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Mitigating Climate Change using Artificial Intelligence

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Abstract- *In this article, we analyse the role that artificial intelligence (AI) could play, and is playing, to combat global climate change. We outline how machine learning can be an effective tool for cutting greenhouse gas emissions and assisting society with climate change adaptation. In partnership with other sectors, we identify high impact issues—from smart grids to disaster management—where there are current gaps that can be filled by machine learning. Although AI has many benefits, there are certain drawbacks that prevent it from being widely used in climate change research. Recommendations are offered to ensure that AI is successfully applied in current and future climate change challenges.*

Keywords: **Artificial Intelligence; Climate Change; Groundwater contamination; Sustainability; Machine Learning; Greenhouse emissions.**

1. INTRODUCTION

Climate change is one of the most pressing issues of our time. Its effects are already being seen on a global scale and are expected to increase exponentially, with disproportionate effects on the most marginalised populations in the world [1]. The intensity and frequency of storms, droughts, fires, and flooding have increased [2]. Global ecosystems are evolving, affecting human reliance on agriculture and natural resources. To combat climate change, society as a whole must take action using a variety of communities, methods, and instruments [3]. The primary and well-known area of computer science that works with creating intelligent systems and finding solutions to issues similar to the human intelligence system is known as artificial intelligence (AI). Applications of AI to systems are mostly intended to improve computer capabilities that are related to human understanding, such as learning, problem solving, reasoning, and perception [4]. Healthcare, smart cities and transportation, e-commerce, banking, and academics are just a few of the industries where AI is finding practical applications. Machine learning, deep learning, and data analytics are additional divisions of AI. These methods are mostly employed in the fourth industrial revolution (Industry 4.0), block chain, cloud computing, and the internet of things (IoT) [5]. The major reasons why AI is flourishing are its special abilities to decide, learn, and modify a system based on past data. Due to the inclusion of intelligence, flexibility, and intentionality in AI-based systems' proposed algorithms, AI's importance is continuously growing throughout time. [6]. Artificial intelligence (AI), has a lot of potential to speed up plans for climate change adaptation and mitigation in fields including energy, land use, and disaster response (see Key Areas). However, there are now several roadblocks and difficulties that prevents AI from reaching its full potential in this area. In this research, we aim to provide an actionable set of recommendations on what can be done to facilitate AI for climate impact. AI may help advance and broaden our understanding of climate change, and it is becoming an increasingly important component of a set of answers that are necessary to properly address the climate catastrophe by delivering far greener, more sustainable, and effective solutions. This paper aims to provide an overview of where machine learning can be applied with high impact in the fight against climate change, through either effective engineering or innovative research. It is important to note that AI systems are applicable to almost all interdisciplinary fields, and they have played their potential role in various applications for optimization, classification, regression, and forecasting. Although there are numerous uses of AI in advancing sustainability [7]. We in this research focus strictly on the intersection of AI with climate action, which is already a very broad topic.

2. LITERATURE REVIEW

David Rolnick et al., Tackling Climate Change with Machine Learning (2019)

The paper discusses about the severity of the climate change and how machine learning can be used to solve the problems related to it to some extent. The paper calls on the Machine Learning. The report appeals to the ML community to support efforts being made worldwide to combat climate change. According to the research, improvements to land use, buildings, transportation, and electricity systems are sufficient to reduce GHG emissions. The research comes to the conclusion that ML is an important tool that contributes to the answer rather than providing it entirely. ML can speed up scientific advancement and improve system performance to increase efficiency, lowering GHG emissions. Although this is the case, the paper claims that climate-relevant data's nature presents both difficulties and opportunity. Data may be confidential or contain sensitivity personal data. Where datasets are included, they might not be built up with a particular goal in mind, unlike standard ML benchmarks that have a clear goal. Datasets may contain information drawn from a variety of sources, which must be merged using advance knowledge.

3. ARTIFICIAL INTELLIGENCE

Artificial Intelligence is defined as 'the science and engineering of making intelligent machines' as termed by Stanford Professor John McCarthy in the year 1955. Artificial Intelligence methods can loosely be divided into symbolic approaches, which rely on predefined rules and logic to derive results, and statistical approaches, which rely on induction from data rather than deduction from rules [8]. AI may be characterised as a set of multipurpose tools and techniques designed to simulate and/or improve upon processes that would have seemed intelligent had a human performed them [9]. AI systems are applicable to almost all interdisciplinary fields and they have played their potential role in various applications for optimization, classification, regression and forecasting. The recent developments and popularity of AI is largely due to its sub branch known as Machine Learning. Machine Learning is a subset of Artificial Intelligence, which provides machines the ability to learn automatically and improve from experience without being explicitly performed. Thus, in ML algorithm the exact nature of the computations performed is not specified in advance, but instead is learned by the algorithm by identifying the patterns within the data, which can be used to make predictions on new data. While Artificial Intelligence has already a significant impact in the fight against climate change, there currently exists a number of bottlenecks and challenges that impede AI from realizing its full potential in this matter [10]. Therefore, it is extremely important to develop, deploy and govern AI responsibly in the context of climate change so that the methods are not only effective but also ethically sound.

3.1 Avoiding and minimising the risks

When it comes to ethical risks, employing AI in the context of climate change is less risky [11] than using AI in fields like health and criminal justice, where collecting personal information and making judgments that directly affect people is the norm. However, it is crucial to prevent or reduce any potential ethical issues in order to maximise the benefits of AI in the battle against climate change. The first set of dangers is related to how AI models are created and developed [12]. The majority of data-driven approaches to AI are supervised, meaning they "learn" to cluster, classify, predict, or decide based on new, previously unobserved data by first being "trained" on existing labelled data. This raises the possibility of unintended bias influencing the conclusions reached by an AI system. This could result in prejudice and unjust treatment of some people or groups. The potential loss of human autonomy brought on by some climate-focused AI systems is a second set of hazards [13,14]. Large-scale, coordinated effort is needed to combat climate change, as well as deliberate adjustments in each person's behaviour. Understanding individual behaviour, according to [15], "may help signal how it can be nudged," such as by reducing people's "psychological distance" from the climate problem, assisting them in visualising its effects, or inspiring them to take environmental action. Since there is much debate about how nudging affects individual autonomy [16] and whether it interferes with people's ability to make "free choices" [17], adopting such a strategy in the context of the environment necessitates finding the right balance between upholding individual autonomy and enacting extensive climate-friendly policies and practises [18]. AI applications to combat climate change have the danger of violating privacy in addition to fair treatment and autonomy. Insofar as AI systems rely on non-personal data, such as meteorological and geographic data, to comprehend the climate catastrophe, privacy concerns are unlikely to be raised. However, developing measures to reduce emissions would necessitate data that reflect trends in human behaviour, where privacy issues might be more pertinent. For instance, the effectiveness of AI systems depends on detailed information about energy demands, which is frequently available in real time, in control systems intended to reduce carbon footprints in a variety of contexts, such as energy storage [19], industrial heating and cooling [20], and precision agriculture [21]. The information gathered can include sensitive personal information, putting both an individual's and a group's privacy at danger [22].

3.2 Nations using Artificial Intelligence to combat climate change

As per the climate update issued by the World Meteorological Organization (WMO), there is a 40% chance of the annual average global temperature temporarily reaching 1.5°C above the pre-industrial level in the next couple of years [210].

India- In order to combat climate change, India is utilising AI and IoT. IoT is in charge of acquiring data from sensors, whereas artificial intelligence serves as the analytics engine. In addition to improving deforestation tracking, building sustainable infrastructure, finding new materials, and forecasting natural disasters like hurricanes, landslides, and earthquakes, these technologies are helpful in enabling precision agriculture on a large scale.

Japan- Since March 11, 2011, both the use of coal-fired power and GHG emissions have increased dramatically in Japan. AI has a significant impact on addressing climate change-related problems and assisting the nation in achieving new economic growth.

Germany- Manufacturing companies in Germany are increasingly using AI innovation to streamline product development and creation and see huge potential to reduce their energy and resource usage. Expanding the use of machine learning in assembly reduces the use of natural resources, energy use, and CO2 emissions.

Russia- By 2030, Russia has promised to cut greenhouse gas emissions by up to 70% from 1990 levels, presuming that its extensive forests would be able to absorb all of the carbon dioxide that can be. With the aid of instruments that enhance the creation of clean energy, understand carbon footprints, and produce new low-carbon materials, Russian researchers are doing their best to meet the goal.

Rank	Rank change	Country	Score**	Categories
1.*	–	–	–	
2.	–	–	–	
3.	–	–	–	
4.	2 ▲	Denmark	76.92	
5.	-1 ▼	Sweden	74.46	
6.	2 ▲	Norway	73.62	
7.	-2 ▼	United Kingdom	73.29	
8.	-1 ▼	Morocco	71.64	
9.	0 –	Chile	69.66	
10.	0 –	India	69.22	
11.	4 ▲	Lithuania	65.06	
12.	0 –	Malta	64.39	
13.	6 ▲	Germany	63.82	
14.	-3 ▼	Finland	62.74	
15.	-1 ▼	Switzerland	61.98	
16.	1 ▲	Portugal	61.45	
17.	6 ▲	France	61.33	
18.	3 ▲	Luxembourg	61.03	
19.	10 ▲	Netherlands	60.81	
20.	0 –	Ukraine	60.52	
21.	1 ▲	Egypt	59.83	
22.	-6 ▼	European Union (27)	59.53	
23.	new	Philippines	58.98	
24.	10 ▲	Greece	58.55	
25.	new	Colombia	58.11	
26.	-13 ▼	Latvia	58.06	
27.	-3 ▼	Indonesia	57.39	
28.	-10 ▼	Croatia	56.26	
29.	3 ▲	Mexico	56.19	
30.	-3 ▼	Italy	55.70	
31.	-5 ▼	Thailand	55.28	
32.	6 ▲	Estonia	55.25	
33.	-8 ▼	Brazil	55.17	
34.	7 ▲	Spain	54.71	
35.	-7 ▼	New Zealand	54.49	
36.	-1 ▼	Austria	52.80	
37.	-4 ▼	China	52.66	
38.	-8 ▼	Romania	52.59	
39.	-2 ▼	South Africa	51.56	
40.	-9 ▼	Slovak Republic	50.90	
41.	8 ▲	Cyprus	50.89	
42.	0 –	Turkey	50.75	
43.	new	Viet Nam	49.35	
44.	0 –	Bulgaria	49.02	
45.	0 –	Japan	48.94	
46.	-7 ▼	Ireland	48.29	
47.	-1 ▼	Argentina	47.50	
48.	-12 ▼	Belarus	46.91	
49.	-9 ▼	Belgium	46.27	
50.	1 ▲	Slovenia	43.73	
51.	-4 ▼	Czech Republic	42.53	
52.	-4 ▼	Poland	41.01	
53.	-3 ▼	Hungary	40.71	
54.	-11 ▼	Algeria	40.24	
55.	6 ▲	United States	37.90	
56.	-4 ▼	Russian Federation	35.00	
57.	-1 ▼	Malaysia	34.37	
58.	-4 ▼	Australia	30.41	
59.	-6 ▼	Korea	27.28	
60.	-3 ▼	Chinese Taipei	27.11	
61.	-3 ▼	Canada	26.73	
62.	-3 ▼	Islamic Republic of Iran	26.35	
63.	-3 ▼	Saudi Arabia	24.45	
64.	-9 ▼	Kazakhstan	19.81	

Rating
Very High
High
Medium
Low
Very Low

Index Categories
GHG Emissions (40% weighting)
Renewable Energy (20% weighting)
Energy Use (20% weighting)
Climate Policy (20% weighting)

Table 1: Climate Change Performance Index 2022.
Source: ccpi.org

Australia- In an effort to keep up with the rapid shift in dangerous conditions, Australia's tropical marine research agency is accelerating face recognition technologies to analyse coral reef study images.

United States- The goal of the USA is to eliminate all emissions from the economy by 2050.

3.3 Climate Change Performance Index

According to Climate change performance Index 2022, Denmark is the international role model when it comes to combating climate change with the rank of 4. With the United Kingdom (7th), India (10th), Germany (13th), and France (17th), four G20 countries are among the high-performing countries in CCPI 2022.

4. CLIMATE CHANGE: THE CATASTROPHE

Climate change is a phenomenon of the change of weather patterns over a period. Human and natural influences have a massive role in this phenomenon. Accumulation of greenhouse gases is the major reason of climate change. Greenhouse gases trap heat to maintain the earth's temperature to sustain life [39]. However, humans have been contributing to an increase in the atmospheric CO_2 concentrations and other green-house gases due to the result of increased fossil fuel burning and deforestation [26]. The Global average surface temperature has risen at an average rate of 0.17˚F per decade since 1901 [24]. The years between 2015 and 2019 were the warmest years on record while the decade 2010-2019 have shown a huge spike in the surface temperature making it the warmest decade on record. [31,24]

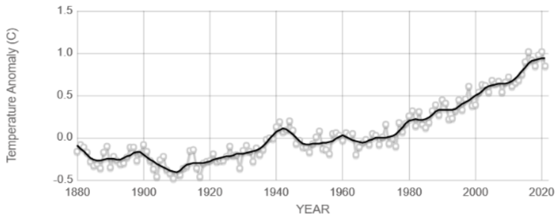

Fig 1: Instrumental temperature data 1880-2020. *Source: NASA Goddard Institute for Space Studies (GISS)*

CO_2 is the one of the main important greenhouse gases to Earth's energy balance [31]. The concentration of carbon dioxide in Earth's atmosphere is currently at nearly 419 parts per million (ppm) in 2022 and rising. Scientists have found a distinctive isotopic fingerprint in the atmosphere proving that such a spike in the concentration is due to human activities [32,34] Human and industrial activities have dramatically raised the CO_2 content by almost 50% since 1750 [33]. Other greenhouse gases like Methane, Nitrous oxide and Halocarbons too have risen significantly due to human activities, agricultural activities and chemicals. As the temperature rises, more evaporation takes place, reducing surface water. As a result, soils and vegetation become drier. This makes periods with low precipitation drier than they would be in cooler conditions. The lack of water in regions due to climate change makes it difficult for underdeveloped land to provide proper vegetation. Local air quality can be affected by climate changes. As pollutants are emitted into the air, they can alter the climate. The presence of ozone in the atmosphere warms the climate, while different components of particulate matter (PM) can either warm or cool it.

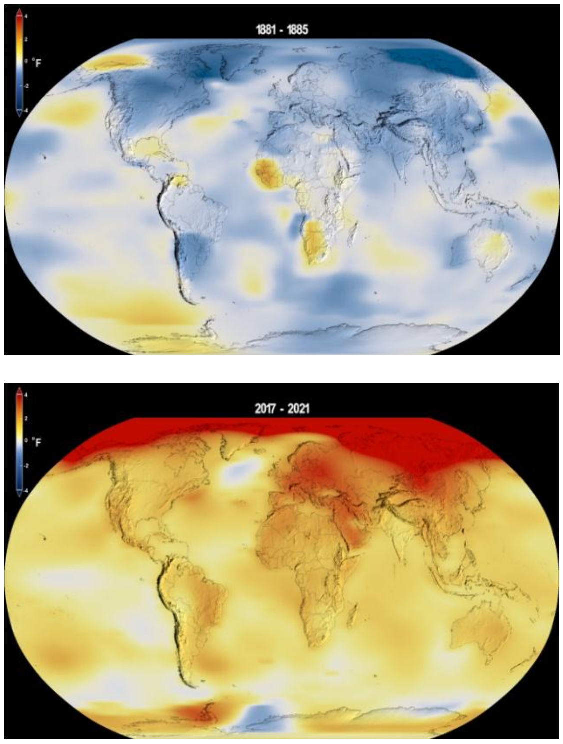

Fig 2: Comparison between Global temperature anomalies between 1881 and 2021. *Source: NASA's Scientific Visualization Studio*

Climate change increases the production of allergenic air pollutants, including mold and pollen. Wildfires linked to climate change could also significantly reduce air quality. The unprecedented rate of global warming is increasing ocean temperatures and acidification, which threatens marine biodiversity. Historically, monuments like Taj Mahal were designed based on the climate of the area [25]. The white marble has become yellow due to high levels of air pollution. Dust, black carbon, and organic carbon are also abundant in Agra, which absorb light [36]. In several places of the intricate floral inlay works, greenish black patches are visible due to bugs breeding in stagnant water and infesting the marble walls [36]. The effects of climate change are disrupting weather patterns, resulting in extreme weather events, unpredictable water availability, and contaminating water supplies. Impacts of this kind can have a drastic impact on the quantity and quality of water that humans need to survive [23]. Due to climate change, heavy downpours, droughts, and rising water temperatures are more frequent, altering the quality of our drinking water and recreational water. These changing conditions are ideal for bacteria and viruses to thrive, causing illnesses such as legionella, campylobacter, and cholera when in contact with humans. In addition, climate change can lead to a decrease in precipitation and an increase in droughts. As carbon dioxide emissions rise, ocean temperatures and acidity increase due to climate change.

More potent Tropical Cyclones are probably being fuelled by the warming of the ocean's surface caused by anthropogenic climate change. Rising sea levels, which most certainly significantly contribute to human climate change on a global scale, increase the destructive capacity of individual tropical cyclones through flooding. Furthermore, increased atmospheric moisture brought on by human-caused global warming is expected to result in higher rates of tropical cyclones precipitation [37]. Possible consequences of anthropogenic climate change include an increase in the proportion of category 4 and 5 intense tropical storms. It is predicted that this percentage of powerful tropical cyclones will rise even further, bringing with it a greater percentage of storms with more destructive wind speeds, greater coastal flooding, and more intense precipitation rates [37]. Warm, humid air serves as the fuel for tropical cyclones. There may be more of this fuel available because climate change is raising ocean temperatures. Rapidly strengthening cyclones, however, are difficult to predict, which increases the risk to coastal settlements [38].

4.1 Climate change link to groundwater contamination

To begin with, contamination is the process of addition of undesirable substances to the groundwater that in turn affect the nature [42]. A number of interacting forces place the river at risk, including pollution, urbanization, overexploitation, and climate change. Consequently, the Yamuna ranks among the most polluted rivers in India and the world [35]. Water deficits have arisen due to climate change's impact on India's monsoon cycle, resulting in short-duration, high-intensity rainstorms, and insufficient rainfall. In addition, climate change contributes to serious droughts, quick storm bursts, and floods, which cause deaths, property damage, and additional pollution of the Yamuna River. In addition to the flood damage and pollution, soil erosion is exacerbated by the Yamuna's waters absorbing atmospheric carbon emissions and acidifying them [35]. Five years ago, it was determined that Yamuna pollution was a threat to the Taj Mahal, attributing the nesting of insects whose excrement was leaving patches on the marbles to the production of phosphorous in the river's water [25]. According to a recent study titled "Role of air pollutant for deterioration of Taj Mahal by identifying corrosion products on the surface of metals," hydrogen sulphide, which is released from the polluted Yamuna, is more corrosive than sulphur dioxide, which is produced by industrial pollution and was previously held responsible for the deterioration in the Taj's marble [41]. The gas responsible for the odour may be causing more damage, as hydrogen sulphide (H_2S) produced from polluted Yamuna water had a stronger corrosive impact than sulphur dioxide (SO_2) generated by industrial pollution in Agra city [36]. Biochemical oxygen demand (BOD) is the minimal amount of oxygen needed by the river to decompose and manage the organic materials in the water, whereas dissolved oxygen (DO) measures the existence of the gas and, consequently, life in the water. 5 mg/l is the permissible level for DO. BOD should ideally range between 1 and 3 mg/l. Furthermore, the faecal coliform (MPN/100ml) should be in between 500 and 2500. However, when the "Delhi Pollution Control Committee" conducted a monthly study on Yamuna in July 2022, it was found out that when the river reached in Okhla Barrage, the BOD was 70 mg/l; faecal Coliform was 630000 MPN or most probable number per 100 ml, drastically exceeding the limits. It shows that there are higher disease-causing pathogens present in the river [40]. Due to a lowering of the groundwater table near or below the well's bottom or from low and inadequate maintenance, many groundwater wells have become contaminated, unprotected, or on the verge of failing. These wells won't be able to provide water during emergencies and calamities, which will affect millions of people's ability to maintain their livelihoods. They either will become contaminated by flooding or dry out as a result of droughts. The likelihood of water supply salinity issues is increased by projected sea level rise and excessive groundwater extraction in coastal regions and on small islands. Groundwater quality and quantity are always intimately correlated with conditions for recharging. With addition to being affected by the amount of annual precipitation, the latter is also influenced by the qualities of the land's surface, the vegetation it is covered in, and the properties of the soil. Groundwater will be indirectly impacted by global warming as part of climate change. The thawing of large regions of permafrost at high latitudes will release enormous amounts of methane gas and acidic pore water. Rivers may be fed more by sporadic rains than by glaciers and snow caps on mountains, which once produced flow during lengthy seasonal periods. Less groundwater will be recharged by such rivers, and such streams may even lose water to the ground instead of supplying it [43]. Depending on the properties of the contaminant, (physical, chemical, biological properties) that has been released into the ground, may move through the aquifer in the same pattern that ground water, although some contaminants may not because their physical and chemical properties do not always follow ground water flow. It is possible to predict to some extent, the transport along the aquifer of those contaminants. Ground water pollution can occur from on-site sanitation systems, landfill leachate, effluents from waste water treatment plants, leaking sewers, petrol filling stations or from excessive application of chemical fertilizers in agriculture. These pollutants often create a plume within the aquifer. Because of the slow movement of contaminants, they tend to remain concentrated in the form of a plume that flow alongside the ground water [42].

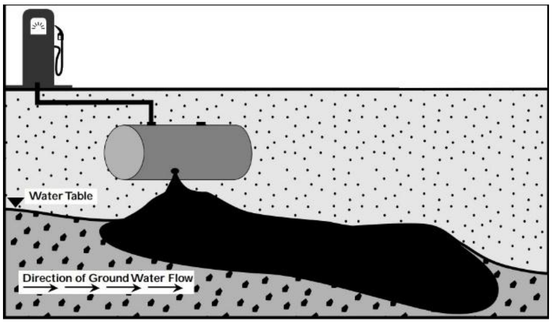

Fig 3: Contaminant Plume, *Source: US Environmental Protection Agency*

Naturally occurring pollutants in the ground water include microorganisms, dissolved solids and chlorides, radionuclides, radon, nitrates and nitrites, heavy metals, cadmium, iron, manganese and fluoride are responsible for the contamination of ground water [42]. Saltwater intrusion moving into the aquifers lead to the degradation of ground water including drinking water sources [44]. The saltwater rises 40 feet for every 1 foot of fresh water depression and forms a cone of accession. Saltwater intrusion can affect the quality of water not only on well sites but also in underdeveloped portions of an aquifer [45]. Another root cause of ground water contamination is the effluents from septic tanks. The septic systems that are designed improperly or the systems that are not maintained on a regular basis can contaminate the ground water with bacteria, viruses, nitrites, detergents, oils and chemicals. Commercially available synthetic septic tank cleaners (such as 1,1,1-trichloroethane) can contaminate the water supply wells and interfere with natural decomposition processes in the septic systems [42,46]. Underground storage tanks are usually used to store chemicals and petroleum products. If the underground storage tanks develop cracks or gets corroded due to aging, then the chemicals present in the tank can seep through the soil and reach the ground water. Improper chemical storage and poor quality containers can be a major threat to ground water. At the site of accidental slip, the chemicals are often diluted with water and then washed into the soil, which increases the possibility of ground water contamination [47].

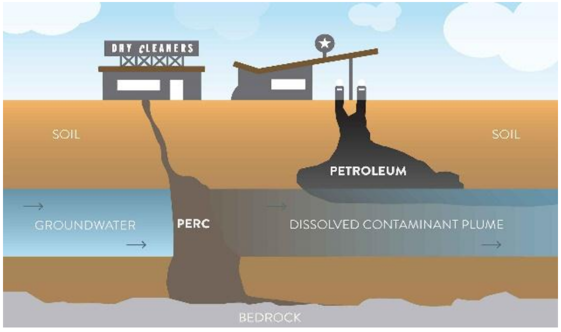

Fig 4: Contamination through on-site petroleum spill, *Source: Enviro Forensics*

Landfills affect ground water through the formation of leachate, which contains calcium chloride, magnesium, sulphate, nitrogen, copper, nickel and lead, which makes it highly alkaline in nature. It is these alkaline substances that constitute to the contamination of ground water by altering the state on an aquifer and in turn make the ground water unstable for drinking and other primary use [48,49]. Sewer pipes carry wastes, which may contain organic matter, inorganic salts, heavy metals, bacteria, viruses and nitrogen. The fluids may then leak from the pipe and seep into the soil and can cause the contamination of the ground water [42]. Studies have shown that pesticides can reach water bearing aquifers below the ground from the applications onto the crop fields, which in turn leads to contamination of the ground water [50]. Processes such as diffusion, dispersion, adsorption and speed of moving water often facilitate the movement. But in general, the movement of the contaminants within the aquifer is usually slow and it is in the form of plume. As the plume spreads, it might connect with springs and ground wells, making them unsafe for human consumption [51,52,53].

5. USING ARTIFICIAL INTELLIGENCE IN COMBATING CLIMATE CHANGE

While AI has a great potential to enable climate mitigation strategies, it also comes with a lot of risks and pitfalls that are connected with the opportunities. In the end, AI is a tool, not an end goal, and we should use it in the right way and at the right time. We must first critically examine the problems and societal contexts we are trying to address. We must pay close attention to the problem framing and recognize that AI is not itself a solution. Climate change and the environment are interconnected through AI on several levels. Quantifying these impacts, both positive and negative, relates to how it is used [54]. It is important to take into account both negative and positive impacts when developing and implementing new technologies. Numerous responsible AI principles, including fairness and equity, accountability, safety, privacy, security, and robustness, are applicable across application domains [55,56,57]. However, it is remarkable how these principles manifest themselves in circumstances that are related to the climate. In situations like power grids and industrial processes, where mistakes can have serious repercussions or where digitalization may introduce new cyber security concerns, safety considerations are especially crucial. Notably, to ensure that initiatives are well-founded and that no new damages or unforeseen consequences arise later on in the project lifecycle, these concerns should be a core and on-going element of scoping, developing, deploying, and managing AI and climate projects.

		Causal inference	Computer vision	Interpretable models	NLP	RL & Control	Time-series analysis	Transfer learning	Uncertainty quantification	Unsupervised learning
Mitigation	**Electricity systems**									
	Enabling low-carbon electricity		•	•		•	•		•	•
	Reducing current-system impacts		•				•		•	•
	Ensuring global impact		•					•		•
	Transportation									
	Reducing transport activity		•				•		•	•
	Improving vehicle efficiency		•			•				
	Alternative fuels & electrification					•				•
	Modal shift	•	•				•		•	
	Buildings and cities									
	Optimizing buildings	•				•	•	•		
	Urban planning		•				•	•		•
	The future of cities				•			•	•	•
	Industry									
	Optimizing supply chains		•			•	•			
	Improving materials									•
	Production & energy		•	•		•				
	Farms & forests									
	Remote sensing of emissions		•							
	Precision agriculture		•			•	•			
	Monitoring peatlands		•							
	Managing forests		•			•	•			
	Carbon dioxide removal									
	Direct air capture									•
	Sequestering CO_2		•						•	•

Table 2: Climate change solution domains. *Source: Tackling Climate Change with Machine Learning*

Key areas where AI can facilitate climate action include –

- **Improving Predictions-** AI has the ability to forecast the future using historical data. For instance, AI can estimate agricultural productivity at the minute level as extreme weather threatens food security or minute-level forecasts of solar power generation to help balance the electrical grid.

- **Distilling raw data into actionable information-** By scaling up the annotations that people could make more laboriously, AI can find relevant information among vast amounts of unstructured data. AI can, for instance, use satellite imagery to pinpoint deforestation, identify places at risk of coastal flooding, or search through huge databases of corporate financial reports for information related to climate change.

- **Optimizing complex systems-** Given a complex system with numerous variables that may be adjusted simultaneously, AI approaches are good at optimising for a particular aim. For instance, AI can be used to improve freight transportation timetables or lower the energy required to heat and cool a building

- **Accelerating scientific modelling and discovery-** By combining known physics-based limits with approximations discovered from data, AI can frequently speed up the process of scientific

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discovery itself. For instance, AI can swiftly replicate elements of climate and weather models to make them more computationally tractable, and it can identify promising candidate materials for batteries and catalysts to speed up research [58].

After outlining the broad roles that AI may play in strategies for climate change mitigation we now give a high-level overview of some of the specific applications that AI can use to have an impact on the climate, sector by sector. Many of these applications are already starting to be implemented, while the majority are actively being developed [59].

5.1 Tackling emissions from electricity systems using AI

These days most of the electricity systems are built based on data, and many industries are moving towards smart grids which are driven by AI and ML [60,61,62]. Electricity is one of the main reasons for the emission of greenhouse gases [63]. These gases absorb and emit radiations within the thermal infrared range, causing the greenhouse effect. One of the ways to tackle climate change is to source low-carbon electricity. There are mainly two types of low-carbon electricity variable low carbon electricity and controllable low carbon electricity. The variable source depends on external factors of the environment. On the other hand, controllable sources can be controlled by the people and can be turned on and off. These two sources affect the electricity systems differently and so they provide distinct opportunities for ML techniques. Nowadays electricity is delivered from the producers to customers through electric grids or interconnected networks, where the power generated must be equal to the power consumed at every moment. Today it is provided by coal and natural gas plants which produces a huge amount of CO_2 [64]. ML can reduce these emissions using necessary technologies.

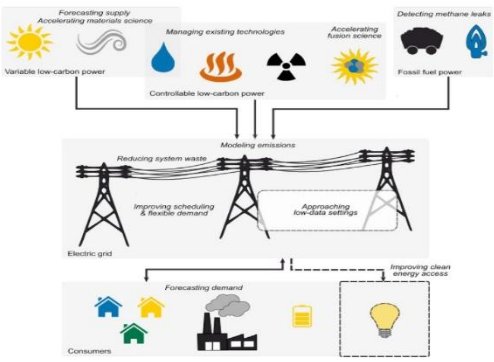

Fig 5: Methods to reduce emissions from electricity systems using ML, *Source: Tackling climate change using ML*

The need of electricity must be forecasted beforehand. Better short term forecasting can allow the operators to reduce their dependency on polluting the plants and alongside manage the increasing amount of variable sources. Better long term forecasting can enable the operators to determine when and where the plants should be built. The forecasting must be very accurate and this is where ML can help. ML uses methods like fuzzy logic and hybrid physical models, and take different approaches to measure the quality of certainty or uncertainty. At a smaller level, some demands have been understood, by clustering households [65,66] or by using game theory, optimization, regression or online learning [67,68,69]. Most of the previous works on this has used domain-agnostic techniques, future ML algorithms will need to use domain-specific insights. For instance, weather can be a source for the generation of electricity and hence ML algorithms forecasting these quantities should make conclusions from innovations in climate modelling, weather forecasting and in hybrid physics-plus-ML modelling techniques [70,71,72]. In a power system, engineers determine how much power each generator can produce, interpretable ML and automated visualization techniques could help engineers to understand the forecasting methods and improve the scheduling of low carbon. Currently scientists and physicists are working to come up with new materials that can conserve energy or harness them from variable sources. An example of this is solar fuel, this allows to capture the solar energy when the sun is shining and can store this energy for use later on when the sun is not shining. This process can be automated by ML by combining the existing heuristics with experimental data, physics and logical reasoning to extend the present physical knowledge. Generally for improving the material science, ML techniques such as supervised learning, active learning and models have been used to design materials [73,75]. For example: recent studies have used tools from AI and physics to propo0se a material's crystal structure with the aim of making solar fuels. Some studies have made it possible to make lithium-ion batteries using ML [74]. Controllable sources can use ML to achieve climate change goals by making very few alterations to how electric grids are run. Many low carbon technologies are commercially available like geothermal, nuclear fission and dam-based hydropower. Using satellite imagery and seismic data, [76,91]. ML can manage and identify sites that are available for geothermal energy. The satellite imagery can also help in detecting cracks that can be useful to maintain nuclear reactors [91]. This can also be done by high sensor and simulation data [92]. Nowadays nuclear reactors consume a lot more energy than they produce, [77,78] which causes emission of huge amount of CO_2 in the atmosphere. ML can be a helping hand in such case to produce safe and carbon free electricity. Fusion reactors have a large number of tuneable parameters, ML can help prioritize which parameter configurations should be explored during physical experiments [79]. Sometimes the reactors may heat up and may cause instabilities, these can be solved using support vector machines, adaptive fuzzy logic, decision trees and deep learning on the data that that were previously disruptive [80,81,82,83,84,85]. ML models would need to use a combination of stimulated and experimental data that would account for the different physical characteristics, data volumes or accuracies for different types of reactors. At any place where methane is being used, there must be a chance that there would be a leakage of methane into the environment. ML can be used in such cases in which sensors or satellite data are used to proactively suggest pipeline maintenance or to detect existing leaks [86,87][93,94,95]. In addition to detection, ML can also help to reduce emissions from transportation of solid fuels, identify storage plants and optimize powerplant parameters to reduce CO_2 emissions. Electricity is transported from factory generators to homes, during this transportation, some of the energy gets lost due to the heat produced due to resistance. ML can help prevent these avoidable losses through predictive maintenance or by suggesting proactive electricity grid upgrades. This can be done using predictive maintenance using LSTMs (long short-term memory), Bipartite ranking and neural network-plus-clustering techniques on electric grids [88,89,90].

5.2 Transportation and AI

About 25% of energy-related CO_2 emissions are linked to the transportation industry. The number of vehicle-miles travelled can be decreased with the use of ML by reducing the need for long trips, enhancing loading, and improving vehicle routing. Ground-based counters placed on certain roadways are used traditionally to measure traffic. There are several technologies employed, including pneumatic tubes and inductive loop detectors. Video surveillance systems are sometimes used to monitor traffic, particularly when it comes to automating the computer vision-based counting of bikes and pedestrians. These roads are modelled by looking at known traffic patterns for comparable roads because counts for most roads are frequently only available over short time periods. ML techniques can aid in the input of missing data for precise bottom-up estimation of greenhouse gas emissions and are also used in car emission simulation models [96-108]. Both reducing sprawl and improving mobility can help to cut GHG emissions. Demand modelling based on machine learning can help alleviate climate change by improving the operating efficiency of modes that produce high amounts of CO_2, such as aircraft. ML can assist in predicting runway demand and aircraft taxi time in order to reduce unnecessary fuel burned in the air and on the ground owing to airport congestion [109,110,111]. Freight consolidation is the practise of clustering shipments together to cut down on journeys and, consequently, GHG emissions. ML forecasts demand or arrival times, identifies and plans around transportation delays or disruptions, and clusters providers based on their geographical locations and frequent shipping destinations [112].

There are numerous prospects for ML to help improve mode integration in the passenger and freight industries. By lowering rail operations and maintenance costs and foreseeing track deterioration, ML can also help to improve the performance of low-carbon modes [113, 114]. By enhancing estimates of bike demand and inventory, Ml can assist in resolving the issue of bike sharing rebalancing, whereby shared bikes accumulate in one area while being in short supply in other locations. One of the main causes of climate change is commercial aircraft. The toxic chemicals and particles it emits, like lead, nitrogen oxides, sulphur oxides, carbon dioxide, and others, have a significant impact on our climate. Global aviation produced 936 million metric tonnes of CO_2 in 2020 (pre-Covid). 11,843,000 tonnes of CO_2 were released into the atmosphere in 2019 by Indian scheduled passenger airlines flying to and from domestic locations [115]. According to updated research published in the journal Atmospheric Environment in January 2021, the climate impact of aviation in 2011 was 3.5% of all anthropogenic warming, and it was presumably the same amount in 2018 [116]. In a paper titled "Helping Reduce Environmental Impact of Aviation with Machine Learning," it is suggested that ML be used for two different things: 1) improving winds aloft forecast, and 2) determining flight regulations that are best for time to destination [117]. It mentions that the network of aircraft already in the air is used as surrogate sensors that continually update and inform about the winds. Systems with machine learning capabilities can choose the best flight paths, reduce operating expenses, and increase client retention. Numerous route variables, including flying effectiveness, air navigation fees, fuel consumption, and anticipated congestion level, can be examined for this use case [118].

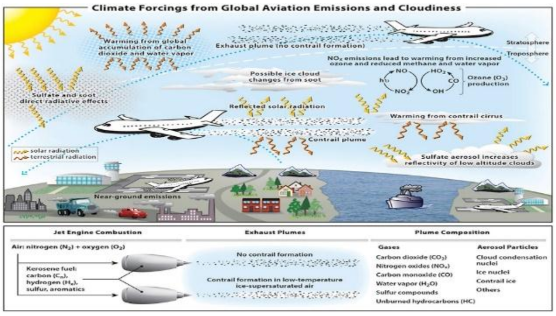

Fig 6: An illustration of the effects of aircraft on the climate. *Source: Contribution of global aviation to anthropogenic climate forcing for 2000 to 2018*

Ships move well over 80% of all global trade in terms of volume, and they are the most fuel-efficient form of transportation in terms of gCO_2/ton-km. international shipping, which in 2018 accounted for 2.02% of global CO_2 emissions, is one aspect of the business that has a significant carbon impact [119, 120]. The final report on the GHG research from the IMO, which was just released, states that the proportion of global CO_2 emissions attributed to shipping increased from 2.76% in 2012 to 2.89% in 2018. The overall GHG emissions from shipping increased by 9.6% from 977 million tonnes in 2012 to 1076 million tonnes in 2018. The study forecasts that by the year 2050, shipping emissions could accelerate by up to 50% over 2018 levels due to the significant predicted expansion in transportation demand. The yearly global contribution is anticipated to be 13% for sulphur oxides (SO_x) and 15% for nitrogen oxides due to the high sulphur content of the majority of marine fuels (NO_x) [119,120,121]. Emissions from shipping have a negative impact on human health, causing 14 million episodes of childhood asthma each year as well as over 400 000 premature lung cancer and cardiovascular disease deaths. According to a report titled "A road toward low-carbon shipping: Improving Port Operations Planning," we can improve port operations planning and scheduling using machine learning. In order to improve port operations scheduling and planning, the study recommends a supplementary system. With the help of this technology, planning will be much more reliable, and ship speed will be suitably optimised. There are two marine sources of data that the system will use - port operations data and Automatic Identification System (AIS) data [119].

5.3 How AI is helping in cities?

While a quarter of the world's energy-related emissions are attributable to buildings, cutting-edge techniques combined with simple adjustments might cut emissions for already-existing structures by up to 90% [122]. It is an established truth that as a result of climate changes, more people in areas with frequent lethal heat waves would need access to air conditioning. Due to their extremely prolonged lifespans, buildings must be both newly constructed and retrofitted to be as energy-efficient as possible. By providing infrastructure, economic incentives, or energy standards for buildings, urban planning and public policy can significantly contribute to the reduction of emissions [123]. ML can assist in the selection of methods that are customised for certain buildings and can also aid with their implementation through sophisticated control systems. Urban planners can utilise ML to collect and interpret data to help guide policy decisions. Forecasts of energy use are typically made using models of a building's physical structure, which are basically massive thermodynamic simulations. The use of machine learning can greatly accelerate these computations, either by disregarding physical knowledge entirely, by incorporating it into the computation, or by learning to approximate the physical model to reduce simulation costs [124-129]. Hidden Markov models, sparse coding methods for structured prediction, harmonic analysis that can identify the unique characteristics of specific appliances, and deep neural networks are promising ML solutions to this issue [130-133]. Statistical ML provides techniques for causal inference to assess the accomplishment or failure of energy efficiency interventions. Buildings with intelligent control systems can reduce their carbon footprint by consuming less energy and by providing a way to incorporate lower-carbon sources into their electricity mix [134]. By enabling systems and devices to adjust to usage patterns, machine learning in particular can lower energy consumption. Additionally, structures can respond to grid signals, granting grid operators more flexibility and cutting customer costs. Through fault detection, ML can automate building diagnostics and maintenance. Deep neural networks have the potential to monitor and optimise the operation of smart building equipment and connection networks, though these systems do waste energy on their own. Rebound effects are likely to occur in some circumstances [135], resulting in an increase in building energy use of typically between 10 and 20% [136].

From other sorts of available data, ML is uniquely capable of estimating energy use and GHG mitigation possibilities at scale. Urban building energy models offer streamlined data on the energy consumption of all structures throughout a city. The location, geometry, and numerous other interesting characteristics, including building footprint, usage, material, roof type, nearby surroundings, etc., are all included in UBEMs. From such features, ML can be used to estimate energy use. The best buildings for retrofitting can be identified using ML algorithms. You might employ basic building attributes and nearby environmental variables, both of which could be scaled [137, 138]. Through web scraping and text mining, ML can also extract data on climate change-related urban challenges. Applications for smart cities must transfer large amounts of data instantly. Large sensor networks need to pre-process a lot of data in order to send only the relevant portions rather than all the raw data being gathered. This is where machine learning comes in [139,140,141]. Smart city initiatives have the potential to improve urban sustainability and promote low-carbon lifestyles when appropriately included into urban design. [142,143,144]. The level of urban expansion and the local growth in the vicinity of transportation hubs both have an impact on the development of effective public transportation, according to ML-based study [145,146]. Machine learning and artificial intelligence (ML and AI) can help coordinate district heating and cooling networks, solar power generation, and charging stations for EVs and bicycles. They can also be used to improve public lighting systems by adjusting light intensity based on previous foot traffic patterns [144, 147].

5.4 AI tools for industrial emissions

Upon spending billions of dollars for gathering data, [149] by ML researchers, it is found that industrial production, logistics and building materials are the leading cause of Greenhouse gas emissions [148]. This can be reduced by the use of ML by helping to shape supply chains perfectly, improve production quality, predict machine breakdowns, optimize heating and cooling systems and emphasize on using clean electricity instead of fossil fuels [150,151,152,153].

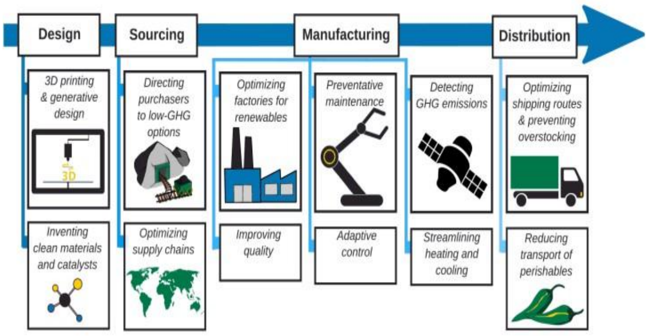

Fig 7: Selected opportunities to use ML to reduce greenhouse gas emissions in industries, *Source: Tackling climate change using ML*

ML can help in by reducing emissions in supply chains by predicting the supply and demand of the place where a particular item gets transported, identifying low carbon products and optimizing transport routes. Some methods are explained below. With growing demands of goods, producers these days tend to produce excess goods, which often lead to wastage. ML may be able to mitigate the issue of overproducing goods by improving the demand forecasting. [154,155] Nearly one-third of all food that is being produced globally is being wasted [159]. ML can help reduce food wastage by optimizing the delivery routes and forecasting beforehand what kind of food is preferred by majority of the customers, ML also can help by improving refrigeration systems [156] in which the refrigerator could be fitted with suitable sensors which could detect foods that are going to get spoilt and could be sold or consumed beforehand [157].

Construction in 20th and 21st century involves cement and steel as the main materials for any structure. Cement produces a lot of heat in the form of CO_2. ML can minimize this emission by reducing the need of carbon-intensive materials and redesigning of the construction materials. To reduce the use of cement and steel, researchers have combined ML with generative design to develop structural products that require less raw materials and thus reducing the greenhouse gas emission. Assuming that there are going to be future advances in material sciences, ML research could potentially draw upon open databases such as the Materials Project [160] and the UCI Machine Learning Repository [161] to invent new climate-friendly materials [162]. ML can help in redesigning of industrial machinery on low-carbon energy instead of coal, oil or gas. When given necessary data, the machinery on site about all relevant process, ML can improve the efficiency of HVAC systems and other industrial control mechanisms. To reduce greenhouse gas emissions from industrial machinery, ML techniques such as image recognition, regression trees and time delay neural networks could be used [163,164]. A technique called DeepMind is being used to optimize the cooling centres of Google's internal servers by predicting and efficiently optimizing the power usage efficiency (PUE), thus reducing cooling costs. [151,156]. ML could be used to predict the damages in the machinery that is currently in use and can also help in better understanding of how to best minimize greenhouse gas emissions for specific equipment and processes. For example, creating a digital twin model of some industrial equipment could enable a manufacturer to identify and prevent undesirable scenarios, as well as virtually test a new set of code before uploading it to the actual factory [158,166].

5.5 Protecting Forests using AI

For millions of years, plants, microorganisms, and other living things have been removing CO_2 from the atmosphere. The majority of this carbon is continuously oxidised and recycled through the carbon cycle, and some are stored as coal and oil deep underground.

However, a sizable portion of this carbon is sequestered in the biomass of trees, peat bogs, and soil. Through deforestation and unsustainable agriculture, our existing economy promotes behaviours that release a significant amount of this carbon that has been trapped. In addition to these consequences, raising cattle and growing rice releases methane, a greenhouse gas that is much more potent than CO_2 itself. Land use by humans is estimated to be responsible for about a quarter of GHG emissions [167]. AI can facilitate responsible land uses practices and nature-based solutions for carbon sequestration, in many ways. Real-time GHG maps could assist us in quantifying emissions from agricultural and forestry activities and monitoring emissions from other industries. Regulations or incentives that could promote improved practises could benefit from the guidance provided by such information. Standard satellite imaging gives RGB images with a much greater resolution which could be used in an ML algorithm. 14% of GHG emissions are attributable to agriculture. In order to replenish the nutrients that farming techniques remove from the soil, nitrogen-based fertilisers must be used. Massive amounts of energy, or around 2% of the world's total energy consumption, are used to synthesise these fertilisers [168]. Furthermore, some of this nitrogen is transformed into nitrous oxide, a greenhouse gas that is nearly 300 times more harmful than carbon dioxide, while other nitrogen is kept in the soil or taken up by plants. Such industrial agricultural strategies eventually focus on improving the uniformity and predictability of farms. There is a need for sophisticated instruments that would enable farmers to labour at scale while yet adjusting to the needs of the land. This strategy is frequently referred to as "precision agriculture." Precision farming can be made possible by more intelligent robotic tools. The University of Sydney is developing a robot called RIPPA that can mechanically weed, apply targeted pesticides, and suck up bugs [169]. It is outfitted with a hyperspectral camera. With solar power, it can traverse 5 acres every day and gather massive datasets for ongoing development [170]. Similar prospects for the creation of novel ML algorithms are provided by numerous different robotic systems. Since current robots still occasionally get stuck, are only optimised for specific types of crops, and rely on ML algorithms that may be quite sensitive to changes in the environment, there is still a lot of room for progress in this area. There are numerous other ways where ML might benefit precision agriculture. Intelligent irrigation systems can reduce pests that flourish in high moisture conditions and save a lot of water. [171]. Additionally, ML can be useful for weed, pathogen, and soil sensing [172,173,174]. Crop yield forecasting can be aided by machine learning [175], and macroeconomic models can even help farmers forecast crop demand and choose what to plant at the start of the season [176]. The biggest source of carbon sequestration on Earth, peatlands (a type of wetland ecosystem) occupy only 3% of the planet's surface area but store twice as much carbon as all of the world's forests combined [177]. However, as peat dries up, it decomposes and releases carbon while also becoming more flammable [177,178]. To determine the peat thickness and evaluate the carbon store of tropical peatlands, machine learning (ML) was applied to characteristics collected from remote sensing data. Advanced machine learning may be able to detect the risk of fire and assist create accurate monitoring solutions at a reasonable cost. By identifying suitable planting sites, keeping track of plant health, evaluating weeds, and examining trends, machine learning (ML) can be useful in automating large-scale afforestation. Regions that are more at risk can be identified using drought forecasts [179] and estimates of the water content of the tree canopy [180]. Reinforcement learning is utilised in [181,182] to forecast the spatial progression of forest fire. This aids firemen in determining when to put out a fire and when to let it burn [183]. Firefighters can do controlled burns and cut specific sections with the use of good instruments to assess regions that are more at danger and halt the spread of fires. Tools for monitoring deforestation can offer useful information for educating policymakers and law enforcement in situations where deforestation may be taking place illegally. Using remote sensing pictures, ML can distinguish between selective and clearcutting [184,185,186,187]. Foresters may now use ML technologies to decide when to harvest, where to fertilise, and what roads to construct.

5.6 Removal of Carbon Dioxide using AI

In order to achieve important climate goals, many experts contend that global emissions must become net-negative or that we must remove more CO_2 from the atmosphere than we emit [188,189]. Although research on negative emissions has advanced significantly [190-194] the CO_2 removal industry itself is still in its infancy. Simply permitting or encouraging more natural CO_2 uptake by plants is one of the most effective strategies. Other plant-based technologies include bioenergy that captures carbon dioxide and bio char, which burns plants in a way that sequesters carbon dioxide (while also producing energy or fertiliser as a valuable by-product) [190,195,196]. Building facilities to capture CO_2 from industrial operations, ambient air, or even power plant exhaust is another strategy. [197]. Although this "direct air capture" (DAC) method presents technical challenges, it requires little land and, to the best of our knowledge, has negligible adverse effects on the ecosystem [198]. The fundamental principle of DAC is to release CO_2 in pure form for sequestration by blowing air onto CO_2 sorbents, which are either solid or in solution and function somewhat like sponges but for gas

[190,191]. Although CO_2 sorbents are getting better [199,200], there are still problems with efficiency and long-term deterioration, which could present chances for machine learning. To increase sorbent reusability and CO_2 uptake while limiting the energy needed for CO_2 release, ML could be utilised to speed up materials discovery and process engineering workflows [199-202]. ML may also assist in the development of components that are resistant to corrosion and can sustain high temperatures as well as in the optimization of their design for air-sorbent contact (which strongly impacts efficiency [203] To prevent re-release into the atmosphere, CO_2 must be sequestered or kept after it has been captured, securely and on a large scale. Direct injection into geologic formations, such as saline aquifers, which are often comparable to oil and gas reserves, is the most well-understood method of CO_2 sequestration [204]. Many facets of CO_2 sequestration may benefit from machine learning. First, ML can assist in characterising and identifying potential storage places. Using ML for subsurface imaging based on unprocessed seismograph traces, oil and gas industries have shown encouraging results [205]. These models and the data that supports them could probably be repurposed to aid with CO_2 capture as opposed to release. Second, ML can assist in maintaining and monitoring operational sequestration sites. Uncertainty quantification in a worldwide CO_2 storage simulation study was recently made successful utilising convolutional image-to-image regression algorithms [206]. Noisy sensor measurements must be converted into conclusions about subsurface CO_2 flow and remaining injection capacity [207]. Monitoring for CO_2 leaks is also essential [208]. Recently, machine learning (ML) techniques have been used to monitor suspected CO_2 leakage from wells [209] and computer vision technologies for emissions detection.

6. CONCLUSION

This research concludes that a set of practical suggestions can be offered to help AI for climate effect. Nearly all inter-disciplinary subjects can benefit from using AI systems. In ML algorithms, the precise nature of the computations carried out is not stated in advance; instead, the algorithm learns by seeing patterns in the data that can be used to generate predictions on brand-new data. This paper emphasises the problems brought on by climate change and lists the urgent measures that should be implemented. Keeping in mind that AI is only a tool and not an end, it can predict the future and assist in gathering data to reduce climate change and water contamination. However, we must not forget the risks associated with the use of AI, hence, it should be used in such a way that its effects are maximized as we have researched in this paper. While the majority are actively being developed, many of these applications are already beginning to be used.

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