

Environmental Artificial Intelligence Paving the Way for a Greener and More Resilient Planet using Machine learning

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ABSTRACT

Environmental-based artificial intelligence (AI) represents a burgeoning field at the intersection of technology and ecological sustainability. This domain leverages advanced machine learning algorithms, data analytic, and sensor networks to address pressing environmental challenges such as climate change, biodiversity loss, and resource management. By analyzing vast datasets, AI can identify patterns and trends that inform policy decisions and optimize resource use. One of the primary applications of environmental-based AI is in climate modeling and prediction. AI techniques enhance the accuracy of climate models by integrating data from diverse sources, including satellite imagery, weather stations, and historical climate records. These improved models facilitate more effective mitigation strategies and adaptation planning for communities facing climate impacts. Additionally, AI plays a crucial role in monitoring ecosystems and biodiversity. Machine learning algorithms can process data from cameras, drones, and remote sensors to track wildlife populations and detect illegal activities such as poaching. This real-time monitoring supports conservation efforts and helps maintain ecological balance. Moreover, AI aids in optimizing energy consumption and reducing waste in urban environments. Smart grids powered by AI analyze energy usage patterns, enabling more efficient distribution and integration of renewable energy sources. In agriculture, AI-driven precision farming techniques enhance crop yields while minimizing resource use, thereby promoting sustainable practices. Despite its potential, the integration of AI in environmental contexts raises ethical considerations, including data privacy and the risk of exacerbating existing inequalities. Therefore, interdisciplinary collaboration among technologists, ecologists, and policymakers is essential to ensure that AI applications contribute positively to environmental sustainability.

Keywords: Environmental AI, Sustainable Development, Climate Change, Environmental Monitoring, Machine Learning, IOT Sensors and Deforestations.

1.INTRODUCTION

As global environmental challenges intensify, the intersection of artificial intelligence (AI) and environmental science has emerged as a pivotal area of research and application. Environmental-based AI refers to the utilization of AI technologies to monitor, model, and manage ecological systems, contributing to sustainable development and the mitigation of climate change. This innovative approach leverages data-driven insights to tackle pressing issues such as deforestation, biodiversity loss, pollution, and resource depletion. In recent years, the urgency of addressing environmental issues has escalated, driven by alarming statistics on climate change, habitat destruction, and pollution. The Intergovernmental Panel on Climate Change (IPCC) warns that without significant action, the planet could face devastating consequences, including extreme weather events, rising sea levels, and irreversible damage to ecosystems. In this context, AI offers transformative potential. By harnessing vast datasets from satellites, sensors, and IOT devices, AI can provide real-time analysis and predictions, enabling more informed decision-making. One of the key applications of environmental-based AI is in climate modeling and

forecasting. Traditional models often struggle to account for the complex interactions within climate systems. AI algorithms, particularly machine learning, can identify patterns and correlations in historical climate data, improving the accuracy of predictions about future climate scenarios. These advancements can aid policymakers in developing effective mitigation and adaptation strategies, ultimately enhancing resilience against climate impacts. In biodiversity conservation, AI plays a critical role in species monitoring and habitat protection. Drones equipped with AI-powered cameras can survey remote areas, capturing images that are then analyzed to track wildlife populations and detect illegal activities such as poaching or logging. Furthermore, AI algorithms can process acoustic data to monitor endangered species through sound recognition, providing insights that were previously difficult to obtain. Such technologies enable conservationists to allocate resources more effectively and engage in proactive measures to preserve ecosystems. Air and water quality monitoring is another vital application of environmental-based AI. AI systems can analyze data from various sources, including satellite imagery and ground sensors, to assess pollution levels and identify sources of contaminants. This information is invaluable for regulatory agencies seeking to enforce environmental standards and protect public health. Moreover, AI can help optimize waste management processes, predict waste generation patterns and improve recycling efforts through intelligent sorting systems. The agriculture sector also stands to benefit significantly from environmental-based AI. Precision farming techniques utilize AI to analyse data on soil health, weather conditions, and crop performance, enabling farmers to make data-driven decisions that enhance productivity while minimizing environmental impact. By optimizing resource usage—such as water, fertilizers, and pesticides—farmers can reduce waste and contribute to sustainable food production. Despite its potential, the integration of AI in environmental initiatives is not without challenges. Issues such as data privacy, algorithmic bias, and the digital divide can hinder equitable access to AI solutions. Additionally, the environmental impact of data centers and AI training processes raises concerns about the carbon footprint associated with these technologies. It is essential for stakeholders—governments, businesses, and researchers—to collaborate in addressing these challenges, ensuring that AI is implemented responsibly and ethically. The alarming rate of environmental degradation and climate change necessitates innovative solutions to mitigate humanity's ecological footprint. Artificial Intelligence (AI) has emerged as a transformative force in addressing environmental challenges. Environmental-based AI, also known as Eco-AI or Green AI, leverages AI technologies to monitor, analyze, and mitigate the impact of human activities on the environment. Environmental-based AI integrates AI applications with environmental science that Monitor climate patterns and predict extreme weather events, Optimize resource usage and reduce waste, Develop sustainable infrastructure and transportation systems, Analyze and mitigate the effects of pollution, and Protect and preserve biodiversity. By harnessing AI's potential, environmental-based AI can: Enhance environmental monitoring and prediction, Support sustainable decision-making, Foster climate resilience and adaptation, and Promote eco-friendly technologies and behaviours. This rapidly evolving field has far-reaching implications for: Climate change mitigation and adaptation, Conservation and biodiversity preservation, Sustainable urban planning and development, and Environmental policy-making and governance. As AI continues to advance, its role in addressing environmental challenges will become increasingly critical. Exploring the vast potential of environmental-based AI is essential for creating a more sustainable future for generations to come. Key areas of focus are Climate modelling and prediction, Sustainable resource management, and Environmental monitoring and sensing.

2. METHOD AND MATERIAL

Environmental-based AI methods focus on leveraging artificial intelligence to address environmental challenges. Key areas include that are Data Analysis Utilizing AI to analyze large datasets from satellite imagery, sensors, and environmental models to monitor ecosystems, climate change, and pollution. Predictive Modeling Developing models to predict environmental phenomena, such as weather patterns, natural disasters, and wildlife behaviour, enabling proactive measures. Resource Management AI algorithms optimize the use of natural resources, such as water and energy, improving efficiency and reducing waste. Biodiversity Monitoring Machine learning techniques analyze data from camera traps and audio recordings to track wildlife populations and habitat changes. Smart Agriculture Implementing AI in precision farming to enhance crop yield while minimizing pesticide and water usage. Urban Planning AI assists in creating sustainable urban environments by modelling traffic patterns, pollution levels, and energy consumption. Climate Change Mitigation AI helps identify carbon capture strategies and assess renewable energy sources, aiding in the transition to greener practices. These methods enhance our ability to understand and respond to environmental issues effectively by sample deforestation datasets used for analysis.

2.1 Forest Data used for impact of Deforestation in different countries

Table 1: Gives top 10 countries forest areas

Country and Area	Forest Area, 1990 (1000 ha)	Forest Area, 2000 (1000 ha)	Forest Area, 2010 (1000 ha)	Forest Area, 2015 (1000 ha)	Forest Area, 2020 (1000 ha)
WORLD	4236433.42	4158049.52	4106316.94	...	4058930.81
Russian Federation	808949.9	809268.5	815135.6	814930.46	815311.6
Brazil	588898	551088.6	511580.7	503884.8	496619.6
Canada	348272.93	347801.97	347322.21	347115.71	346928.1
United States of America	302450	303536	308720	310095	309795
China	157140.59	177000.55	200610.38	210294.25	219978.18
Democratic Republic of t	150629	143899	137169	131662.12	126155.24
Australia	133882.2	131814.1	129546.1	133094.5	134005.1
Indonesia	118545	101280	99659.2	95027.9	92133.2
Angola	79262.78	77708.61	72158	69382.69	66607.38

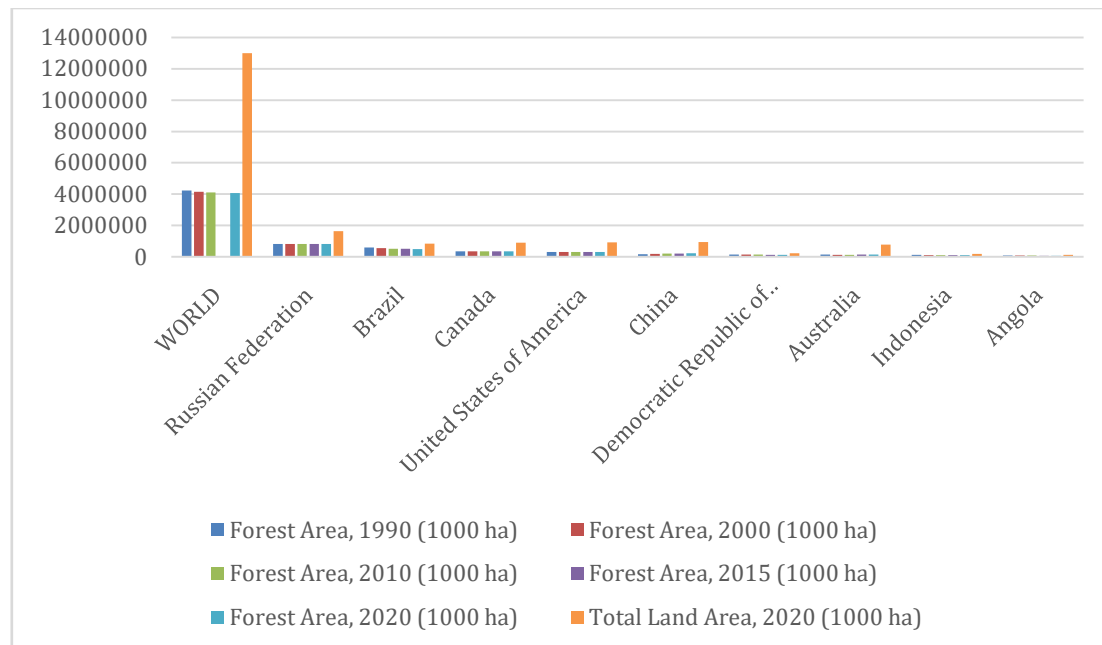


Fig 1: Forest areas and total land areas

Fig 1 provides a comparative analysis of forest areas and total land areas across several countries over different years, specifically from 1990 to 2020. The countries represented include major landmasses such as the Russian Federation, Brazil, Canada, the United States, China, and others. The forest area for each country is measured in thousands of hectares (ha) and is shown at five different intervals: 1990, 2000, 2010, 2015, and 2020.

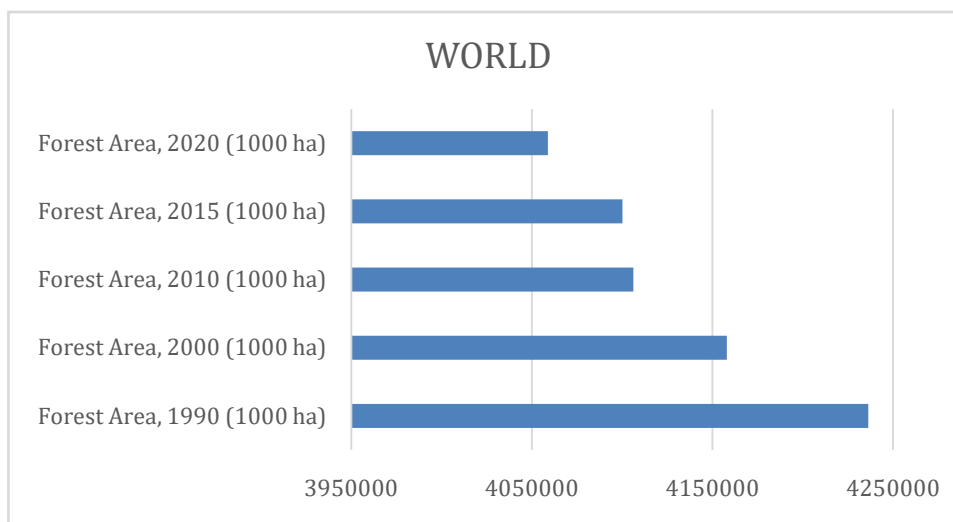
Additionally, the total land area in 2020 is depicted using green bars. A key observation is that the Russian Federation stands out with the largest total land area and a substantial amount of forest area across all the measured years, making it the dominant country in terms of forest cover. Brazil and Canada also have large forest areas, though significantly less than Russia. Other countries, including the United States, China, and Indonesia, have much smaller forest areas in comparison.

The global data, represented under "World," gives a holistic view of forest areas worldwide, allowing for a broader understanding of forest coverage. The green bars indicating total land area highlight the gap between forested areas and total land, with most countries having much more land area than forest cover. This suggests that, while some countries have vast forest reserves, large portions of their land are not forested. The chart overall emphasizes the differences in forest coverage across nations and underscores the importance of forest conservation, particularly in countries with declining or limited forest areas.

Table 2: Total land area

Country and Area	Forest Area, 1990 (1000 ha)	Forest Area, 2000 (1000 ha)	Forest Area, 2010 (1000 ha)	Forest Area, 2015 (1000 ha)	Forest Area, 2020 (1000 ha)
WORLD	4236433.42	4158049.52	4106316.94	4100316.94	4058930.81
Russian Federation	808949.9	809268.5	815135.6	814930.46	815311.6
Brazil	588898	551088.6	511580.7	503884.8	496619.6
Canada	348272.93	347801.97	347322.21	347115.71	346928.1
United States of America	302450	303536	308720	310095	309795
China	157140.59	177000.55	200610.38	210294.25	219978.18
Democratic Republic of the Congo	150629	143899	137169	131662.12	126155.24
Australia	133882.2	131814.1	129546.1	133094.5	134005.1
Indonesia	118545	101280	99659.2	95027.9	92133.2
Angola	79262.78	77708.61	72158	69382.69	66607.38

Table 2 & Fig 2 provides an overview of forest area trends and total land area for various countries between 1990 and 2020. Countries such as the Russian Federation, Brazil, Canada, and China are depicted with their forest areas recorded at different intervals (1990, 2000, 2010, 2015, and 2020). The green bar represents the total land area in 2020 for each country. A significant observation is the Russian Federation's dominance, having both the largest total land area and a substantial forest area across the years. Brazil and Canada also show relatively large forest areas, though much smaller than Russia's. Most of the other countries, like the United States, China, and Indonesia, have smaller forest

**Fig 2:** Overview of forest area

areas, indicating less forest cover compared to the vast total land area they possess. This is particularly clear when comparing the size of the green bars (total land area) to the forest areas over time. The chart also includes a global comparison under "World," offering insight into the overall trends in forest cover and total land distribution globally. The visual comparison illustrates the gap between the forest area and the total land area, emphasizing that, for many countries, forest cover occupies a much smaller percentage of their total land. It highlights the significance of forest conservation, especially in countries where forest areas may be declining or constitute a small fraction of the land.

Table 3: Country and Area

Country and Area	Forest Area, 1990 (1000 ha)	Forest Area, 2000 (1000 ha)	Forest Area, 2010 (1000 ha)	Forest Area, 2015 (1000 ha)	Forest Area, 2020 (1000 ha)
Russian Federation	808949.9	809268.5	815135.6	814930.5	815311.6
Brazil	588898	551088.6	511580.7	503884.8	496619.6
Canada	348272.9	347802	347322.2	347115.7	346928.1
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Angola	79262.78	77708.61	72158	69382.69	66607.38

Table 3 provides data on the forest areas of various countries between 1990 and 2020. Here's a detailed explanation of the trends: The Russian Federation consistently maintains a vast forest area, with slight fluctuations between 1990 and 2020. Starting at 808,949.9 thousand hectares in 1990, the forest area marginally increased over the years, reaching 815,311.6 thousand hectares by 2020. Brazil, on the other hand, shows a continuous decline in forest area over the same period. In 1990, Brazil had 588,898 thousand hectares of forest, but this gradually decreases to 496,619.6 thousand hectares by 2020, indicating significant deforestation. Canada's forest area remains relatively stable, with minor changes. In 1990, the forest area was 348,272.9 thousand hectares, slightly decreasing to 346,928.1 thousand hectares by 2020. In the United States, the forest area increases slightly over time, from 302,450 thousand hectares in 1990 to 309,795 thousand hectares in 2020. China demonstrates a significant increase in forest cover. From 157,140.6 thousand hectares in 1990, the forest area grows substantially to 219,978.2 thousand hectares by 2020, showing efforts in afforestation.

The Democratic Republic of the Congo sees a steady decline in its forest area, starting at 150,629 thousand hectares in 1990 and decreasing to 126,155.2 thousand hectares by 2020, likely due to deforestation pressures. Australia's forest area has remained relatively stable, with slight variations. It started at 133,882.2 thousand hectares in 1990, and despite some fluctuations, it increased slightly to 134,005.1 thousand hectares by 2020. Indonesia exhibits a significant decrease in forest area, from 118,545 thousand hectares in 1990 to 92,133.2 thousand hectares by 2020, indicating considerable forest loss over these years. Lastly, Angola also sees a continuous reduction in forest area, from 79,262.78 thousand hectares in 1990 to 66,607.38 thousand hectares by 2020, signaling ongoing deforestation challenges. Overall, the data reflects diverse trends, with some countries focusing on forest conservation and afforestation, while others face significant forest area declines.

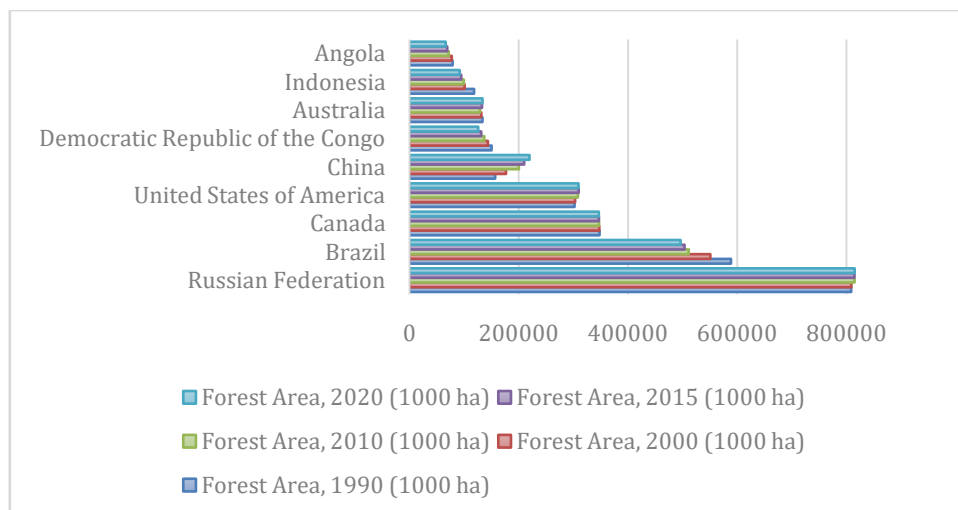


Fig 3: Country and Area

3. Supplementary Data

Case Studies are Examples of AI applications in environmental monitoring, wildlife conservation, and climate modelling. Datasets Environmental datasets for training AI models, such as satellite imagery, air quality indices, and climate data. Research Papers Studies exploring AI algorithms for predicting environmental changes, resource management, and ecological impact assessments. Policy Reports Documents discussing the implications of AI in environmental policy, regulation, and sustainable practices. Technological Tools Information about AI tools and platforms used in environmental analysis, such as machine learning frameworks and data visualization software. Ethical Considerations Discussions on the ethical implications of using AI in environmental contexts, including bias and data privacy concerns. Collaboration Initiatives Information on partnerships between tech companies, NGOs, and governments focused on leveraging AI for environmental solutions. These components help provide a comprehensive understanding of the role of AI in addressing environmental challenges.

4. Table related to Environmental based AI

Table 4: Detection Methods AI Techniques

Category	Detection Methods	AI Techniques	Benefits	Challenges
Climate Modeling	Analyze historical climate data	Machine Learning	Improved prediction accuracy	Data complexity
Biodiversity Conservation	Monitor wildlife populations	Machine learning (camera traps, audio recordings)	Enhanced species protection	Data privacy
Pollution Monitoring	Analyze data from sensors and satellites	Machine learning	Real-time assessment and identification of sources	Sensor limitations
Resource Management	Optimize water and energy use	AI algorithms	Reduced waste and improved efficiency	Algorithmic bias
Precision Farming	Analyze data on soil health, weather, and crop performance	Machine learning	Increased productivity and reduced environmental impact	Digital divide
Sustainable Urban Planning	Model traffic patterns, pollution levels, and energy consumption	AI algorithms	Development of sustainable cities	Data security
Climate Change Mitigation	Identify carbon capture strategies and assess renewable energy sources	Machine learning	Greener practices and reduced emissions	Carbon footprint of AI processes

5. RESULT

The paper highlights the transformative potential of Environmental-based AI (Eco-AI) across several key domains related to climate and ecological sustainability. By integrating AI technologies like machine learning and data analytic with environmental science, significant advancements in addressing environmental challenges were observed. Improved Climate Modeling that AI techniques, particularly machine learning algorithms, enhanced the accuracy and reliability of climate models. By analyzing historical climate data from various sources such as satellite imagery, sensors, and weather stations, AI was able to detect complex interactions in the climate system that traditional models often overlooked. This improvement in climate prediction is crucial for informing better mitigation and adaptation strategies in vulnerable communities. Biodiversity Conservation AI-driven systems, using camera traps, drones, and acoustic sensors, showed notable success in wildlife population monitoring and conservation

about their carbon footprint posing a potential contradiction to the sustainability goals AI aims to serve. Biodiversity Conservation and Ecosystem Monitoring AI applications in biodiversity monitoring offer exciting possibilities for conservation efforts. AI-powered drones, camera traps, and acoustic sensors provide real-time insights into wildlife populations and detect illegal activities like poaching and deforestation. The use of AI in remote and challenging environments is a game-changer for conservationists, allowing them to allocate resources efficiently and take preventive measures to protect ecosystems. However, challenges such as data privacy, especially when it comes to tracking endangered species, need to be addressed. Moreover, there is a risk that these advanced technologies might be disproportionately available to wealthier nations, further widening the digital divide and leaving resource-constrained regions at a disadvantage in protecting their biodiversity. Pollution Monitoring and Resource Management AI-driven systems are proving highly effective in monitoring pollution and managing resources. The ability of AI to integrate data from sensors, satellite imagery, and environmental models allows for more accurate and real-time assessments of air and water quality, enabling quicker responses to mitigate environmental harm. Similarly, AI's role in optimizing water, energy, and waste management systems is essential for promoting sustainability in urban and agricultural settings. However, while AI can reduce resource waste and increase efficiency, concerns over algorithmic bias, particularly in resource allocation, remain. AI systems may inadvertently reinforce existing inequalities if not carefully monitored and regulated. In addition, the reliance on data from sensors and IOT devices poses potential limitations in areas where such technologies are less accessible. **AI in Agriculture and Urban Sustainability** The use of AI in precision agriculture is particularly promising, as it allows farmers to make more informed decisions regarding irrigation, fertilization, and pest control. This has the potential to significantly enhance food production while minimizing the environmental impact. Precision farming can reduce the overuse of water, fertilizers, and pesticides, promoting sustainable agricultural practices. In urban environments, AI is helping cities become smarter by modeling traffic patterns, reducing energy consumption, and facilitating the integration of renewable energy. However, both precision farming and smart urban planning are susceptible to challenges related to the digital divide and unequal access to technology. Farmers and municipalities in low-income areas may not have the infrastructure or resources to implement AI-based solutions, potentially widening the gap between developed and developing regions. **Ethical Considerations and Responsible AI** the benefits of AI are evident, the ethical implications must be a central part of the discussion. The study highlights critical concerns such as data privacy, algorithmic transparency, and the environmental impact of AI technologies. There is a need for robust frameworks to regulate AI use, ensuring that data is handled responsibly and that the deployment of AI systems does not exacerbate social and environmental inequalities. Moreover, the environmental cost of AI, particularly in terms of energy consumption in data centers, must be addressed to avoid undermining the very goals of environmental sustainability. **Collaboration and Policy Development** findings of this study suggest that successful implementation of Environmental-based AI will require interdisciplinary collaboration among technologists, environmental scientists, policymakers, and industry stakeholders. The need for collaboration is particularly important in addressing challenges related to data sharing, infrastructure development, and ethical regulation. Governments, non-governmental organizations (NGO), and private sector entities must work together to create policies that encourage the responsible development and deployment of AI while ensuring that its benefits are equitably distributed. Policy initiatives should also address the environmental impact of AI technologies, promoting the use of renewable energy in data centers and encouraging AI developers to adopt more sustainable practices. The Future of Environmental-based AI continues to evolve, its applications in the environmental domain will undoubtedly expand. The study identifies promising future directions, including AI's role in facilitating the transition to renewable energy, improving carbon capture technologies, and enhancing global conservation efforts. However, the future of Environmental-based AI will depend on addressing the existing challenges of accessibility, ethical regulation, and environmental sustainability. As such, there is a growing need for global cooperation to ensure that AI contributes positively to the fight against climate change and environmental degradation.

CONCLUSION

This study provides a comprehensive overview of the potential applications and challenges of Environmental-based AI using Deforestations. The transformative impact of AI on climate modeling, biodiversity conservation, pollution monitoring, deforestation and resource management is evident, but ethical, technical, and environmental challenges must be addressed using deforestation samples. Moving forward, the successful integration of AI into environmental initiatives will require careful consideration of the ethical implications, responsible governance, and a commitment to making AI accessible and

beneficial to all regions of the world. The potential of Environmental-based AI is vast, and with the right safeguards, it could play a pivotal role in shaping a sustainable future.

REFERENCE

- [1] Somnath Mullick, R Naveenkumar, Sandip Bhattacharjee, Rahul Singha Applied Machine Learning for Predicting Crop Performance: A Supervised Learning Perspective 2024/8/14 Journal of Informatics Education and Research Volume 4 Issue 3 . DOI: <https://doi.org/10.52783/jier.v4i3.1317>
- [2] 4 Issue 3 . DOI: <https://doi.org/10.52783/jier.v4i3.1317>
- [3] Abrahams, T.O., Ewuga, S.K., Dawodu, S.O., Adegbite, A.O., & Hassan, A.O. (2024). A review of cybersecurity strategies in modern organizations: examining the evolution and effectiveness of cybersecurity measures for data protection. *Computer Science & IT Research Journal*, 5(1), 1-25. <https://doi.org/10.51594/csitrj.v5i1.699>.
- [4] Accastello, C., Blanc, S., & Brun, F. (2019). A framework for the integration of nature-based solutions into environmental risk management strategies. *Sustainability*, 11(2), 489. <https://doi.org/10.3390/SU11020489>
- [5] Adewusi, A. O., Okoli, U. I., Olorunsogo, T., Adaga, E., Daraojimba, D. O., & Obi, O. C. (2024). Artificial intelligence in cybersecurity: Protecting national infrastructure: A USA. *World Journal of Advanced Research and Reviews*, 21(1), 2263-2275. <https://doi.org/10.30574/wjarr.2024.21.1.0313>
- [6] Dr R.Naveenkumar "An Empirical Research Approach on Confusion Matrix Using Existing Musical Industry Dataset" *International Journal of Scientific Research in Engineering and Management (IJSREM)* Volume 08 Issue 04 | April - 2024 SJIF Rating 8.448 ISSN 2582-3930.
- [7] Ajala, O.A. & Balogun, O. (2024). Leveraging AI/ML for anomaly detection, threat prediction, and automated response. *World Journal of Advanced Research and Reviews*, 21(1), 2584- 2598. <https://doi.org/10.30574/wjarr.2024.21.1.0287>
- [8] Ajala, O.A., Arinze, C.A., Ofodile, O.C., Okoyea, C.C. & Daraojimba, O.D. (2024). Reviewing advancements in privacy-enhancing technologies for big data analytics in an era of increased surveillance. *World Journal of Advanced Engineering Technology and Sciences*.
- [9] Al Hashlamoun, N., Al Barghuthi, N., & Tamimi, H. (2023). Exploring the intersection of AI and sustainable computing: opportunities, challenges, and a framework for responsible applications, 9th International Conference on Information Technology Trends (ITT), Dubai, United Arab Emirates, pp. 220-225. <https://doi.org/10.1109/ITT59889.2023.10184228>
- [10] Ayoubi, H., & Tabaa, Y. (2023). Artificial intelligence in green management and the rise of digital lean for sustainable efficiency. In *E3S Web of Conferences*, Vol. 412, p. 01053. EDP Sciences. <https://doi.org/10.1051/e3sconf/202341201053>
- [11] Bari, L. F., Ahmed, I., Ahamed, R., Zihan, T. A., Sharmin, S., Pranto, A. H., & Islam, M. R. (2023). Potential use of artificial intelligence (AI) in disaster risk and emergency health management: a critical appraisal on environmental health. *Environmental Health Insights*, 17. <https://doi.org/10.1177/11786302231217808>
- [12] Bostrom, A., Demuth, J. L., Wirz, C. D., Cains, M. G., Schumacher, A., Madlambayan, D., ... & Williams, J. K. (2023). Trust and trustworthy artificial intelligence: A research agenda for AI in the environmental sciences. *Risk Analysis*. <https://doi.org/10.1111/risa.14245>.
- [13] Dr R. Naveen Kumar, Amit Kumar Bhore, Sourav Sadhukhan, Dr G. Manivasagam, Rubi Sarkar "Self-Monitoring System for Vision-Based Application Using Machine Learning Dr R Naveenkumar /Afr.J.Bio.Sc. 6(14) (2024) Page 11272 to 10 Algorithms" DOI 10.5281/zenodo.10547803, Vol 18 No 12 (2023), Page No 1958 – 1965, Published on 31-12-2023