *et al*., 2024; Okolie *et al*., 2024). UAVs use infrared and multispectral cameras to detect heat emissions and pollutant dispersion patterns. Drones equipped with onboard AI processors can analyze data in real time, identifying emission leaks and structural anomalies in industrial facilities. UAVs complement satellite monitoring by providing high-resolution, localized data that enhances the accuracy of AI-driven emission detection models (Alozie, 2024).

Ground-based sensors offer real-time, high-precision data collection to validate satellite and UAV observations (Sam-Bulya *et al*., 2024). These sensors include; Measure CO_2, CH_4, NO_2, and particulate matter (PM) concentrations in industrial and urban areas. Use laser and radio waves to detect aerosol and gas concentrations in the atmosphere. Provide continuous data streams for AI algorithms to analyze real-time emission levels and predict pollution trends (Jessa, 2024). Ground-based sensors act as a vital validation tool for AI-powered remote sensing models, ensuring accuracy and reliability in emission monitoring efforts.

AI-powered computer vision has transformed remote sensing by enabling automated, large-scale, and precise environmental monitoring (Onukwulu *et al*., 2024). By leveraging ML and DL techniques, computer vision enhances the ability to analyze satellite, UAV, and ground-based sensor data for detecting carbon emissions and environmental changes. Satellite-based remote sensing provides global coverage, UAVs offer localized and flexible monitoring, and ground-based sensors ensure real-time, high-precision data validation. Together, these technologies form an integrated framework for AI-driven emission monitoring, supporting sustainable industrial practices and informed urban planning (Jessa and Ajidahun, 2024; Oluokun *et al*., 2024). As AI continues to advance, its application in remote sensing will play a crucial role in mitigating climate change and ensuring a cleaner, healthier environment.

2.2 Carbon Emission Sources in Industrial and Urban Environments

Carbon emissions are a major contributor to climate change, driven primarily by human activities in industrial and urban settings (Onukwulu *et al*., 2024). Understanding the sources of these emissions is crucial for developing effective mitigation strategies. Industrial sectors, including factories, power plants, and refineries, are among the largest contributors to carbon emissions. Additionally, urban areas generate significant emissions through transportation, construction, and energy consumption. Despite technological advancements, accurately monitoring and measuring carbon emissions remains a significant challenge due to complex emission patterns, data collection limitations, and regulatory gaps (Nwulu *et al*., 2024).

Industries play a crucial role in global economic development but also contribute significantly to greenhouse gas (GHG) emissions (Lawal *et al*., 2024). The primary industrial sources of carbon emissions include; Manufacturing processes consume vast amounts of energy, leading to substantial CO_2 emissions. Industries such as cement, steel, and chemical manufacturing are particularly carbon-intensive. The cement industry alone contributes approximately 8% of global CO_2 emissions due to the high energy requirements of clinker production (Onukwulu *et al*., 2024). Similarly, steel manufacturing relies heavily on coal-powered blast furnaces, making it one of the largest industrial emission sources. Fossil fuel-based power generation remains the dominant source of global energy, accounting for a significant portion of CO_2 emissions (Akinsooto *et al*., 2024). Coal, oil, and natural gas-fired power plants release large amounts of carbon dioxide into the atmosphere. Despite the growth of renewable energy, many regions still rely on fossil fuels, making power generation a major challenge in reducing emissions. Efforts to transition to cleaner energy sources, such as wind, solar, and nuclear, are ongoing but require significant investment and infrastructure changes (Oyedokun *et al*., 2024). Oil refineries process crude oil into usable fuels such as gasoline, diesel, and jet fuel, releasing considerable carbon emissions in the process. The refining process involves combustion, chemical reactions, and energy-intensive operations that contribute to air pollution. Petrochemical industries, which produce plastics, fertilizers, and synthetic materials, also generate substantial emissions due to their reliance on fossil fuel-based feedstocks (Oyedokun *et al*., 2024). Industrial emissions are not limited to CO_2 alone; they also include methane (CH_4), nitrous oxide (N_2O), and other pollutants that contribute to global warming. Reducing industrial emissions requires cleaner production technologies, carbon capture and storage (CCS), and policy-driven incentives for low-carbon alternatives.

Urban environments are significant contributors to global carbon emissions due to high population density, energy consumption, and transportation needs (Oluokun *et al*., 2024). The main urban emission sources include as shown in figure 2.

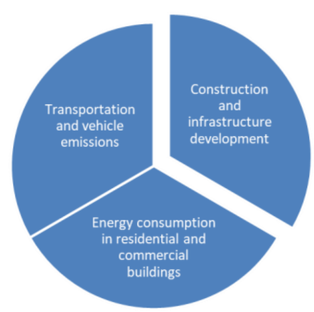

Figure 2: Main urban emission sources

Road transportation accounts for nearly 25% of global CO_2 emissions, with cars, buses, trucks, and motorcycles burning fossil fuels for mobility (Akinsooto *et al*., 2024). The combustion of gasoline and diesel releases carbon dioxide and other pollutants such as nitrogen oxides (NO_x) and particulate matter (PM) (Oyedokun *et al*., 2024). While electric vehicles (EVs) and public transportation improvements offer cleaner alternatives, the transition to low-emission transportation is still in progress in many cities (Nwulu *et al*., 2024). Urban expansion and infrastructure projects contribute significantly to carbon emissions. The production of construction materials, such as cement and steel, requires high energy consumption, leading to large CO_2 emissions. Additionally, construction activities involve heavy machinery powered by fossil fuels, further increasing emissions. Green building techniques and energy-efficient construction materials are being explored to reduce the carbon footprint of urban development (Arinze *et al*., 2024). Buildings contribute to urban carbon emissions through heating, cooling, lighting, and electrical appliances. The use of fossil fuel-based energy sources for electricity and heating results in high CO_2 emissions. In many cities, outdated infrastructure and inefficient energy use exacerbate the problem. Transitioning to renewable energy sources, improving insulation, and implementing smart energy management systems can significantly reduce emissions from buildings (Oyedokun *et al*., 2024).

Despite the growing urgency to address climate change, monitoring and measuring carbon emissions remain complex and challenging due to several factors; One of the major challenges in emission monitoring is the availability and accuracy of data (Ayanponle *et al*., 2024). Industrial emissions vary by production processes, energy sources, and operational efficiencies, making it difficult to standardize measurement techniques. Similarly, urban emissions fluctuate based on traffic patterns, energy consumption, and seasonal variations, requiring continuous monitoring. Many developing regions lack the technological infrastructure for real-time emission monitoring. While satellite-based remote sensing, ground-based sensors, and AI-powered computer vision are improving carbon monitoring capabilities, these technologies require significant investment and technical expertise. Additionally, industries may lack incentives to install monitoring systems due to economic constraints or regulatory loopholes (Oluokun *et al*., 2024). Global carbon monitoring efforts depend on regulatory frameworks and international agreements such as the Paris Agreement. However, inconsistent policies, weak enforcement mechanisms, and lack of transparency in reporting emissions hinder progress. Some industries may underreport emissions to avoid penalties, making it difficult to track actual carbon output. Strengthening environmental regulations and promoting carbon pricing mechanisms can encourage more accurate reporting and accountability (Ayanponle *et al*., 2024; Ajayi *et al*., 2024). Many emissions are indirect, occurring across supply chains and outsourced manufacturing processes. Accurately tracking the entire lifecycle of emissions, from production to end-use, remains a significant challenge.

Carbon emissions from industrial and urban environments are among the leading causes of climate change, requiring urgent and comprehensive mitigation efforts. Industrial sources such as factories, power plants, and refineries contribute substantial emissions, while urban areas generate carbon output through transportation, construction, and energy consumption (Agbede *et al*., 2024; Akinsooto *et al*., 2024). Despite advancements in monitoring technologies, challenges in data accuracy, regulatory enforcement, and indirect emissions persist. Addressing these challenges requires a multi-faceted approach, integrating AI-powered remote sensing, stricter environmental policies, and widespread adoption of sustainable practices (Adeleye *et al*., 2024; Ajiga *et al*., 2024). By improving emission tracking and promoting cleaner alternatives, industries and cities can play a pivotal role in reducing global carbon footprints and mitigating climate change impacts.

2.3 AI Techniques for Carbon Emission Detection and Analysis

Artificial intelligence (AI) has revolutionized carbon emission detection and analysis by enabling precise, automated, and large-scale monitoring as explain in table 1. Traditional carbon emission measurement methods rely on ground-based sensors and manual data collection, which can be limited in scope and efficiency (Onukwulu *et al*., 2024). AI-powered techniques leverage advanced image processing, deep learning models, and sensor fusion to enhance detection accuracy in industrial and urban settings. This explores key AI-driven approaches, including image processing and pattern recognition, deep learning architectures, multispectral and hyperspectral imaging integration, and the fusion of satellite imagery with sensor data.

Table 1: AI techniques for carbon emission detection and analysis

AI Technique	Description	Application in Carbon Emission Detection	Advantages
Convolutional Neural Networks (CNNs)	Deep learning models specialized in image analysis	Identifying carbon emission sources from satellite/aerial imagery	High accuracy in feature extraction
Recurrent Neural Networks (RNNs) & Long Short-Term Memory (LSTM)	Models designed for sequential data analysis	Tracking emission trends over time from sensor and satellite data	Effective for time-series predictions
Generative Adversarial Networks (GANs)	AI models that generate synthetic data to enhance training	Enhancing low-resolution satellite images for better emission detection	Improves data quality and resolution
Support Vector Machines (SVMs)	Supervised learning algorithm for classification tasks	Classifying pollution levels based on spectral data from remote sensing	Works well with smaller datasets
Random Forest & Decision Trees	Ensemble learning methods for classification and regression	Identifying emission hotspots based on historical pollution data	High interpretability
Unsupervised Clustering (K-Means, DBSCAN, Hierarchical Clustering)	Groups data points based on similarities	Detecting anomalous emission patterns in urban environments	No need for labeled data
Principal Component Analysis (PCA)	Dimensionality reduction technique	Extracting essential emission-related features from large datasets	Reduces computational complexity
Reinforcement Learning (RL)	AI models that learn through trial and error	Optimizing emission reduction strategies in industrial operations	Adaptive to real-world scenarios
Edge AI for On-Site Processing	AI models deployed on local devices rather than cloud	Real-time emission monitoring from IoT-enabled sensors	Reduces latency and bandwidth usage
Explainable AI (XAI) Techniques	Methods to make AI predictions more interpretable	Ensuring transparency in emission analysis for policy-making	Improves trust and regulatory compliance

Image processing and pattern recognition techniques play a fundamental role in detecting and analyzing carbon emissions (Ajiga *et al.*, 2024). Remote sensing images, captured by satellites, drones, and ground-based sensors, provide valuable insights into air pollution and greenhouse gas (GHG) emissions. AI-based image processing techniques analyze these images to identify emission sources, track pollution dispersion, and estimate emission levels. Several key methods enhance emission detection through image processing; Edge detection and segmentation, algorithms such as the Canny edge detector and watershed segmentation identify emission plumes, smoke, and gas leaks in satellite and aerial images (Onukwulu *et al*., 2024). Object detection and classification, AI models trained on emission signatures classify industrial stacks, vehicles, and urban heat islands contributing to carbon output. Temporal changes in images are analyzed to detect emission trends and anomalies, improving predictive analytics for environmental monitoring. Pattern recognition further improves emission analysis by identifying recurring emission patterns and correlating them with industrial activities and traffic congestion (Kokogho *et al*., 2024; Elete *et al*., 2024). AI-driven models can differentiate between natural atmospheric variations and human-induced emissions, leading to more accurate assessments.

Deep learning models have significantly improved the ability to analyze and interpret remote sensing data for carbon emission detection (Afolabi *et al*., 2024). Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and Transformers have been widely adopted in this field. CNNs are particularly effective for analyzing remote sensing images due to their ability to recognize spatial patterns. These models automatically extract emission-related features such as gas dispersion, temperature anomalies, and industrial activities. Pre-trained CNNs, such as ResNet and VGGNet, are commonly used for classifying and segmenting emission sources in satellite imagery. GANs enhance carbon emission detection by generating high-resolution synthetic images that improve the quality of remote sensing data. By training on real-world emission datasets, GANs can create realistic simulations of pollution spread, enabling researchers to predict future emission trends and assess the impact of regulatory interventions (Sam-Bulya *et al*., 2024; Akhigbe *et al*., 2024). Transformer-based models, such as Vision Transformers (ViTs), have emerged as powerful tools for remote sensing image analysis. Unlike CNNs, transformers process entire images simultaneously, capturing long-range dependencies between features. This capability makes them highly effective for analyzing complex emission patterns over large geographical areas.

Multispectral and hyperspectral imaging techniques provide detailed spectral data that enhance carbon emission detection beyond traditional optical imaging (Egbuhuzor, 2024). These advanced imaging modalities capture emissions in various wavelength bands, including infrared, which is particularly useful for detecting gases such as CO_2 and methane. AI-powered algorithms analyze multispectral and hyperspectral data to improve emission detection through; AI models decompose mixed spectral signals to isolate specific greenhouse gases from background noise (Ajayi *et al*., 2024). Machine learning techniques, such as Principal Component Analysis (PCA) and autoencoders, detect deviations in spectral data that indicate abnormal emissions. AI classifiers categorize emission sources based on spectral signatures, while regression models estimate emission concentrations. By integrating AI with multispectral and hyperspectral imaging, researchers can enhance the precision of emission detection, enabling policymakers and environmental agencies to implement targeted mitigation strategies (Alozie *et al*., 2024).

Combining satellite imagery with ground-based and airborne sensor data significantly improves the accuracy and reliability of carbon emission analysis (Ewim *et al*., 2024). AI-driven sensor fusion techniques integrate multiple data sources to provide a comprehensive view of emission dynamics. Merges images from different sensors to create high-resolution emission maps. Extracts complementary features from various data sources, enhancing classification accuracy. Combines predictions from multiple AI models to improve robustness and reliability. AI-powered Internet of Things (IoT) sensors deployed in industrial zones and urban areas continuously collect real-time emission data. These sensors communicate with satellite-based AI models, refining emission estimates by correlating ground observations with remote sensing data. AI models trained on historical emission data predict future pollution levels and provide early warnings for regulatory authorities

(Afolabi *et al*., 2024; Collins *et al*., 2024). Predictive analytics enable proactive decision-making, helping governments enforce environmental policies and industries optimize carbon reduction strategies. AI techniques have transformed carbon emission detection and analysis, offering unprecedented accuracy and scalability. Image processing and pattern recognition methods enhance the identification of emission sources, while deep learning models, including CNNs, GANs, and transformers, improve remote sensing analysis (Folorunso *et al*., 2024). The integration of AI with multispectral and hyperspectral imaging enables precise gas detection, while sensor fusion techniques combine satellite and ground-based data for comprehensive monitoring. These advancements empower policymakers, environmental agencies, and industries to implement data-driven solutions for mitigating carbon emissions and addressing climate change challenges (Jahun *et al*., 2021; Onukwulu *et al*., 2022).

2.4 Applications of AI-Powered Computer Vision in Carbon Monitoring

The integration of artificial intelligence (AI) and computer vision in remote sensing has revolutionized the monitoring and analysis of carbon emissions (Egbuhuzor *et al*., 2022). AI-powered computer vision systems leverage satellite imagery, unmanned aerial vehicles (UAVs), and sensor networks to detect, analyze, and predict carbon emissions in both industrial and urban environments. These applications contribute to enhanced environmental monitoring, policy enforcement, and climate impact assessment (Collins *et al*., 2022). This explores the key applications of AI-powered computer vision in carbon monitoring, focusing on detecting industrial emissions using AI-enhanced satellite imagery, monitoring urban air quality through UAV-based computer vision, and predictive analytics for emission trends and climate impact assessment.

Industrial emissions are a major contributor to greenhouse gases (GHGs), particularly carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O). Factories, power plants, and refineries release significant amounts of these gases, necessitating effective monitoring solutions (Egbuhuzor *et al*., 2023). AI-enhanced satellite imagery provides an advanced approach to detecting and analyzing industrial emissions at a large scale. AI-powered computer vision models process satellite images to identify emission sources, quantify pollutant concentrations, and track dispersion patterns. Several key techniques contribute to this capability as shown in figure 3;

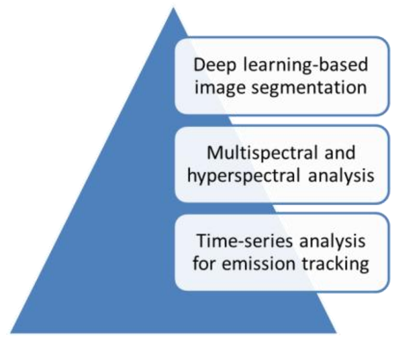

Figure 3: Key techniques in applications of AI-powered computer vision in carbon monitoring

Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) segment satellite images to distinguish emission sources from surrounding environments (Fredson *et al*., 2022). AI models can differentiate between industrial plumes and natural atmospheric variations. Multispectral and hyperspectral analysis, AI algorithms analyze spectral data from satellites, such as those provided by Sentinel-5P and Landsat, to detect specific gas emissions. Infrared imaging is particularly effective for identifying CO_2 and CH_4, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks analyze historical satellite data to detect trends in industrial emissions over time. This helps regulatory agencies assess the effectiveness of pollution control measures. By automating the analysis of satellite imagery, AI-powered computer vision enhances real-time monitoring and ensures that industries comply with environmental regulations (Nwulu *et al*., 2023).

Urban environments contribute significantly to carbon emissions due to vehicular traffic, energy consumption, and construction activities (Chukwuneke *et al*., 2021). Monitoring air quality in cities is crucial for public health and environmental sustainability. AI-powered UAV-based computer vision offers a flexible and efficient solution for real-time air quality monitoring. UAVs equipped with AI-enhanced cameras and sensors can collect high-resolution images and gas concentration data from various urban locations. The advantages of UAV-based carbon monitoring include; AI-powered drones use image processing techniques to detect pollutant hotspots, such as high-traffic areas and industrial zones (Okolie *et al*., 2021). UAVs equipped with hyperspectral cameras and infrared sensors measure CO_2, CH_4, and NO_2 levels. AI algorithms analyze sensor data to determine pollution intensity and dispersion. AI-driven object detection models identify vehicles in real-time and estimate their emission contributions. Integrating drone data with traffic flow analysis helps urban planners implement policies to reduce vehicular pollution. By utilizing AI-powered UAVs, cities can monitor air quality dynamically, respond to pollution events, and develop data-driven urban sustainability strategies (Jessa, 2017).

Predictive analytics, powered by AI and machine learning, plays a crucial role in forecasting emission trends and assessing their impact on climate change (Basiru *et al*., 2023). AI models trained on historical emission data and climate patterns provide insights into future pollution levels and help design mitigation strategies (Okolie *et al*., 2022). Key predictive analytics techniques in carbon monitoring include; Algorithms such as Gradient Boosting Machines (GBMs), Random Forests, and Neural Networks process large datasets to identify emission trends. These models help policymakers understand the progression of industrial and urban emissions over time. AI-powered simulations integrate emission data with climate models to assess potential environmental impacts. By analyzing temperature changes, weather patterns, and atmospheric carbon levels, AI can predict long-term consequences of current emission trends (Nwulu *et al*., 2023). AI models detect emerging pollution trends and provide early warnings for regions at risk of exceeding safe air quality limits. These insights enable timely interventions, such as traffic restrictions and industrial emission controls. Predictive analytics enhances decision-making by providing governments, industries, and environmental agencies with data-driven recommendations for reducing carbon footprints. AI-powered computer vision has transformed carbon monitoring by enabling precise, scalable, and real-time emission detection (Egbumokei *et al*., 2021). AI-enhanced satellite imagery improves industrial emission tracking, UAV-based monitoring enhances urban air quality assessments, and predictive analytics provides insights into future emission trends. These advancements contribute to environmental policy enforcement, sustainable urban planning, and climate change mitigation efforts (Fredson *et al*., 2021; Basiru *et al*., 2023). By leveraging AI-driven solutions, researchers and policymakers can develop more effective strategies for reducing carbon emissions and ensuring a healthier, more sustainable future.

2.5 Challenges and Limitations

Artificial intelligence (AI) has revolutionized carbon emission detection through remote sensing, predictive modeling, and real-time monitoring (Basiru *et al*., 2023). However, despite its potential, AI-driven approaches face several challenges and limitations that hinder their effectiveness and widespread adoption. These challenges include data availability and quality issues, concerns about model interpretability and accuracy, and ethical and policy considerations that affect the implementation of AI-powered monitoring systems. Addressing these limitations is essential for developing reliable and scalable AI solutions for carbon emission detection.

One of the most significant challenges in AI-driven carbon emission detection is ensuring the availability and quality of data. AI models require vast amounts of high-resolution, accurately labeled data to train and perform effectively. Remote sensing technologies, including satellite imagery and drone-based monitoring systems, generate massive datasets, but these datasets often suffer from inconsistencies due to factors such as atmospheric interference, cloud cover, and sensor calibration errors (Fredson *et al*., 2021; Anaba *et al*., 2022). The lack of standardized datasets for training AI models further complicates data reliability, leading to inconsistencies in emission estimations across different regions and timeframes. Moreover, ground-based sensors, which provide essential real-time emissions data, are not uniformly distributed. Many developing regions lack the infrastructure for comprehensive sensor deployment, resulting in data gaps that hinder AI-based analysis (Basiru *et al*., 2023). Data privacy concerns also pose restrictions on access to industrial emission records, making it difficult for researchers to validate AI models using ground-truth data. Addressing these issues requires collaborative efforts between governments, industries, and research institutions to create standardized, high-quality datasets that improve AI performance in emission detection.

AI models, particularly deep learning architectures such as convolutional neural networks (CNNs), generative adversarial networks (GANs), and transformers, offer high accuracy in emission detection and analysis (Egbuhuzor *et al*., 2021; Fredson *et al*., 2022). However, their complexity often results in a lack of interpretability, making it difficult for policymakers and environmental scientists to understand how decisions are made. This “black box” nature of deep learning models raises concerns about transparency, as stakeholders require clear explanations of how AI systems classify emissions, differentiate pollution sources, and predict future trends. Furthermore, model accuracy is influenced by biases in training data, sensor limitations, and environmental variability (Agbede *et al*., 2023). AI models trained on limited datasets may struggle to generalize their predictions to new geographical areas, reducing their reliability in diverse environments. Additionally, adversarial conditions such as extreme weather, urban heat islands, and industrial byproducts can introduce noise into the data, reducing the precision of AI-driven carbon footprint assessments. Developing more interpretable AI models with explainable AI (XAI) techniques and integrating uncertainty quantification methods can enhance trust in AI-powered emission monitoring (Fredson *et al*., 2021; Amafah *et al*., 2023).

The deployment of AI for carbon emission detection raises several ethical and policy challenges that must be addressed for responsible implementation (Elete *et al*., 2022). One major concern is data privacy, particularly when monitoring emissions from industrial facilities. Companies may be reluctant to share emissions data due to fears of regulatory penalties, competitive disadvantages, or public scrutiny. Ensuring secure data sharing protocols and regulatory compliance frameworks is essential to balance transparency with corporate confidentiality. Additionally, AI-powered monitoring systems must align with international climate policies and legal frameworks. The regulatory landscape for AI in environmental monitoring is still evolving, and inconsistent policies across different jurisdictions create uncertainties in AI adoption (Olisakwe *et al*., 2021; Basiru *et al*., 2023). Governments must establish clear guidelines on AI-driven emission monitoring, including data governance, accountability measures, and mechanisms for verifying AI-generated emission reports. Another ethical challenge involves the socio-economic implications of AI deployment. While AI can enhance carbon emission monitoring efficiency, it may also lead to job displacement in traditional environmental monitoring roles. Policymakers must address workforce transitions by investing in AI education and reskilling programs to ensure that affected workers can adapt to AI-integrated monitoring systems. While AI presents a promising approach for carbon emission detection and analysis, several challenges must be addressed to improve its effectiveness. Data availability and quality issues impact model performance, while interpretability and accuracy concerns limit trust in AI-driven monitoring systems (Jessa, 2023). Ethical and policy challenges further complicate implementation, necessitating clear regulatory frameworks and responsible AI deployment strategies. Overcoming these limitations requires interdisciplinary collaboration among AI researchers, environmental scientists, policymakers, and industries to ensure that AI contributes to sustainable and transparent carbon emission monitoring (Fagbule *et al*., 2023; Nwulu *et al*., 2023).

2.6 Future Directions and Opportunities

The integration of artificial intelligence (AI) and computer vision into remote sensing has significantly improved the accuracy and efficiency of carbon emission monitoring (Onukwulu *et al*., 2023). As AI technology continues to advance, new opportunities are emerging to enhance real-time carbon tracking, develop smarter monitoring systems, and establish stronger regulatory frameworks. This explores future directions in AI-powered carbon emission detection, focusing on advancements in AI models, emerging technologies such as edge computing and the Internet of Things (IoT), and the policy implications of AI-driven carbon tracking systems.

AI models have evolved rapidly, with increasing capabilities in processing and analyzing vast amounts of environmental data (Opia *et al*., 2022). Future advancements in AI-powered carbon emission tracking will likely focus on enhancing real-time monitoring through improved deep learning architectures and hybrid AI techniques. Traditional deep learning models require large datasets for training. Self-supervised learning (SSL) and few-shot learning (FSL) will enable AI systems to recognize emission patterns with minimal labeled data, making real-time monitoring more efficient. Federated learning enables multiple devices, such as satellites, drones, and ground sensors, to collaboratively train AI models without sharing raw data (Chukwuneke *et al*., 2022). This enhances privacy while ensuring accurate carbon emission analysis across different geographic locations. A key challenge in AI-powered environmental monitoring is the interpretability of deep learning models. Neural-symbolic AI combines machine learning with rule-based reasoning, providing greater transparency and reliability in carbon tracking. With these advancements, AI models will not only detect emissions more accurately but also provide real-time insights for proactive environmental management (Akinsooto *et al*., 2014).

The integration of AI with emerging technologies such as edge computing and IoT is set to revolutionize carbon monitoring. These technologies enhance real-time data collection, processing, and analysis, reducing latency and improving the efficiency of emission detection systems (Olisakwe *et al*., 2022). Edge computing reduces the reliance on centralized cloud processing by performing AI computations closer to the data source. This enables faster and more localized carbon emission analysis, making it particularly useful for UAV-based air quality monitoring and industrial emission tracking. IoT sensors embedded in urban infrastructure, industrial facilities, and transportation networks can continuously collect air quality data. AI-powered IoT systems analyze this data in real-time to detect pollution hotspots, helping cities implement dynamic emission control strategies. Ensuring the accuracy and authenticity of carbon emission data is crucial for regulatory compliance. Blockchain technology can provide a decentralized and tamper-proof system for recording AI-driven emissions data, fostering greater transparency and trust among stakeholders (Akintobi *et al*., 2023). These emerging technologies will enhance the scalability, accuracy, and reliability of AI-powered carbon emission tracking, enabling more proactive environmental management.

As AI-powered systems play a growing role in carbon emission monitoring, regulatory frameworks must evolve to ensure ethical, transparent, and effective implementation (Oyedokun, 2019). Policymakers will need to address several key areas; Regulatory bodies should establish standardized protocols for AI-driven emission detection to ensure consistency and reliability across different industries and regions. This includes defining acceptable AI model performance metrics and validation procedures. The widespread deployment of AI-powered surveillance systems raises privacy concerns, particularly in urban areas. Policymakers must create legal frameworks that balance environmental monitoring with individual privacy rights. Governments can encourage industries to adopt AI-powered carbon tracking by providing tax incentives, subsidies, and regulatory benefits for companies that implement AI-based sustainability solutions. Climate change is a global challenge that requires cross-border cooperation. International organizations, such as the United Nations and the European Commission, can facilitate AI-powered carbon monitoring initiatives to track and mitigate emissions on a global scale. By integrating AI-driven carbon tracking into policy frameworks, governments and environmental agencies can ensure that AI technologies contribute effectively to global sustainability goals (Adewoyin *et al*., 2022).

The future of AI-powered carbon emission tracking is driven by advancements in AI models, the adoption of emerging technologies, and the development of robust regulatory frameworks. Real-time emission tracking will become more precise with self-supervised learning and federated AI techniques, while edge computing and IoT will enhance data collection and processing (Basiru *et al*., 2023; Elete *et al*., 2023). To maximize the benefits of these technologies, policymakers must establish clear regulations that ensure transparency, data integrity, and ethical AI deployment. By leveraging AI for environmental sustainability, industries and governments can take proactive steps toward reducing greenhouse gas emissions and mitigating climate change.

CONCLUSION

AI-driven techniques for carbon emission detection and analysis have demonstrated significant potential in enhancing environmental monitoring and sustainability efforts. By leveraging image processing, deep learning models, and data fusion techniques, AI enables accurate and real-time tracking of carbon footprints across urban and industrial settings. However, several challenges persist, including data availability and quality concerns, model interpretability, and ethical and policy considerations. Addressing these limitations is critical to fully realizing the potential of AI in carbon emission monitoring.

AI-powered computer vision plays a crucial role in sustainable urban and industrial planning by providing high-resolution spatial and temporal insights into emission patterns. Through remote sensing and sensor integration, AI enables policymakers and urban planners to identify pollution hotspots, optimize transportation networks, and implement adaptive mitigation strategies. Additionally, AI-driven predictive models can support proactive decision-making, allowing industries to minimize emissions through optimized energy consumption and process improvements. As cities and industries transition toward greener practices, AI-powered monitoring solutions will become essential for enforcing regulatory compliance and achieving carbon neutrality goals.

Despite these advancements, further research is needed to enhance AI's accuracy, transparency, and scalability in emission monitoring. Developing more interpretable AI models and improving data-sharing frameworks will strengthen trust in AI-driven insights. Additionally, policy support is essential to establish standardized regulations for AI-based environmental monitoring, ensuring ethical implementation and data security. Governments, industries, and researchers must collaborate to integrate AI solutions into global sustainability initiatives effectively. By fostering interdisciplinary innovation and policy alignment, AI can drive transformative change in carbon emission management, contributing to a more sustainable and climate-resilient future.

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