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Reducing Carbon Footprints by Adopting Effective and Smart Technology Applications & Role of Green Audit

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ABSTRACT

Already, climate change is harming both urban and natural systems, leading to worldwide economic losses of more than $500 billion. This is a problem that AI might help with in part because it uses data from the internet to generate quick recommendations based on reliable projections of future climate change. Here we take a look back at some of the most recent developments in the field of artificial intelligence as it pertains to reducing deforestation, creating resilient cities, improving energy efficiency, transportation, grid management, building design, transportation, precision agriculture, industrial processes, and the fight against climate change.

Improving energy efficiency may help mitigate climate change, according to our findings. In instance, smart manufacturing has the potential to cut building energy usage by 30–50% while also reducing waste and carbon emissions. Approximately 70% of the world's natural gas producers use AI systems to improve the precision and dependability of weather predictions. Electricity expenses may be cut by 10-20% by optimising power system efficiency with the use of smart grids and artificial intelligence. Around 60% less carbon dioxide emissions are possible with intelligent transportation systems. In addition, using AI into natural resource management and resilient city planning may have a multiplicative effect on sustainability efforts.

INTRODUCTION

Climate change, one of the most pressing environmental issues facing by mankind today, is being accelerated by the emissions of carbon dioxide from industrial production. Natural catastrophes are becoming more often, food production is declining, sea levels are rising, and biodiversity is disappearing as a result of climate change, says Shivanna (2022). According to Yue and Gao (2018), the widespread use of fossil fuels in industrial processes is the main driver of global carbon dioxide emissions. Therefore, the battle against climate change must prioritise the reduction of emissions, the increase of efficiency, and the development of renewable energy sources. The transition from a society dependent on fossil fuels to one dependent on electricity may have a positive effect on environmental conservation, according to Fang et al. (2023). With the use of AI-enabled deep neural networks, tasks like discovery, distribution, and transmission might be automated, significantly reducing energy usage (Farghali et al. 2023). As the effects of climate change worsen daily, many are hopeful that AI could provide a solution. Artificial intelligence (AI) has enormous potential in the energy industry to ease the transition to renewable energy sources and take advantage of the expanding opportunities given by the IoT. It might improve decision-making, regulate autonomous software, and play a crucial role in energy supply as a dominant force in the energy business. Additionally, solar radiation modelling, renewable energy system optimisation and simulation, urban power load prediction, and urban building heat load prediction have all made substantial use of AI (Al-Othman et al. 2022).

Here are a few ways AI can help reduce climate change: better weather prediction (McGovern et al., 2017), smart buildings that collect and sense data to predict thermal comfort (Ngarambe et al., 2020), models to reduce fertiliser usage (nutrient cycling and crop productivity), smart waste management systems, resilient cities (Allam and Dhunny, 2019), and sustainable forest management practices (deforestation reduction, efficiency, precision).

Smart Technology Applications

Saving energy

These days, energy concerns rank high among the world's most important issues. The ever-increasing global population and economy have caused energy consumption to skyrocket (Chen et al. 2022). Simultaneously, the challenge of attaining sustainable development via prudent energy use is becoming more pressing (Chen et al. 2023). Improving energy efficiency and decreasing energy waste are efficient measures that may be adopted to manage the growing energy demand while simultaneously reducing negative environmental impacts (Cai et al. 2019). New possibilities and challenges have emerged in this area as a result of AI's steady ascent as a tool for improving energy efficiency and sustainable development.

Through intelligent control, optimisation of production and consumption, and demand forecast, artificial intelligence (AI) might enhance energy utilisation in the energy industry. According to Khalilpourazari et al. (2021), this has the potential to encourage sustainable growth while simultaneously reducing energy expenditures and pollution. This is why the question of how AI might boost energy efficiency has piqued the attention of many academics and companies. The study conducted by Kumari and colleagues in 2020. Intelligent use of AI has the potential to boost energy efficiency, promote sustainable development, and usher in a brighter future for human civilisation, according to proponents of the theory. As a result, Table 1 provides an analysis of how AI technology is being used to improve energy efficiency.

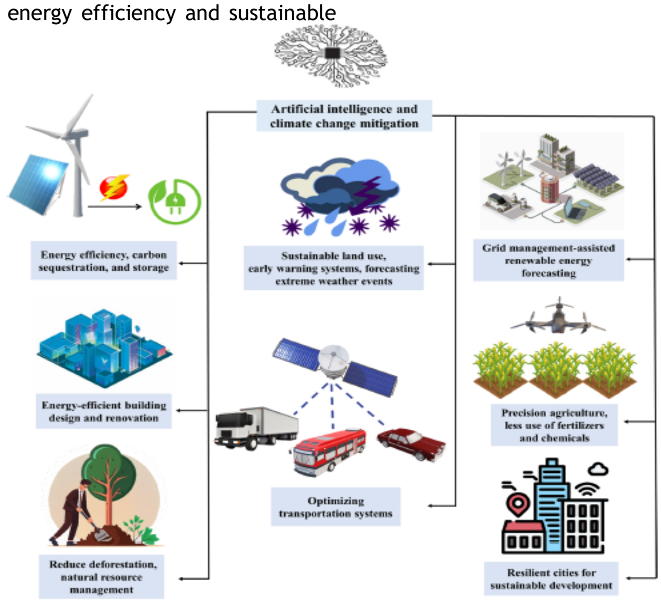

Fig. 1 Utilisation of AI to mitigate climate change's negative effects.

There have been new possibilities and difficulties in improving energy efficiency and achieving sustainable development brought about by the advent of artificial intelligence as a game-changing technological tool. This has had a significant impact on the energy industry. the findings of a study that demonstrates the successful use of artificial intelligence in several domains related to energy efficiency, such as thermal management, issue identification and diagnosis, and energy audits. Energy storage optimisation, comfort prediction and management, and demand response. Applications of AI in these areas have had a favourable influence on energy efficiency, waste reduction, and sustainable development (Chopra et al. 2022). However, enhancing energy efficiency via the use of AI is an ongoing pursuit. Accurate data input and well selected AI algorithms are crucial to the system's performance, say Arumugam et al. (2022).

Research out of Italy and Japan demonstrates that AI-powered energy management solutions are popular and effective. While research into predictive maintenance using AI is still in its infancy, results from a UK study indicate promising early results.

And in nations like India and China, AI is helping with things like renewable energy integration and demand response.

Data suggests that further research is required to draw firm conclusions on the efficacy of artificial intelligence (AI) applications across several domains of energy efficiency. This means that more research is needed to establish the efficacy of certain applications (Carbon et al., 2006).

The outrageous price tag of AI systems has been a source of worry for some researchers (Enholm et al., 2022). This is due to the fact that certain companies may find it very costly to create and implement AI-based solutions (Ahmed et al. 2022b). Another major obstacle to AI's broad usage in energy efficiency is the lack of data and skilled AI professionals (Chai et al. 2022). Despite these limitations, Forsyth et al. (2007) predict that the use of artificial intelligence technology for energy efficiency would expand in response to the growing need to decrease energy consumption, lessen environmental effect, and attain sustainable development.

In this part, we will examine AI-based technologies in detail with the aim of improving energy efficiency. Scientists have shown that AI has the potential to significantly boost energy efficiency and promote greener economic development. While the potential of AI still need further testing, it has shown efficacy in several sectors. It is not being widely used due to financial constraints and a lack of accessible expertise. Nevertheless, future efforts to use AI to energy efficiency hold promise.

The process of capturing and storing carbon

According to Liu et al. (2022b) carbon sequestration and storage play a crucial role in measures aimed at mitigating climate change. Kaack et al. (2022) found that applying AI to this area may greatly improve the efficiency and efficacy of these procedures. Utilising tech-nologies based on artificial intelligence may help identify suitable geological formations for carbon storage and predict how carbon dioxide will behave once it is added to storage locations.

In addition, AI can keep an eye on storage locations to make sure carbon dioxide is safely buried and improve the injection process. Artificial intelligence (AI) has the potential to speed up mineral carbonation, a novel approach to carbon sequestration that transforms carbon dioxide into stable minerals (Ding et al. 2022).

In conclusion, climate goals and sustainable development may be advanced via the use of AI in carbon sequestration and storage. the steps involved in using AI for carbon sequestration and storage, and how it may help achieve climate objectives and sustainable development. Using AI, we can lessen the effects of climate change and cut emissions of greenhouse gases, which will speed up the process of reaching carbon neutrality.

The use of AI for carbon sequestration and storage has been on the rise recently (Qerimi and Sergi 2022). how AI could improve these processes by finding suitable geological formations to store carbon, making predictions about how carbon dioxide will behave once it's in the storage sites, making injection processes more efficient, keeping an eye on the sites, and coming up with new ways to sequester carbon. In addition, according to Jahanger et al. (2023), artificial intelligence may help achieve carbon neutrality and sustainability goals by decreasing emissions of greenhouse gases and lowering the rate of climate change. Thus, artificial intelligence's ability to sift through mountains of geological and engineering data in search of suitable storage locations and injection process optimisation is a major plus for carbon sequestration and storage.
Artificial intelligence can also monitor the location to ensure the underground gas is kept trapped indefinitely and forecast how carbon dioxide will behave in storage facilities (Kushwaha et al., 2023). One of its merits, according to Zhang et al. (2022), is its capacity to produce novel techniques of carbon storage, such as stimulating the development of materials with potential uses in long-term carbon dioxide management.
There are a number of challenges to using AI into carbon sequestration and storage (Hasan et al. 2022). A lack of domain knowledge and the necessary implementation funds are two major hurdles. Furthermore, there may be ethical and legal issues with using AI to oversee and manage carbon storage facilities (Swennenhuis et al., 2022), therefore it's important to be cautious that the technology doesn't have any negative effects on the environment.

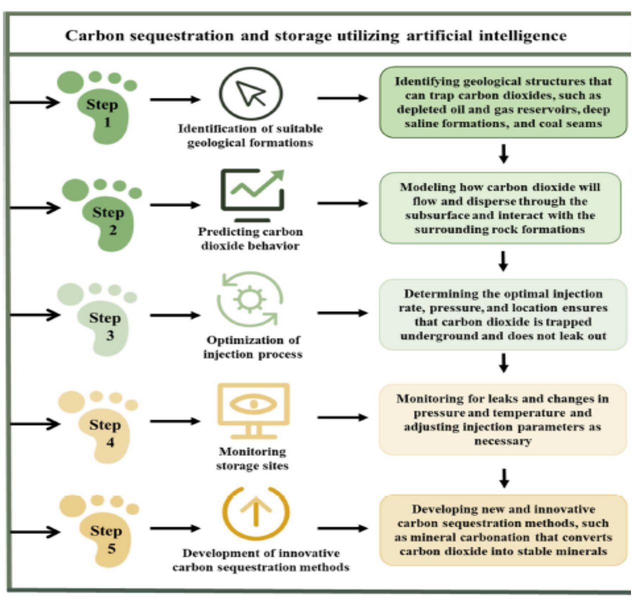

Fig. 2 Artificial intelligence for carbon sequestration and storage.

The following graphic illustrates five separate steps for integrating AI with carbon sequestration and storage. Achieving climate targets and supporting sustainable development are both emphasised by the crucial role of artificial intelligence. Using geological data analysis, the graphic shows how artificial intelligence can forecast how carbon dioxide would behave when injected at storage locations and find formations that are good candidates for carbon storage. Furthermore, it shows how AI can make injection processes more efficient, which increases carbon storage, and how site monitoring can guarantee the safety of subterranean carbon dioxide sequestration.
Further, AI might speed up the development of new carbon storage solutions, which could lead to unforeseen outcomes (Delanoë et al. 2023). We could expect to see a rise in the use of AI for carbon sequestration and storage as time progresses and technology becomes more accessible. Thus, attaining sustainability objectives and carbon neutrality requires guaranteeing the ethical and responsible use of AI technology. The potential advantages of AI for carbon sequestration and storage cannot be fully exploited without more development and research to tackle the obstacles in this field.
All things considered, artificial intelligence has the potential to make carbon sequestration and storage more efficient and effective, which might lead to better climatic outcomes and more sustainable economic growth in the long run. Possible applications of this technology include studying geological formations for carbon storage, optimising injection operations, predicting the behaviour of carbon dioxide, discovering new and novel ways of carbon sequestration, and monitoring storage sites. On the other hand, there are obstacles to using AI in this domain, such as expenses, inadequate understanding, ethical and legal quandaries, and possible detrimental effects on the ecosystem (Garnett et al., 2006).
Artificial intelligence (AI) helps reduce carbon emissions and increase renewable energy generation (Kruse et al., 2021), however the technology is still in its early stages and faces several challenges. Algorithmically enhance the power system's stability analysis to deal with the exponentially increasing sample data generated by the system's operation. Timely disaggregation of up-to-date data is essential. As a result of the time required, learning could lag behind changes to the data. Traditional approaches, such as reverse trajectory and time domain simulation, need less historical data than AI. Aims of the learning model created by Xu and Yin (2015) were enhancing prediction efficiency, decreasing spatial input dimensions, removing duplicate components, and selecting/extracting relevant grid information. Lastly, AI has shown its value in this field by helping to find renewable energy sources and preventing infrastructures from collapsing. Because the production of renewable energy sources is unpredictable, too much electricity will be wasted and too little will affect people's daily lives. In order to reduce energy waste, grids are coordinated by artificial intelligence systems that forecast the output of renewable energy. The use of AI to aid power grid management has been widely recognised and beneficially used (Lillywhite et al., 2007).
AI has the potential to analyse vast quantities of data and enhance several facets of buildings. These facets include HVAC, lighting management, building envelope optimisation, integration of renewable energy sources, energy modelling, predictive maintenance, and more. By analysing data on occupancy rates and weather conditions, artificial intelligence algorithms may make adjustments to HVAC, lighting, and other systems to decrease energy waste (Chen et al. 2022a). Furthermore, by analysing data on building orientation and weather conditions, among other aspects, artificial intelligence technology may aid in the construction of building maintenance structures. One way that buildings may lessen their impact on the environment is by using renewable energy sources. Artificial intelligence can help in this process.
Buildings can have their HVAC systems optimised, lighting controlled, building envelopes optimised, energy consumption simulated, and maintenance needs predicted with the help of artificial intelligence technologies, as shown in the illustration. By analysing building data, lowering energy use, and enhancing occupant comfort, the image also successfully shows how artificial intelligence technology may give realistic optimisation solutions. Furthermore, the picture shows how AI may be used to foretell when building systems would need repair.
In addition, research shows that there are other benefits to using AI for energy-efficient building design and retrofitting, such as the ability to analyse large amounts of data quickly and accurately. As a result, AI systems can spot potential areas for energy optimisation that humans may miss. For example, AI has the ability to detect trends in energy consumption that humans can't see, which means building operators may make adjustments that can lead to substantial savings in energy. Furthermore, SAHEB et al. (2022) found that AI may improve building energy models, which can guide design and renovation choices. Integrating AI into energy-efficient building design and retrofitting also allows for real-time system monitoring and adjustment, which is another advantage. During the life of the building, this may lead to better energy efficiency. Building systems may be adjusted by artificial intelligence algorithms to accommodate various elements such as occupancy patterns and weather conditions. According to Lee et

al. (2019), this feature also enables predictive maintenance of building systems, which helps to reduce downtime and save energy loss due to malfunctioning systems.

In conclusion, the portion that was discussed before emphasises that improving energy efficiency via retrofitting and AI-powered building design offers a great chance to reduce carbon emissions and energy consumption in the built environment. More energy efficiency and occupant comfort may be achieved via the optimisation of building systems and design with the use of artificial intelligence algorithms.

The innovative and ground-breaking solutions that will emerge from the continuing research and development in this area are expected to significantly enhance energy saving and sustainability in the built environment.

Influence of AI on Transportation System Optimisation for Reducing Greenhouse Gas Emissions

The transportation industry is responsible for over one-third of the world's greenhouse gas emissions.

Reducing emissions from transport has risen to the forefront of global climate change efforts. According to Fatemidokht et al. (2021), one potential approach is to use artificial intelligence to improve transport networks while reducing carbon footprint. In order to improve transportation systems, artificial intelligence can optimise public transportation, control demand, manage fleets, create autonomous cars, and refine routes. By analysing vast amounts of data on traffic patterns, passenger demand, and weather conditions, algorithms powered by artificial intelligence may find ways to improve transportation systems' efficiency while reducing emissions. A more sustainable transport industry, lower emissions of greenhouse gases, and huge savings in the long run are all possible outcomes of this. Thus, the several ways AI may be used to optimise transportation networks and reduce their carbon footprint. It also shows the possible advantages and disadvantages of applying these solutions (Padgett et al., 2008).

Transport systems put artificial intelligence to good use. Figure 5 shows how transport routes may be optimised using AI, taking into account aspects including weather, road conditions, and traffic patterns (Chavhan et al. 2020). Time savings, better fuel economy, and less pollutants are all possible outcomes of this. In addition, found that AI can optimise fuelling and maintenance schedules, two aspects of vehicle fleet management. Transportation systems may reduce fuel consumption and downtime by using predictive analytics to foresee when repair is needed and when to replenish. States that develop self-governing automobiles has the ability to greatly decrease emissions by improving fuel economy and reducing traffic congestion. Autonomous cars may be managed with the help of AI algorithms, which can improve their performance and reduce their energy use.

In addition, Nikitas et al. (2020) found that public transport systems, including scheduling and route planning, may benefit from artificial intelligence.

Transportation systems may optimise routes and reduce empty buses or trains by assessing data on passenger demand and traffic-patterns; this improves efficiency and decreases emissions.

One potential application of AI in public transportation is to encourage people to switch to cleaner forms of transportation like electric cars or public transportation, which produce less emission (Olayode et al. 2020). More environmentally friendly forms of transportation may be encouraged by transportation systems by analysing user behaviour and preferences.

International Convention: Strategies Employed by the UNFCCC to Reduce Carbon Emissions Through Smart Technology Innovations and Green Audits.

The United Nations Framework Convention on Climate Change (UNFCCC) is a global treaty constitutionalized in 1992 to mitigate climate change by decreasing greenhouse gas (GHG) emissions and fostering sustainability. One of the focused aims is to reduce carbon footprints by designing policies, using advanced technologies, and conducting Green Audits.

1. Role of UNFCCC in Carbon Footprint Reduction

The UNFCCC is critical towards facilitating international climate deals and measures, for instance:

• Kyoto Protocol (1997): Set legally binding emission reduction targets for developed countries (Grubb et al., 1999).

• Paris Agreement (2015): Seeks to restrict increase of global temperature to less than 2°C with nationally determined contributions (NDCs) (Rogelj et al., 2016).

• Carbon Market Mechanisms: Uses Cap-and-Trade Systems and Carbon Credits as incentives for emission reductions (Stavins, 2008).

• Climate Finance and Technology Transfer: Helps developing countries access green technologies through the Green Climate Fund ((GCF) Zhang & Chen, 2015).

2. Importance of Smart Technology Applications in Reducing Carbon Foot Prints

Smart technologies are essential in lowering the carbon footprints across sectors. These cover:

a. Incorporation of New Forms of Energy

- Smart grids increase effectiveness of distribution of energy coming from solar, wind, or body of water (Fang et al., 2012).
- Intelligent systems for power consumption management improve the efficiency of the use of electricity (Ding et al., 2019).

b. IoT and AI for Emission Management and Tracking

• Smart sensors enabled with IoT measure energy consumption and emissions in real time (Gubbi et al., 2013).

• Actionable insights powered by AI analytics help in minimizing productive emissions by restructuring them (Rolnick et al., 2019).

c. Sustainable Mobility and Transportation

- EVs and intelligent traffic management systems control energy utilization and emissions (Sperling & Gordon, 2009).
- Reduction of fossil fuels dependency is achieved by optimally using high-speed rail and public transport (Banister, 2008).

d. Technologies for Eco-Friendly Construction

- Smart HVAC enables reduction of energy above required levels as its temperature settings are adjusted automatically (Kumar & others 2019).
- Eco-friendly and energy conserving buildings materials are employed in LEED certified designs (Newsham et al., 2009).

3. Importance of Green Audit in Carbon Management

A. Green Audit evaluates the current operations of the organization to determine its environmental impacts with regard to set sustainability objectives. Its major parts include:

a. Assessment of the carbon footprint scale

- Measurement of Scope 1, Scope 2, and Scope 3 emissions (Huang et al., 2009).

- Identifies processes with high emissions and the potential for improvement (Pandey et al., 2011).

b. Analysis of the productivity and efficiency of energy and resources

- Review of Operations Energy, Water, and Materials Utilization (Christ & Burritt, 2013).

- Proposals for waste reduction and recycling initiatives (Singh et al., 2012).

c. Adherence to environmental Protection norms

- Ensure compliance to ISO 14001 (Environmental Management Systems) and country's laws (Boiral, 2007).

- Assists corporations pursuing their ESG (Environmental, Social and Governance) objectives (Friede et al., 2015).

The UNFCCC together with the application of smart technologies and the Green Audits works towards achieving lower carbon footprints, environmental sustainability, and a greener economy. The use of AI, the IoT, and firm-wide data analytics in the context of climate action will further enhance global efforts to reduce carbon emissions.

The need is to combine green initiatives, legislation, and technology to ensure effective long-term climate change adaptation and carbon neutrality.

The Role of AI in Biodiversity Conservation Efforts

AI Technology Applications Artificial Intelligence (AI) has proven to be an invaluable asset in biodiversity conservation by complementing existing efforts in species monitoring, habitat conservation, and ecosystem forecasting. Actions that would otherwise require resource-intensive human effort are done using automated data analysis, machine learning, and even predictive modelling.

A. Towards Species Recognition and Monitoring

- Computer Vision and Deep Learning: AI-powered image riconition systems are capable of identifying species from camera trap images, satellite imagery, or drone footage. (Waldchen & Mader, 2018).

- Bioacoustics Monitoring: AI analyzes audio recordings to identify endangered species and changes to biodiversity. (Stowell et al., 2019).
- Citizen Science and AI: Android applications such as iNaturalist uses AI to assist users in identifying species for contribution to biodiversity databases. (Van Horn et al., 2018).

B. Towards Habitat and Ecosystem Preservation

- Remote Sensing and Satellite Imagery: Satellite data, when processed through AI powered tools, can provide information regarding the rate of deforestation, land use changes and other forms of habitat destruction. (Joshi et al., 2016).
- Predictive Modeling: Machine learning is being used to predict the impact climate change will have on species distribution and stratagenic frameworks for conservation efforts. (Harris et al., 2018).
- Drone Surveillance: AI driven drones are equipped to supervise and report illegal activities such as poaching, deforestation and other forms marine ecosystem health in real-time (Olivares-Mendez et al., 2015).

C. Using Artificial Intelligence for Wildlife Poaching and Unlawful Trade Accentuation

- Predictive Policing Models: AI algorithms assist in estimating poaching risks by analyzing the spatial and temporal patterns of previous poaching activities (Gholami et al., 2020).
- Blockchain AI Integration: Tracking using AI alongside blockchain technology increases the integrity of trade conducted within wildlife and helps to reduce illicit trafficking (Furlan et al., 2020).

D. AI for Enhancing Decision Making on Conservation Strategies Planning

- Analysis of Large Datasets on Conservation: Artificial intelligence analyzes innumerable data of environmental sensors, genetic libraries and ecological surveys to formulate relevant strategies for conservation (Deneu et al., 2021).
- Planning Climate Change Adaptation Measures: Simulations carried out by AI help the policymakers to outline ways to adapt with climate changes and slow down the rate of loss of biodiversity (Pearson et al., 2019).

Some Illustrations of Biodiversity Conservation Efforts:

1. India – AI Induced Enhancements for Tiger Conservation

- The Wildlife Institute of India (WII) integrates AI-based camera traps and machine learning algorithms to isolate particular tigers by examining their distinct stripe variations.
- Using AI to probabilistically foretell movement and human-wildlife conflict zones assists the decision makers with more effective conservation measures.
- The PAWS (Protection Assistant for Wildlife Security) system developed by Google and WCS (Wildlife Conservation Society) helps predicts probable poaching activities and conditions, allowing rangers to strategically patrol GBP (Greater Nahanni Ecosystem) which is located in Cruz Indian national parks.

Impact: Enhanced efforts in tracking the number of tigers and a decrease in illegal hunting activities.

2. USA – The Use of Artificial Intelligence in Safeguarding Endangered Species of Birds

- The Cornell Lab of Ornithology employs bioacoustic AI technology to monitor some species of birds such as the Kirtland's Warbler and the California Condor which are 'endangered' under the international conservation.
- Algorithms analyze huge volumes of sound data collected from remote regions of forests to extract calls of birds and calculate the size of the population.

Impact: Planning conservation activities and tracking populations of birds with real-time analytics generated by AI.

3. Africa – Drones and AI Technology for Fighting Poaching Activities

- At night in South Africa and Kenya National Parks, AI drones with thermal imaging cameras view the landscape to detect intruders.
- The AI software analyzes the footage collected from a drone, distinguishing between animals and people and alerting park rangers in real-time.

Impact: Reduction of the number of poaching activities at the chief national parks of Republic of South Africa such as Kruger National Park and Maasai Mara.

4. Australia – Sole AI Technology for Protection of Coral Reefs

- The Australian Institute of Marine Science (AIMS) trained the AI Coral Net system to monitor the condition of coral reefs using computer vision technology instead of image recognition to observe underwater objects.
- The AI bots check for strong bleaching events, reef cover, and severe damage to the reefs physiologically.

Impact: Quicker and precise collection of data helps in conserving the reef, especially in the case of climate change that threatens the Great Barrier Reef.

5. Brazil – AI for Deforestation Detection in the Amazon

• With aid from INPE, the Brazilian government utilizes AI as well as satellite imagery to combat illegal deforestation in the Amazon region.

• A combination of Google Earth Engine and AI models scans the area for potential tree loss, and consequently sends alerts to law enforcement agencies.

Impact: Helps with the early detection of illegal logging activities, improves response time, and tries to stop large scale deforestation from happening.

Methodology

The purpose of this study is to examine the impact of smart technology applications and green audits on carbon footprint reduction using a mixed-method approach, which combines qualitative and quantitative research approaches. The research is structured around secondary data sources, including journal articles, reports, and case studies, to provide a comprehensive understanding of how artificial intelligence (AI) and smart technologies contribute to climate change mitigation. A literature review is conducted to identify key trends and advancements in energy efficiency, carbon sequestration, and sustainable industrial processes. Quantitative data from existing studies are used to analyze the impact of smart technology using AI in optimizing power systems, predicting energy demand, and reducing greenhouse gas emissions. In addition, case studies from different industries are examined to highlight real-world applications of AI-driven sustainability solutions. The study also incorporates policy analysis to assess governmental and corporate strategies for integrating AI into environmental sustainability. The findings will be interpreted using statistical and thematic analysis, ensuring a holistic evaluation of AI's role in reducing carbon footprints and achieving long-term sustainability goals.

Objectives

1. To analyze the impact of artificial intelligence and smart technology applications on energy efficiency and carbon footprint reduction.
2. To examine the role of AI in optimizing energy grids, transportation systems, and industrial processes for sustainability.
3. To explore the effectiveness of AI-driven carbon sequestration and storage techniques in mitigating climate change.
4. To assess the contributions of AI-powered smart cities and resilient urban planning in reducing environmental impact.
5. To evaluate green audit frameworks and their integration with AI technologies for enhancing corporate sustainability practices.
6. To identify challenges and policy implications associated with AI adoption in environmental management and climate mitigation strategies.

Findings

There are still significant problems with artificial intelligence technologies, even though they may help optimise transportation systems, which would cut carbon emissions and get the transportation sector closer to carbon neutrality. A lot of data, including personal information about users, has to be aggregated and interpreted before artificial intelligence technology can be used in transportation systems.

Protecting the confidentiality of this information is critical for gaining trust in these technologies and preventing their misuse or exploitation. Furthermore, using AI technology requires a substantial financial outlay for infrastructure.

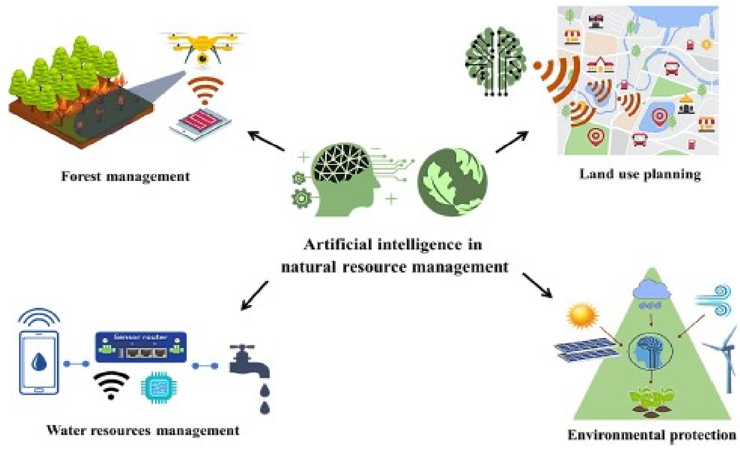

Fig. 3 Using AI to improve transport networks and cut down on emissions of greenhouse gases is crucial.

The image shows how transport systems may be enhanced and carbon emissions can be decreased via the use of artificial intelligence technologies. The statement highlights the possibility of AI optimising transportation routes according to several criteria. Even more impressively, it proves that AI can enhance fleet management efficiency. Moreover, the graphic shows how AI may be used to control driverless automobiles. In the end, the graphic shows that AI can manage transportation service demand and improve public transportation networks.

Modern technology, which encompasses data processing capacities, cameras, and sensors. According to Abduljabbar et al. (2019), smaller transit networks or those in underdeveloped nations may find this to be a major challenge.

In addition, there is an urgent need for well-defined regulations and oversight to guarantee the ethical and responsible use of AI technology in transportation systems, given their increasing popularity. Critical challenges include minimising the worsening of preexisting inequities or prejudices and figuring out who is at fault in incidents involving autonomous cars must be addressed. Also, it has to be acknowledged that driverless cars and other transportation technology driven by artificial intelligence have the potential to oust a lot of truckers and delivery people. It should be a major focus to provide a fair transition for the impacted staff. Lastly, cultural views, user preferences, and faith in these systems are a few of the variables that will determine the acceptability and implementation of transportation technology driven by artificial intelligence. In order to guarantee the success of these technologies, their development should revolve around the users and entail constant consultation with them (Provisor et al., 2007).

Optimisation of transportation routes, management of vehicle fleets, control of autonomous vehicles, optimisation of public transit systems, and management of transportation service demand are some of the ways in which artificial intelligence algorithms can improve transportation systems, as discussed in this section. However, there must be clear law and oversight in place, as well as a large investment in infrastructure, in order to adopt these technologies (Wackernagel et al., 1996).

Responsible and ethical development and deployment of transport systems driven by artificial intelligence depends on addressing these important concerns.

Reducing emissions from fertiliser and chemical usage via the application of artificial intelligence in precision agriculture

Pollinators and the environment are greatly affected by the widespread use of chemical treatments, such as pesticides, to improve agricultural market penetration in response to the ever-increasing need for food. Precision farmers utilise cutting-edge sensors for predictive analytics to improve agricultural production and decision-making. Soil, crop maturity, air quality, weather, equipment and labour availability, and price are all tracked in real-time by these sensors (Raj et al. 2021).

According to Das et al. (2018), the goal of precision agriculture is to maximise agricultural production while minimising environmental impacts. Artificial intelligence is being used to make contemporary agriculture more economical and sustainable. AI helps precision farmers by spotting pests and illnesses, forecasting crop yields, and determining the best times to apply pesticides and fertiliser.

Technology allows for data-input models to evaluate farm structure and efficiency, which in turn leads to improved results (Bacco et al. 2018).

Recent Progress

Recent advances in computer vision, ML, and DL have the potential to greatly improve the speed, accuracy, and efficiency with which agricultural diseases may be identified. Robots and AI are improving to the point where they can mimic human cognition, which boosts efficiency and opens up new avenues for human potential (Barile et al. 2019).

One typical source of herbicide and other chemical residues on plant products is chemical spray transfer, which occurs when the wind transfers mists of spray solutions to nearby fields or crops (Creech et al. 2015). Thanks to precision spraying technology, which may significantly cut down on herbicide use, unnecessary applications of herbicide to duplicated areas are no longer an issue. It is possible to reduce the environmental effect, cost, crop damage, and excessive chemical residues by applying herbicides where weeds are prevalent. More and more, deep learning and convolutional neural networks are being used in agricultural remote sensing applications. The use of computer vision and artificial intelligence by weed-monitoring robots has the potential to reduce the cost of herbicides by 90% and remove 80% of the chemicals now sprayed on crops (Swaminathan et al., 2023). After measuring the soil's nutrient levels and dividing the field into grids, a fertiliser application model determines how much fertiliser to apply using a variable rate applicator. Minimising fertiliser consumption, increasing crop yields, balancing soil nutrients, and reducing air emissions are all possible outcomes of precision fertiliser application. Precision agriculture makes better use of fertilisers and pesticides thanks to artificial intelligence technologies (Wiedmann et al., 2007).

It is possible to maximise plant productivity and create crops that are well-suited to the land via the use of AI and genome editing methods in precision agriculture (Joseph et al. 2021). Reducing chemical runoff from soil may make farming less harmful to the environment by reducing the need for chemical fertilisers. Determined that a 52.6% reduction in pesticide inputs and a 43.6% reduction in pure nitrogen fertiliser inputs could have a positive and substantial effect in the Hafizabad and Sheikhupura districts if rice yields were kept constant. In order to demonstrate that fertiliser application to a particular location efficiently maintains the nutrient balance, Putra et al. (2020) simulated the availability and loss of oil palm nutrients by modelling the quantity of nutrient data held and released by fertiliser application. To optimise the utilisation of water and fertiliser for cotton production, created a system that relies on soil conductivity thresholds. This method

reduces fertiliser and water use by 10.89% by taking soil conductivity and moisture content into account.
Using an unmanned aerial vehicle and the "You Only Look Once" neural system, Chen et al. (2020a) improved pest picture identification to 90%. In order to resolve the issue of leaves being disturbed by propeller wind, stabilised flight unmanned aerial vehicles are used to get high-resolution pest photos. Quicken the process of image recognition to better detect diseases and pests and reduce the usage of pesticides in agricultural settings. An innovative fast and accurate spraying mechanism, a mapping system, and weed detection all come together in the smart sprayer.
With the help of a newly created algorithm, it also creates visual maps. Research by Partel et al. (2019) found that fake and amaranth weeds could be accurately controlled with a 59-71% accuracy rate using a smart sprayer that has an incorporated visual processing unit. This method has the potential to lessen the negative effects on the environment, as well as cut down on pesticide expenses, crop damage, and the danger of excessive herbicide residues. Reducing pesticide spraying by 55% was achieved by Facchinetti et al. (2021) using a "Rover" sprayer truck, which correctly detected colour changes between ground and salad.
The I¬2 PDM system is comprised of a wireless sensor network that collects images, counts of pests, and species via sensor nodes and then saves them in a database for analysis.
This allows for the generation of models that can be visually translated into numerical data. Tomatoes sprayed with the method had their pesticide dosage cut in half, from 235 to 204 L/time, a decrease of 16%; this suggests that the method was successful in reducing pest populations (Rustia et al. 2022).
Finally, AI's scale, robustness, and accuracy allow it to provide real-time data to precision agriculture. By optimising the use of scarce arable land, eliminating unpredictability, and delivering precisely measured amounts of fertilisers and pesticides, precision agriculture—supported by AI—has the potential to increase food production.

Optimisation of industrial processes with the use of artificial intelligence to achieve lower emissions and greater energy efficiency

Green energy strategies have been developed by a number of corporations in recent years in response to the growing awareness of the need to save energy and reduce emissions. There are several obstacles that many industrial firms are now facing as they undergo energy transition. The use of AI, however, may spark novel concepts for the revamping of these businesses. Several excellent management techniques, including comprehensive quality management and the ISO 9000 quality management system, were used by conventional businesses, according to Lei et al. (2023).
A paradigm for managerial excellence. In most cases, a macro view is used while evaluating these management techniques. The digital transformation made possible by the integration of AI into more conventional businesses paves the way for process monitoring at the micro level. By analysing data and feedback mechanisms, artificial intelligence can optimise energy consumption and minimise emissions, resulting in improved efficiency and energy conservation. The use of AI in manufacturing processes is going to be examined in this section.

Optimising industrial processes with artificial intelligence prior to building

Machine learning improves the efficiency of preindustrial process design by controlling the structure of industrial processes and product designs. Neural networks are AI-based computing algorithms that mimic the way the human brain processes and analyses data. Using algorithms, decision logic, and geometric data, artificial intelligence may build process plans via neural network learning. Various aspects, including component shapes and materials, are taken into account while developing manufacturing process plans for new items. A geometry description is the main input to the system. It works in tandem with product modelling efforts, as pointed out by Leo Kumar (2017), and designers may obtain feedback from it fast. From a material utilisation perspective, artificial intelligence can optimise the model to enhance space usage, which in turn saves more resources, increases industrial process efficiency, and reduces emissions. Machine learning finds the most efficient design for manufacturing processes, cutting down on waste and energy use. Data mining, big data, expert systems, machine vision, automation and robots, and machine learning have all been successful in manufacturing. According to Sarker (2022), AI technology has the potential to comprehend the functioning of every process phase, allowing for the prompt identification of problems, adjustments, and optimisations. The same AI may also aid in the allocation of human resources, allowing planners to move projects forward more quickly.
Finally, AI improves the initial design of manufacturing processes via better division of labour and more reasonable product design. In the early phases of design, artificial intelligence helps individuals make more sensible judgements by delivering detailed data, which in turn saves energy.

Using artificial intelligence to optimise the building of industrial processes in the middle stages

In industrial operations, AI is particularly useful for keeping tabs on controls and spotting impending equipment failures. The conventional method of monitoring industrial production processes involves collecting data using physical sensors. However,
Some difficulties arise while using hardware sensors. Considerations like as temperature and humidity in various work settings, onerous customisation needs, sluggish data transmission for measurements, and expensive hardware sensors all influence the outcomes of such assessments. A more traditional method was used by Perera et al. (2023). A few easy tweaks, such removing null or empty data points and replacing them with their corresponding variable averages, resolved the issue. They are not ideal since these technologies may affect how well models work.
The autoencoder is a kind of deep neural network that can rebuild data from several sets and extract relevant information characteristics. Imagine a new soft sensor framework is constructed to develop a variational autoencoder, which is a probabilistic version of the potential variable, which is a random variable. Industrial processes that experience data loss due to malfunctioning sensors may potentially benefit from neural network learning. By addressing the shortcomings of traditional modelling approaches in comparison to models based on classical statistics and machine learning, the most up-to-date AI-based algorithms enable soft sensors to improve computing efficiency and prediction accuracy. With this approach, process monitoring and control may be improved, leading to less material and energy waste as well as fewer pollutants. According to Perera et al. (2023), soft sensors are used to keep an eye on how industrial processes are running. Nonetheless, these problems usually manifest in four ways: dimensionality reduction, process adaptation, missing data from small datasets, and feature extraction from time and space. Experts in a wide range of domains address the problems highlighted in Table 4 by use of AI. Additionally, AI regulates the harmful gas emissions and catalysts used in industrial processes. Refineries may use soft sensors to keep pollutants under control and continually monitor the environment. This has a direct influence on environmental sustainability. Pulp and paper companies may be able to use soft sensors developed by Fernandez de Canete et al. (2021) to monitor bleached effluent levels that include harmful substances. Soft sensors are used by the pulp and paper industry to foretell the requirement for chemical oxygen in order to maximise material efficiency and financial advantage, allowing for significant paper wash-out.
Industrial processes are aided in performing difficult procedures by artificial intelligence. The assembly industry combines mechanical pieces or components into machines by connecting them according to the technical requirements of the design. Using assembly-style preconditioners that may successfully decrease human mistakes, the assembly sector can speed up the utilisation of raw materials and remove certain linkages in industrial processes. According to Cohen et al. (2019), a substantial amount of data analysis is necessary for precomponent manufacture. If issues with component data lead to inefficiency, which in turn lowers business productivity and wastes resources. One of them is for smart manufacturing, as stated by Cioffi et al. (2020). When the factory, supply chain, and consumer demands change, this collaborative manufacturing system responds instantly. An alternative approach is lean manufacturing, which seeks to maximise efficiency while

decreasing costs. To achieve elastic performance, a revolutionary "cyber-physical production system" transforms information from interconnected systems into necessary and predefined processes. The product lifecycle is enhanced with the help of digital twin technology. Both methods have the potential to ensure that the preconditioners are accurate, which would increase efficiency and decrease emissions.

So, to sum up, AI helps soft sensors monitor pipeline data while an industrial operation is underway. Soft sensors aren't perfect, but AI improves upon them by creating models that mitigate their shortcomings. With more precise information, chemical usage can be better managed, and emissions can be cut down.

When it comes to optimising industrial processes, artificial intelligence is most useful in the latter phases. Managers in industrial processes eventually resort to AI in order to fix wasteful and improper allocation of resources. According to Dwivedi et al. (2021), AI boosts productivity by integrating different management techniques. For instance, the enterprise's management may optimise the production line with the aid of artificial intelligence and lean manufacturing, where each production link determines its own efficiency and thus decreases the loss of connected raw resources caused by idle time. The main use of AI in this context is to analyse data and, therefore, to interpret or evaluate outcomes in order to enhance resource and energy management.

The use of AI may improve the efficiency of flexible manufacturing on established assembly lines. Adapting to unforeseen changes in the production process is an essential part of resilient manufacturing in order to keep production activities running smoothly. Intelligent optimisation and field conditions dictate how the control system is changed.

Even when the appropriate managers aren't physically present, AI may upload data from connected devices to the cloud, enabling remote management of production processes. Because of this improvement, the manufacturing process is more adaptable and sturdy. According to Oruganti et al. (2023), this approach helps industrial process assembly lines deal with mishaps and relieves managers of some of the burden that comes with it.

In this part, AI can optimise convection lines in established industrial processes, which lowers the hazards involved. By transferring pertinent pipeline data to mobile devices, it may also provide data support for industrial operations, allowing for remote access to vital information.

To summarise, AI helps reduce scrap rates by improving product design with data modelling and industrial process monitoring using soft sensors. In addition, AI may optimise assembly lines, boost efficiency by doing away with redundant processing stages, aid managers in flexible production, and lighten their workload in established industrial systems. When it comes down to it, AI helps industrial processes run more efficiently by reducing the effect of labour.

Using AI to manage natural resources: cutting down on emissions and deforestation

Worldwide, there has been a lot of interest in the challenges and opportunities of managing natural resources (particularly land, water, and forests) in the last several years. Important ecosystem services and biodiversity-supporting habitats are being lost as a result of deforestation. Some have suggested employing AI models to lessen the impact of this risk. Modelled deforestation rates and incremental deforestation in the Amazon rainforest using a dense neural network for spatially static data and an extended short-term memory network for deforestation data that is time-varying. Predicting the pace of future forest loss, comparing the results, and retraining the model with new data allows us to take proactive steps. Deforestation risk maps were reasonably created in the study areas of Madagascar and Mexico utilising all strategies that made use of publicly available information. Prediction accuracy was made more stable by using Gaussian processes. But the model could only determine whether deforestation risk existed; it had no idea how much or where deforestation would occur or what factors would cause it. In their study, Torres et al. (2020) discovered that a weightless neural network architecture, comprised of an unmanned aerial vehicle and a field-programmable gate array, enhanced visual processing capabilities. This made it possible to better monitor deforestation and evaluate visual navigation in rural green regions. We modelled forest fires and reasonably predicted their origins in Vietnam using particle swarm optimisation neuro-fuzzy, random forest, and support vector machines. The optimal parameter values were likewise determined by the model. Forest fire management and planning may benefit from fire sensitivity maps, which were developed by Tien Bui et al. (2016).

By establishing a biological retreat configuration, Yin et al. (2021) hoped to supervise the restoration of terrestrial ecosystems inside the Changsha-Zhuzhou-Xiangtan urban area. Their intelligent planning framework utilises artificial intelligence. It detects environmental components in current biodefense zones, proving that retreat patterns help comprehend how urban growth affects ecologically important processes, and it gives machine learning credibility when it comes to predicting green resources.

Vegetation screening and backpropagation in ecological berms are based on soil moisture that is vulnerable to climate change. To fix the issues with local minima and make better use of the system's increased processing capability, proposed a genetic algorithm-optimized neural network regression model for Zhejiang provincial roadways.

According to Gautam et al. (2023), artificial intelligence and machine learning are necessary for controlling or managing land pollution. This may be achieved by prediction, clustering, data-centric analysis, and soil quality assessment.

The rising demand for water caused by climate change, urbanisation, and population growth necessitates the use of modern technical platforms for the management of diverse and intricate urban water resources. Adaptive intelligent dynamic water resource planning is a less complicated method of improving water efficiency. It employs a subset of AI technology to preserve the water environment in urban areas. In order to improve the accuracy of evaluating the regional water environment, Liu et al. (2019) enhanced the moth flame method in their projection tracking water quality assessment model by adding dynamic inertia weights, which increase stability and dependability.

Integrating long- and short-term memory with recurrent neural networks allowed us to tackle the problem of shifting climate change inputs on Prince Edward Island. Accurate information on reference evapotranspiration could help with water management and sustainable agriculture by meeting crop water needs. If your potatoes aren't receiving enough water, it could also let you know straight away. In a study conducted in Kurdistan region, Bagheri et al. (2017) used a fuzzy logic model to analyse the cost of leachate concentration at various depths in groundwater. More precise measurement of molybdenum, sodium, and chemical oxygen demand was achieved ($R2 = 0.99998$), and the use of artificial neural networks for leachate evaluation and prediction was proven.

Urban land use planning has a substantial impact on the communities that live in cities and the ecological, social, and economic activities that occur there. These studies may be conducted at a significant save by using aerial image analysis to identify physical surface materials or human land usage.

By using remote sensing imaging technologies, environmental data and geospatial information may be collected via ground observation. It is possible to train deep learning models to accurately identify various kinds of habitations, as well as land cover or land use (Alem and Kumar 2022). Ghavami et al. (2017) demonstrated the feasibility of automated urban land use planning consultations in Zanjan, northwest Iran, by using a multiagent system-based intelligent planning support system and employing Bayesian learning methodologies. Furthermore, when compared to support vector machines, random forests, and k-nearest neighbours, convolutional neural networks outperform them when it comes to land cover/land categorisation.

Figure summarises the critical role that artificial intelligence plays in NRM. 6. Land use planning, water resource management, ecosystem restoration, and forest resource management are all part of this. Machine learning makes it easier to control how resources are used, makes better use of those resources, and cuts down on waste.

Making cities that are both sustainable and resilient via the use of AI

City dwellers make up more than half of the global population; they are a haven for the contemporary, but they also use a lot of power.

The primary tactic for reducing the severity of global warming is reducing emissions of greenhouse gases, which are mostly produced by urban areas and constitute three quarters of all emissions. There is a complicated interaction between climate change, sustainable urban development, and its effects on towns.

Uncertainties and unknown hazards are becoming more prevalent as climate challenges worsen. Anxieties about energy shortages, air pollution, and improper waste management is only one of many urgent issues that people are wondering how "resilient" communities handle catastrophes (Zhu et al. 2019). Following in the footsteps of intelligent cities, the notion of resilient cities has arisen as a means to fortify metropolitan areas against natural catastrophes and facilitate their own recovery from such events. The similarities and contrasts between resilient and smart cities were investigated by Zhu et al. (2020b).

A number of areas of waste management may benefit from the use of artificial intelligence, including waste-to-energy, sorting, models for waste creation, plastic pyrolysis, logistics, disposal, and resource recovery. In addition to enhancing public health, it may aid in the decrease of unlawful dumping. Implementing AI in trash logistics may cut transportation distance by as much as 36.8%, save money by as much as 13.35%, and save time by as much as 28.22%. Improvements in waste pyrolysis, carbon emission estimate, and energy conversion may be achieved by combining chemical analysis with artificial intelligence. The waste management systems in smart cities may be made more efficient and cost-effective using this technology. The idea of resilience has been extensively refined and broadened since its introduction by Holling in 1973 to ecosystem study. Natural calamities like hurricanes, floods, and earthquakes may swiftly devastate towns that are experiencing rapid development. Massive crises can hit cities when terrorist strikes and unexpected viral outbreaks occur. Academics are paying more and more attention to the topic of building resilient cities due to the growing vulnerability of metropolitan areas. When it comes to solving environmental problems, artificial intelligence is not a silver bullet. Nonetheless, it may aid in human planning and the establishment of sustainable lives, making cities more resilient, thanks to its efficiency and reliability as a framework.

Water resource management in cities is becoming more difficult as a result of rising climate uncertainties. Cities become more secure, resilient, and environmentally friendly as a result of AI's logical planning and limitations on the use of water resources. In order to maintain the water environment of urban areas and maximise the use of water resources, introduced an adaptive intelligent dynamic water resource planning system that used artificial intelligence modelling to streamline the information transformation process. In their investigation of potential strategies for the environmentally responsible administration of Ebbsfleet Garden City's water supply, Pluchinotta et al. (2021) used a system dynamics model. Their innovative method utilises a genetic algorithm, a Bayesian framework, and a linked dynamic artificial neural network architecture to forecast the short-term water demand for irrigation with little data. Maurya et al. (2020) have offered a framework for managing and planning urban water resources that relies on stress state response and complete management of urban water resources.

In order to make resilient urban mobility more efficient, the internet of things is also crucial. The internet of things, which makes use of artificial intelligence, has enabled cities to become living organisms with a greater capability for adaptation and interconnection among its numerous parts. With the help of artificial intelligence, the massive volumes of data supplied by the internet of things may be processed to optimise energy usage and resource management. This has the potential to establish a smart network that links all physical objects on Earth. An innovative approach of delegating reasoning calculations to the various nodes in a multilayer IoT network was put out. In order to minimise transmission costs while maintaining an optimal balance in the associated computation time, they developed a dynamic programming approach. In order to facilitate online analysis and evaluation in real-time, create a novel network information physics system, an assessment framework based on machine learning, and an online sorting algorithm. Smart city network architectures are being enhanced by the integration of blockchain technology and artificial intelligence into the internet of things network.

Air pollution hinders healthy ecological progress and also harms human health. Testing and managing air quality is essential for building a resilient city. A one-step model was developed and the air quality index was analysed utilising sensors using linear regression, support vector regression, and gradient enhancement decision trees. Additionally, a new model was created. They focused on assessing the air quality in Manchester and improving the forecast of traffic-related air pollution, and they contrasted it with a particular background statistical model. collected data using decision trees and neural networks, as well as mobile and stationary air quality measurement equipment, and used machine learning methods. According to their research, the main variables impacting the accuracy of nitrogen dioxide concentration forecasts at mobile collecting locations are humidity and noise. Using artificial neural networks and multiple linear regression, compared the air pollution data across the five schools using correlation, various statistical indicators, and residual distribution. When the number of air quality networks is low, they discovered that artificial neural networks perform better computationally.

To sum up, the promotion of urban resilience and sustainable development relies heavily on artificial intelligence technology. Artificial intelligence (AI) can optimise urban operations and resource management using real-time data, analysis, and predictions made possible by big data and deep learning methods. As a result, cities are better able to withstand natural calamities.

Perspective

According to Shao et al. (2022), several sectors are quickly adopting innovative technologies like artificial intelligence. Nonetheless, substantial carbon emissions may be caused by the exponential growth of computational and energy needs linked to several contemporary machine learning systems and technologies. To better evaluate carbon dioxide quantification and the ecological efficiency of industrial activities, machine learning algorithms may create various hierarchies and orders of magnitude among various models. According to He-derson et al. (2020), one way to lessen the impact on the environment is to create and standardise a transparent, reliable, and comprehensive system for determining how much power AI models use. In order to advance the assessment criteria, such as recall, accuracy, or precision, for the project's energy consumption computation, cloud data storage, computer hardware, and hardware suppliers are crucial for evaluating artificial intelligence algorithms' energy consumption. Both state that proper operation of equipment generating renewable energy is necessary for automating system control and improving the automation of grid intelligence. In order to reduce grid instability, advocate for new smart infrastructure that consumes less energy and policies that encourage the sustainable development of AI. In order to facilitate smart grids powered by artificial intelligence, energy segmentation may aid AI ecosystems or systems of systems by facilitating organised data management, data mining capabilities, and machine learning approaches. To go a step further in addressing privacy and security concerns, the electric system's data management systems will need to be reorganised and updated, which would need a substantial initial expenditure. Utility firms will need resources (both time and money) to become "data ready" for the effective implementation of AI solutions. Any investments in the road will have a solid foundation in the data layer.

Using transport networks and IoT devices to gather and analyse data in real-time on the ground, congestion may be significantly reduced. Digital twins may be used for intelligently monitoring surface and subterranean space anomalies in urban building and operation management. With the help of a city information model, one can build a three-dimensional model of the city's space, manage the planning, construction, and operation of urban traffic in three dimensions, simulate, analyse, and verify urban traffic, and intelligently oversee urban transportation. There is a great opportunity to develop autonomous, cost-effective, energy-efficient, and user-friendly agriculture solutions based on the internet of things (IoT) with strong architecture and minimal maintenance by utilising long-range, ZigBee, wireless fidelity, 5G, and new narrow-band IoT communication technologies. Integrating phenotypic and genotypic data at the plot level using artificial intelligence models is one way to tackle complex agricultural challenges. Another approach is to use crop simulation models in combination with remote sensing for crop phenotype data. According to Vinuesa et al. (2020), AI has the potential to bring about beneficial societal and urban changes, as well as aid in the attainment of many sustainable development objectives. Nevertheless, it is equally crucial to push for the establishment of suitable rules and regulations in order to lessen the impact of artificial intelligence on the most susceptible urban and social groups as well as the environment. Finally, AI's algorithmic calculation creates judgements that are optimised, reasonable, and made quickly, which enhances efficiency for future practical applications. By embracing IoT and tel-ecommunication technologies, social transit and agricultural systems may progress, aligning with the goal of sustainable urbanisation.

CONCLUSION

The demand for energy has grown at an exponential rate due to the expansion of the global economy and population. Conventional methods of energy generation have shown to be harmful to the environment, leading to overexposure of the planet to dangerous gases that cause climate change and a heightened risk of catastrophic weather events like tornadoes, hail, and thunderstorms that destroy homes and put lives and property at risk. A new weapon in the fight against climate change, artificial intelligence is showing great promise in the energy industry as a means to solve these problems and lessen their negative impact on the environment. When it comes to energy, artificial intelligence helps mitigate climate change by improving efficiency, anticipating demand, and reducing pollution. AI is being used by several countries to decrease energy waste and increase energy efficiency. Furthermore, AI has enhanced weather prediction tools, allowing for more precise forecasting and modelling, which in turn helps with early warning systems for both preparing for and responding to severe weather. Optimal locations for renewable energy may be more easily identified with the use of artificial intelligence, which allows for a more thorough understanding of natural factors like topography and climate. It has the ability to forecast the generation of renewable energy, modify the output of the grid, and guarantee a constant supply of power. In addition, AI has the potential to improve home design by determining the best orientation for a house and where to put windows, which may lead to less energy use and better living conditions. It is equally important to address traffic pollution, and AI may improve bus systems by training neural networks to optimise routes, vehicle rounds, and passenger traffic using massive data sets.

To lessen the ecological footprint of agricultural pesticides, artificial intelligence is crucial. To help farmers make better choices, use less chemicals, and boost output, precision agriculture uses AI to gather and analyse environmental data pertaining to crop development. When it comes to making decisions in the industrial sector, conventional hardware sensors just don't cut it. By analysing data, creating models, and filling in gaps left by hardware sensors, artificial intelligence helps decision-makers optimise industrial processes, which in turn reduces emissions and energy consumption. AI improves our knowledge of the natural world, which in turn helps us anticipate when forests will be cut down and how many trees will be lost. This information can be used by governments to better safeguard our planet and encourage the use of renewable energy sources. Additionally, AI can help build more sustainable and resilient cities by calculating pertinent data to reduce the impact of harsh weather on inhabitants. Furthermore, decision-makers are provided with correct data and energy efficiency is enhanced by artificial intelligence, which considerably reduces the impact of climate change.

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