Comparative Analysis of Sustainable AI Techniques Used to Reduce the Carbon Footprints in the Healthcare Sector

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Abstract: The healthcare sector plays an important role in human well-being, however, the continuous utilization of its resources has led to environmental degradation. It has become one of the reasons for climate change, primarily through significant carbon emissions and misuse of clinical equipment. With the advancement in ongoing research, efforts are being made for sustainable healthcare development. This review paper compares the existing models and approaches based on sustainable AI to reduce carbon footprints within the healthcare sector. The paper presents a detailed study of existing literature and initiatives that use AI-driven solutions to make healthcare services more eco-friendly and economically feasible.

This paper presents how AI technologies, including machine learning, data analytics, Deep Learning, and optimization algorithms, are being applied in the Supply chain, clinical trials, predictive management, and various other departments of Medicine to prevent carbon emissions arising from infrastructure, data centers, transportation, and medical equipment.

Keywords: Healthcare, Carbon Footprints, Sustainable AI, Deep Learning, Machine Learning, Predictive Management

I.INTRODUCTION

A carbon footprint is a measure of the total amount of greenhouse gases, specifically carbon dioxide equivalents (CO_2), that are directly or indirectly produced by an individual, organization, event, or product throughout its lifecycle. It serves as an indicator of the impact human activities have on the environment, particularly in terms of contributing to global warming and climate change. Common greenhouse gases considered in carbon footprint calculations include carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and fluorinated gases. The assessment involves evaluating the entire supply chain, from raw material extraction to production, transportation, use, and disposal.

The healthcare industry significantly impacts the climate crisis and thus holds a crucial responsibility in addressing and resolving it. Its climate footprint is equivalent to 4.4% of global net emissions (2 gigatons of carbon dioxide equivalent)[1]. The global healthcare climate footprint is equivalent to the annual greenhouse gas emissions from 514 coal-fired power plants. If the health sector were a country, it would be the fifth-largest emitter on the planet. While India has the seventh-largest absolute health sector climate footprint, it has the lowest health-related emissions per capita as compared to other countries in the world[1].

The healthcare sector's carbon footprint comprises 17% from direct facility emissions, 12% from purchased energy, and a significant 71% from the supply chain[1], emphasizing the crucial impact of goods and services production, transportation, and disposal on environmental sustainability as shown in Figure 1. The carbon footprint of healthcare adds to air pollution, extreme weather, and disease changes, affecting respiratory health and spreading diseases. Additionally, healthcare machinery radiation brings risks such as cancer, cell damage, and reproductive issues.

The paradox exists in the healthcare sector where advanced technologies, intended to enhance quality of life, are sometimes the very cause of its degradation. Consequently, diverse sustainable AI methods are created to minimize these effects like Efficient AI Radiology, AI integrated Telehealth, Autonomous Predictive Management, AI in Clinical

Trials, and AI Disease Detection. Each technique has its advantages and drawbacks, leading to different success rates. This review paper examines and contrasts various sustainable AI methods, shedding light on the most suitable, efficient, and successful technique for practical implementation to mitigate carbon footprint impacts.

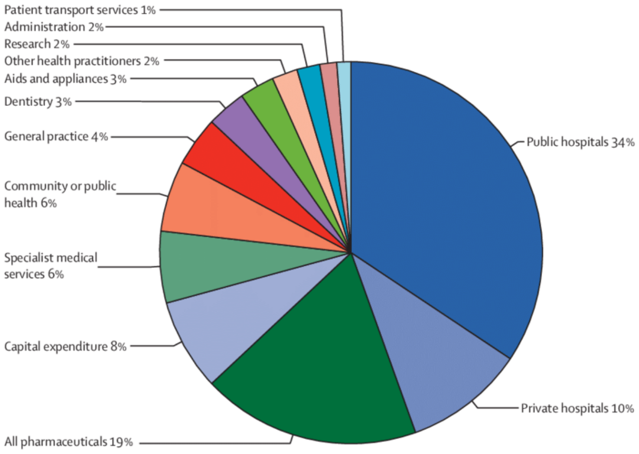

Figure 1[2] . Relative CO2 emission in HealthCare

II.CARBON EMISSION SOURCES IN THE HEALTHCARE SECTOR

A. Radiology

The existing medical guidelines overlook the environmental impact and carbon footprint caused by medical imaging in health care. Among the common cardiac imaging techniques, CO_2 emissions are lowest for transthoracic echocardiography (0.5–2 kg per exam), increase 10-fold for cardiac computed tomography angiography, and 100-fold for cardiac magnetic resonance. It can be inferred that medical imaging is responsible for roughly 1% of the total carbon footprint due to its 10 billion medical examinations conducted annually worldwide as shown in Figure 2. In 2016, the CO_2 emissions caused by magnetic resonance imaging and computed tomography resulted in approximately 0.77% of the total global emissions.[3]
Here are some problems associated with carbon emissions in radiology:

- ***Energy Consumption***: High-powered equipment and imaging modalities, such as CT scans and MRI machines, require a significant amount of energy to operate. The continuous use of these high-powered machines contributes to increased energy consumption, leading to higher carbon emissions.
- ***E-Waste Generation*****:** Improper disposal of unused or non-functional imaging equipment can result in electronic waste, leading to environmental hazards when not managed appropriately.
- ***Resource Intensity*****:** The manufacturing and production of radiological equipment, including the extraction of raw materials and energy-intensive processes, contributes highly to carbon emissions.

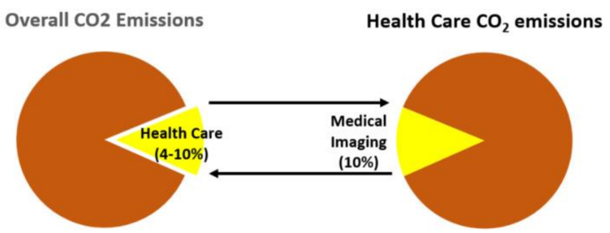

Figure 2.[3] The contribution of healthcare and medical imaging to overall carbon emissions on a planetary scale.

There are significant gaps in the existing theories regarding aspects that contribute to the environmental footprint. Specifically, the impact of manufacturing, installing, and decommissioning imaging equipment, monitors, and

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workstations lacks detailed exploration beyond industry estimations. Setting up the baseline carbon footprint for all diagnostic imaging processes is crucial as an initial step in developing strategies to effectively reduce carbon emissions within the healthcare sector.

B. Healthcare Transportation

Carbon emissions in healthcare transportation arise from diverse activities within the sector, including ambulance services, patient transport, and medical supply distribution. These activities, often relying on fossil fuels, contribute to environmental footprints with greenhouse gas emissions. AI technologies such as telemedicine and remote monitoring aim to reduce the need for physical patient transport, aligning with broader initiatives for environmental responsibility in the healthcare sector.

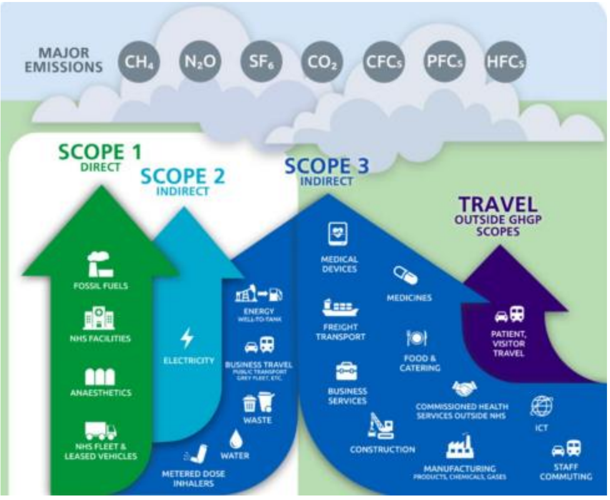

Figure 3.[4] Greenhouse Gas Protocol Scopes in the Context of the NHS8

- ***Patient Transport***: Patient transport contributes to carbon emissions in healthcare mainly through the use of vehicles propelled by fossil fuels. The transportation of patients between medical facilities, residences, and other locations involves ambulances, medical vans, and other vehicles, many of which rely on gasoline or diesel engines. The burning of these fossil fuels releases carbon dioxide (CO_2) and other pollutants into the atmosphere, contributing to the overall carbon footprint of healthcare operations.

Carbon emissions in patient transport are influenced by fuel type and vehicle maintenance. Fuel choice, such as gasoline or diesel, directly impacts emissions due to combustion. Proper vehicle maintenance, including tire inflation and engine tuning, enhances fuel efficiency, reducing the carbon footprint. The type of fuel used and regular maintenance play pivotal roles in determining emission levels and fostering eco-friendliness.

- ***Pharmaceutical Distribution***: The Indian pharmaceutical industry, growing at 13% over six years, has shifted from foreign control to domestic development[5]. Despite significant progress, carbon emissions in healthcare transportation involve challenges. Pharmaceutical distribution's dependence on environmentally influential transport and energy-demanding processes requires urgent adoption of sustainable practices.
- Packaging: Routine care, like tire inflation and engine tuning, enhances fuel efficiency, reducing carbon emissions for a greener and more sustainable transportation approach.
- Temperature Control: It requires refrigerated transport for efficacy and contributes to increased carbon emissions due to increased energy consumption compared to standard transport methods.

- ***Blood and Organ Transportation***: It substantially adds to healthcare-related carbon emissions, primarily due to the vehicles and logistical processes in place for transporting these critical medical supplies. The environmental impact stems from various factors like the type of vehicles used, the distance traveled, the packaging materials, and the

energy-demanding storage conditions. These aspects collectively highlight the need for sustainable practices in medical supply transportation to reduce the carbon footprint associated with this important aspect of healthcare.
Blood and organs often need to be transported urgently, leading to time-sensitive deliveries. This urgency may result in the use of less fuel-efficient transportation methods, such as air transport, which has a higher carbon footprint.

C. Machinery and Infrastructure

The healthcare machinery supply chain has an insightful environmental impact, involving raw material extraction, energy-intensive manufacturing, and the generation of electronic waste (e-waste). This process contributes to habitat destruction, pollution, and carbon emissions. Hospitals, integral to healthcare, show significant energy usage and have a notable environmental footprint.. Their energy needs, including lighting, medical equipment, water heating, and climate control, result in a 2.5 times greater energy consumption compared to commercial buildings. In developing countries like India, where buildings already account for 35% of total energy consumption, hospitals face an annual growth rate of 8% [6]. Addressing energy efficiency and sustainability in both healthcare machinery and infrastructure is essential to minimize environmental degradation.

Energy Consumption

Sources of energy consumption in healthcare are:

- **Energy-Intensive Operations:** Hospitals, pivotal in healthcare, are energy-intensive due to lighting medical equipment, water heating, and climate control needs.
- ***Internal Heat Impact:*** High-power equipment generates internal heat, intensifying the demand for cooling and ventilation systems to maintain optimal operational conditions.
- ***Ventilation and Cooling Systems:*** Hospitals rely on energy-consuming ventilation and cooling systems, adding to their carbon footprint. Adopting energy-efficient technologies and renewable energy sources is crucial for sustainable healthcare operations

Supply Chain Factors

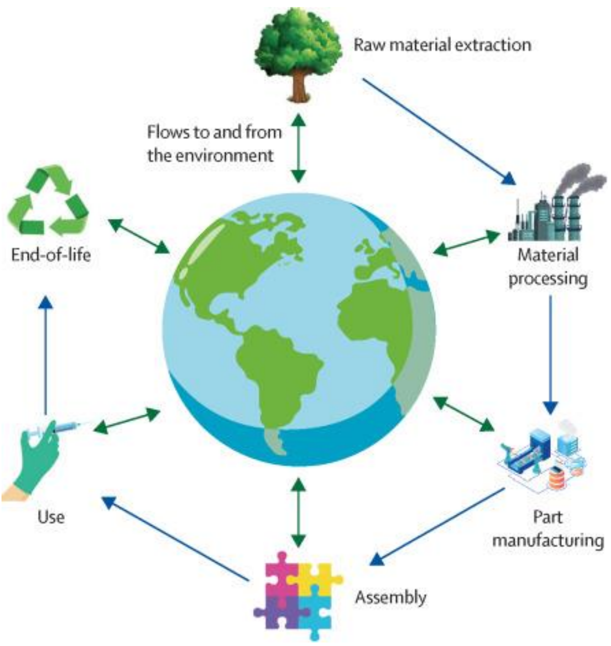

Figure 4.[7] Stages of life cycle assessment

Throughout each phase of healthcare machine production, the environmental impact is substantial as displayed in Figure 4. Raw material extraction and processing, involving metals, plastics, and electronic components, contribute to habitat destruction and water pollution. The production processes for healthcare machines, characterized by a high demand for energy and often dependent on fossil fuels, lead to the generation of greenhouse gas emissions and waste. Packaging, often non-biodegradable, increases environmental pollution. The product's lifespan and efficiency influence its environmental footprint, emphasizing the importance of durability and energy efficiency. E-waste generation, common in electronic healthcare equipment, poses risks if improperly disposed of. Proper end-of-life disposal methods, whether recycling or landfill, are crucial for environmental protection.

Single-use devices:

The widespread reliance on single-use medical devices, often promoted for infection control and value-based healthcare, lacks strong supporting evidence. These devices contribute to 90% of medical device-related waste, leading to harmful emissions and resource depletion[8]. Sterilization processes worsen environmental concerns, requiring specialized disposal. This poses a sustainability challenge for current healthcare practices. Additionally, the increasing use of Single-Use Plastics (SUPs) in items like PPEs, test kits, and medical apparatus adds further strain to waste management, posing significant challenges in the current scenario.

D. Clinical Trials

The acknowledgment of the environmental impact of clinical trials dates back approximately 15 years, with Ian Roberts and the Sustainable Trials Study Group highlighting that "clinical trials contribute substantially to greenhouse gas emissions... notably through energy use in research premises and air travel" as shown in Figure 5. Estimating this finding to the approximately 350,000 national and international trials registered on ClinicalTrials.gov suggests that the combined emissions from all global trials could amount to approximately 27.5 million tonnes of carbon dioxide equivalent.

Examining specific examples, the carbon footprint of CASPS, an international phase 2 clinical trial involving 47 participants, totaled 72 tonnes of CO_2. This footprint was primarily attributed to emissions from the clinical trials unit and staff travel. In contrast, PRIMETIME, a UK-based phase 3 trial with 1962 patients, resulted in a carbon footprint of 89 tonnes of CO_2, with the majority of emissions stemming from trial-specific, in-person participant assessments. These instances underscore the substantial environmental impact associated with both investigational and non-investigational medicinal product trials. [9]

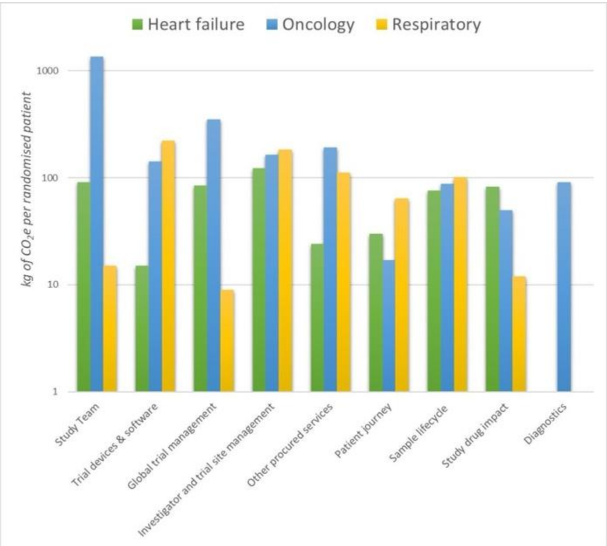

Figure 5[10]. It identifies carbon footprint drivers per patient, including team involvement, sample life cycle, and device provision, with unused supplies adding to CO2 impact.

More problems caused are:

- **Data Management and Storage:** The increasing reliance on electronic data management and storage in clinical trials, including data centers, can result in significant energy consumption and emissions.
- **Waste Generation:** Clinical trials contribute to the overall carbon footprint by producing waste, which includes single-use materials, packaging, and other disposable items.
- **Trial Design and Execution:** Extended periods of resource consumption, including energy and materials, can result from the complexity and duration of certain clinical trials, thereby contributing to carbon emissions.

To achieve maximum efficacy, initiatives to limit clinical trial emissions must include effective plans. This necessitates the establishment of a reliable approach for precisely measuring the carbon footprint associated with these trials, ensuring accurate evaluation and precision reduction plans.

E. Disease Detection

Addressing carbon emissions in medical imaging informatics involves the energy-demanding aspects of progressing clinical practice. The challenge lies in integrating efficient medical data management strategies, particularly with AI in big healthcare data analytics, and adopting eco-friendly approaches in the development of algorithmic methods for disease classification and organ/tissue segmentation.

- ***X-rays, MRIs, and CT Scan Imaging:*** The challenge involves reducing the carbon footprint associated with diagnostic imaging methods such as X-rays, CT scans, and MRI. While X-rays present radiation risks and soft tissue limitations, CT scans involve exposure and potential overuse. MRI scans, though painless, pose challenges like noise and claustrophobia. Accessibility, cost, and imaging constraints further complicate achieving comprehensive diagnostics sustainably.

- ***Biopsy and Genetic Tests:***

Genetic testing, while informative about inherited conditions, poses challenges in predicting symptom onset, severity, and disease progression. Many genetic disorders lack effective treatments, contributing to carbon-intensive healthcare. Biopsy procedures, essential for disease detection, often involve repetition and may require surgical interventions due to challenges in obtaining sufficient tissue through less invasive methods. The intricacies of selecting the most effective imaging guidance further complicate disease detection and contribute to carbon emissions in healthcare.

- ***Nanotechnology:***

Using nanotechnology in disease detection presents challenges for carbon emissions due to the fuel-intensive methods involved in the production, deployment, and disposal of nanomaterials. The production of nanoparticles and their integration into detection systems used in disease detection(an example of the detection of phytopathogen in plants is shown in Figure 6) often requires energy-demanding manufacturing processes.

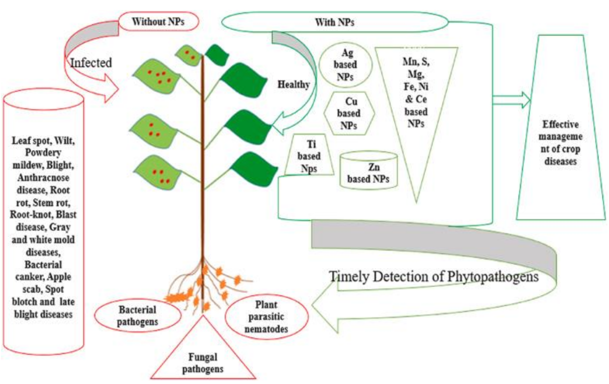

Figure 6[11]. Detection of phytopathogen using nanotechnology

Moreover, the production and implementation of nanotechnology-based diagnostic devices may involve intricate manufacturing processes, transportation, and packaging, all contributing to carbon emissions.

III. AI APPROACHES IN HEALTHCARE

A. Efficient AI Radiology

Green AI is increasingly recognized as a crucial asset in clinical radiology, utilizing significant advances in machine learning. These innovations enable automated, exact detection, and diagnosis of medical images with reduced carbon emissions. Radiologists, healthcare providers, and policymakers anticipate significant enhancements in both efficiency and quality. AI holds the potential for more accurate diagnosis, automating tasks currently resource-demanding for radiologists. The evolving role of AI in radiology represents a pivotal force, assuring enhanced healthcare outcomes and optimized procedures.[12]

1. ***AI1 service of Zebra medical vision***

Zebra Medical Vision[13] addresses the challenges of carbon emissions in healthcare from radiology. As a medical imaging analytics company, it utilizes artificial intelligence and machine learning to analyze medical imaging data, emphasizing the creation of AI-driven tools for the early detection of diverse medical conditions.
Advancements in deep-learning methods involve computers independently determining the significance of radiologic findings in provided images. This process establishes a network of connections, forming a basis for interpreting new images. Artificial intelligence swiftly processes radiologic images and associated data, identifying details that may escape human perception or be overlooked as clinically relevant as shown in Figure 7.
As a result, The company has an initiative called AI1, which focuses on making AI-enabled healthcare solutions, including their algorithms, affordable globally. It offers a flat-rate pricing model per scan, making the technology more accessible.

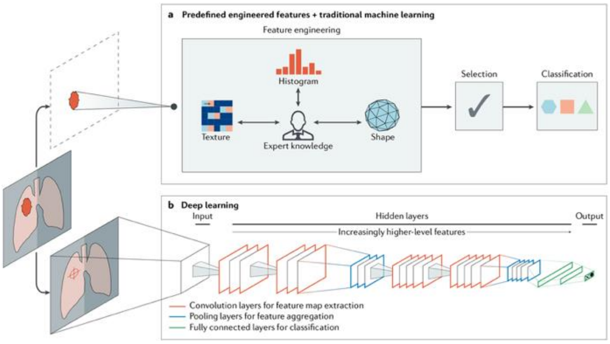

Figure 7[13]. It compares two AI methods for classification: one using expert-engineered features, the other leveraging deep learning for automatic feature extraction, selection, and classification in radionics research.
How Zebra Medical Vision AI solutions impact diagnostic processes:

- **Efficiency Improvement:** Zebra Medical Vision's AI algorithms have increased efficiency in the diagnostic workflow thus helping Radiologists by providing them with more streamlined processes, allowing them to focus on complex cases.
- **Paperless Workflow:** Zebra's AI solutions facilitate a transition to a more paperless workflow by reducing the need for physical copies of images and associated paperwork, thus minimizing resource consumption and waste.
- **Remote Accessibility:** Zebra's AI solutions, offer remote accessibility, thus helping radiologists to work from various locations. This minimizes travel requirements and associated carbon emissions, advancing a sustainable approach to healthcare delivery.

2. AI approach of Google Deep Mind

Google DeepMind[14] introduces CoDoC, an innovative AI system optimizing collaboration between AI tools and clinicians in medical image interpretation. CoDoC intelligently determines when to rely on predictive AI or defer to clinicians. In a large UK mammography dataset, CoDoC achieved a remarkable 25% reduction in false positives, reducing clinician workload by 66%. Google Deepmind achieved an impressive 40% reduction in power consumption, translating to a substantial 15% overall power saving after accounting for various factors. With an annual electricity usage of 4,402,836 MWh in 2014, equivalent to 366,903 US households, the efficiency gain results in significant cost savings, reinforcing the financial benefits of Google's AI investment, including the reported $600 million acquisition of DeepMind in 2014.[15]

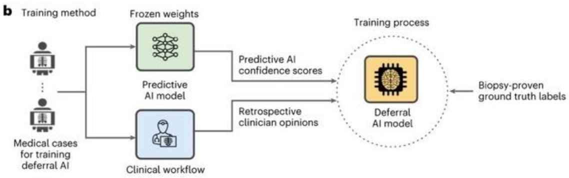

Figure 8[16] .Training Method of CoDoC

Three criteria were selected while developing CoDoC:
- Non-machine learning experts, like healthcare providers, should be able to deploy the system and run it on a single computer.
- Training would require a relatively small amount of data – typically, just a few hundred examples.
- The system could be compatible with any proprietary AI models and would not need access to the model's inner workings or the data it was trained on.

B. AI-integrated telemedicine for a lower carbon footprint in the healthcare sector

Vital healthcare services often exhibit an inverse relationship between complexity and carbon footprint. Complex services have higher carbon intensity and emissions. In-hospital care and frequent patient transport contribute significantly to healthcare's carbon footprint. Hence, transitioning certain healthcare components to telemedicine offers an avenue for eco- and patient-friendly healthcare as shown in Figure 9. While unable to replace in-person doctor-patient communication, telemedicine facilitates continuous, readily accessible, and personalized care—integral aspects of patient-friendly healthcare.
Telemedicine[17] consists of healthcare services delivered remotely with the assistance of telecommunications. The broad definition of telemedicine reflects that this growing field involves various services. Telemedicine is used for prevention and monitoring to replace in-person consultations, but even interventional procedures may be conducted remotely in the future.
In present-day times and, hopefully, in the post-COVID-19 era, teleconsultations have the potential to substitute certain visits. This is particularly beneficial for patients in remote areas where in-person visits are challenging and for those near healthcare facilities where visits might be deemed unnecessary.
The integration of telemedicine and artificial intelligence (AI) holds the potential to further reduce healthcare's carbon footprint. Recent advancements in AI enable the monitoring of patients with chronic conditions and the emergency assessment of patients seeking medical attention with acceptable levels of accuracy and safety.
The synergy between AI and telemedicine is expected to contribute to environmental efforts by decreasing carbon emissions.

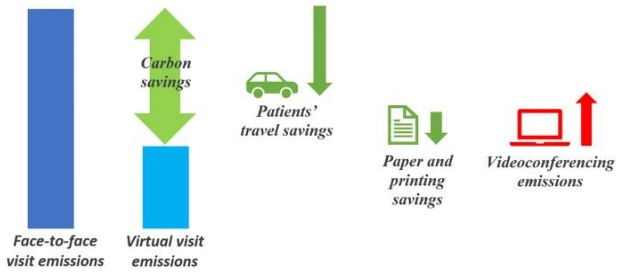

Figure 9[18]. Calculating online visit carbon savings: sum avoided travel, printing benefits, subtracting videoconferencing emissions for net environmental impact assessment.

Ultimately, this initiative requires swift communication. Climate change and telemedicine are technically complex, demanding funding and regulatory backing for implementation. Major corporations like Google and Nokia have already shown support by allocating funds for telemedicine and associated research.

C. Autonomous predictive maintenance in Healthcare

Predictive maintenance[19] leverages industrial IoT for precise identification of equipment maintenance needs, optimizing uptime and reducing costs. Utilizing continuous data from IoT-connected equipment, it offers a detailed performance trend profile. This IoT-driven solution eliminates guesswork in scheduled maintenance, reducing errors and lowering the carbon footprint. In the event of unexpected breakdowns, maintenance services typically resort to energy-intensive emergency repairs, affecting the environment. Predictive maintenance, fueled by sensor data, significantly curtails such interventions, vital for sectors like aviation, where minor overconsumption has notable ecological consequences. This proactive approach not only cuts costs but fosters resource efficiency, enabling engineers to design eco-friendly solutions across industries. Explore our predictive maintenance solution's energy sector use cases for deeper insights.

1. Lifecycle Assessment:

- Life Cycle Assessment (LCA)[20] systematically assesses the environmental impact throughout a product, material, or process's entire life cycle. It frames the environmental consequences of the detailed systems within industrial development. Integrating AI algorithms into studies amplifies problem identification to solution stages, fostering the construction of predictive machine learning models. This merging aids informed decision-making by combining the predictive capabilities of AI with the comprehensive environmental insights provided by LCA.

- Applying Life Cycle Assessment (LCA) as shown in Figure 10 to Building Life Cycle Carbon Emissions (BLCCE) involves orderly assessment of carbon impacts from construction to demobilization. Integrated LCA enhances sustainability, identifying carbon reduction opportunities and guiding eco-friendly construction decisions for a greener environmental footprint.

Figure 10[20] . The linear production model

Using Life Cycle Assessment (LCA) for Building Life Cycle Carbon Emissions (BLCCE) includes a thorough analysis of carbon impacts across a building's lifespan. This analysis spans construction, operation, and decommissioning, offering a key review of the ecological footprint. Integrating LCA into BLCCE enhances sustainability by specifying carbon reduction opportunities and refining resource usage throughout the building's life cycle, guiding informed decisions for environmentally conscious construction practices aligned with conservation objectives.

Steps involved in Life Cycle Assessment of Building Life Cycle Carbon Emissions are:

- Scope Definition: Clearly outline the assessment boundaries, specifying stages like construction, operation, and deactivating for healthcare buildings.
- Inventory Analysis: Collect wide-ranging data on inputs (e.g., raw materials) and outputs (e.g., emissions) across the healthcare building's life cycle.
- Impact Assessment: Quantify environmental consequences, including carbon emissions and resource depletion, to assess the ecological impact.
- Improvement Identification: Assess results to focus areas for carbon reduction and sustainability enhancement in the healthcare building's life cycle.
- Transparent Reporting: Communicate findings openly to stakeholders, nurturing informed decisions and encouraging sustainable practices in healthcare facility design and operation.

Life Cycle Assessment (LCA) is the ideal tool for easing carbon emissions in buildings. It systematically evaluates a building's environmental impact throughout its life cycle, offering insights into carbon reduction possibilities. LCA guides sustainable decisions in construction, ensuring a greener environmental footprint and contributing to overall conservation diligence.

D. AI in the clinical trial

1. Alpha Fold2

AlphaFold2's[21] game-changing achievement in predicting protein structures represents a significant leap in scientific research, particularly in drug discovery. The accurate modeling of three-dimensional protein structures is an everlasting hurdle, and it's in CASP14 with a median backbone accuracy of 0.96 Å, showcasing its superiority. This breakthrough is powered by an end-to-end deep neural network that leverages information from homologous proteins and multiple sequence alignments (MSAs), integrating evolutionary, physical, and geometric constraints for precise predictions.
AlphaFold2 introduces three modules in its architecture. The Input Module processes amino acid sequences, identifying homologs and conducting MSAs to extract co-evolution information, distinguishing itself from traditional homology modeling. The Evoformer Module, with 48 non-shared blocks, dynamically processes MSA and pair representations, enhancing information exchange through transformer-based layers with gated self-attention.[22] The Structure Module, likely a decoder, predicts 3D atom coordinates from abstract representations, completing the protein structure prediction pipeline.
Beyond its impact on drug discovery and biological research, the environmental implications of AlphaFold2's accuracy are noteworthy. Accurate protein structure predictions offer insights into molecular interactions, potentially accelerating drug development. This acceleration could reduce the need for extensive experimental testing, cutting down on the environmental impact associated with laboratory experiments, including resource consumption and waste generation.
Moreover, improved protein structure predictions contribute to the advancement of precision medicine. Tailoring medical treatments based on individual genetic and protein characteristics can lead to more effective therapies, reducing the environmental impact of ineffective treatments and associated resource consumption. By facilitating targeted and efficient drug development, AlphaFold2's advancements align with sustainability goals in the pharmaceutical and healthcare industries.
In conclusion, AlphaFold2's accuracy in predicting protein structures not only transforms drug discovery but also holds promise for minimizing the environmental footprint of experimental processes. The convergence of precision medicine and AI-driven predictions opens avenues for more sustainable and impactful advancements in the biomedical field.

2. AI and ML algorithm by Evinova

The launch of Evinova[23] by AstraZeneca marks a significant step toward revolutionizing the healthcare sector with its digital health solutions. Evinova aims to be a leading provider of these solutions, addressing the needs of healthcare professionals, regulators, and patients alike. The comprehensive goal is to reduce the time and cost associated with developing new medicines, bring healthcare closer to patients, alleviate the burden on health systems, and most importantly reduce carbon emissions.

A key focus of Evinova lies in its application of artificial intelligence (AI) and machine learning (ML) algorithms, particularly in the domain of study design and planning. By leveraging these technologies, clinical development and operations teams can streamline the process of designing optimal studies, taking into account critical variables. This not only enhances the efficiency of trial planning but also holds great promise in reducing the environmental impact associated with resource-intensive trial activities.

Evinova goes beyond conventional considerations by incorporating models to estimate the study's carbon footprint. This demonstrates a commitment to sustainability and offers a unique avenue for teams to make eco-conscious choices in their study designs. Furthermore, the pursuit of opportunities in digital remote patient monitoring aligns with a broader trend toward technologies that can reduce the carbon footprint associated with patient travel and transportation.

In essence, the platform's features, from automatic costs and historical data analysis to carbon footprint estimation, collectively signify a commitment to reducing the ecological impact of healthcare practices. As the healthcare sector moves toward a more sustainable future, Evinova stands at the forefront, offering a promising paradigm for the integration of cutting-edge technology and environmental consciousness in clinical research.

E. Disease Detection in Healthcare

1. *CNN model based on Deep Learning*

The integration of artificial intelligence (AI) and deep learning (DL) models, particularly the widespread use of Convolutional Neural Network (CNN)[24] architectures, has ushered in a transformative era for the diagnosis of COVID-19 and medical image processing. This technological evolution not only addresses the limitations of conventional testing methods like RT-PCR but also introduces alternative diagnostic approaches, leveraging medical images such as Chest X-ray (CXR) and computed tomography (CT).

- Advancements in AI and Deep Learning:

The emergence of AI-based DL models has streamlined the processing of large datasets in various fields, particularly in medicine.

- Prevalence of Convolutional Neural Network (CNN) Architectures in Medicine

CNN architectures are extensively employed in the medical domain for their proficiency in both feature extraction and classification from images.

- Superiority of DL Over Traditional Machine Learning (ML) Methods:

DL models, notably CNNs, outperform traditional ML methods by simultaneously handling feature extraction and classification.

The ability to discern minute details through extracted features enhances the overall effectiveness of DL models.

- Comparison with Traditional Machine Learning Methods:

CNN architectures extract features from images and classify them through fully connected layers, akin to the task performed by ML algorithms.

While the advancement in AI and DL contributes to medical diagnosis efficiency, it also plays a crucial role in reducing the carbon footprint in the healthcare sector.

The integration of AI and deep learning in medical diagnostics, particularly utilizing medical images like CXR and CT instead of traditional RT-PCR testing, holds significant promise for reducing the environmental impact in healthcare. AI-driven diagnostics not only enhance testing efficiency but also minimize the environmental footprint associated with multiple diagnostic procedures. By reducing dependency on resource-intensive imaging techniques and leveraging Transfer Learning with pre-trained CNN models, the healthcare sector can develop more efficient models with a smaller environmental footprint. Additionally, the potential for remote diagnostic support facilitated by AI can decrease carbon emissions linked to travel, contributing to environmental conservation.

2. ML in Liver Histopathology

The ML model developed by Munsterman[25] et al. introduces an innovative approach to quantifying hepatic steatosis in Whole Slide Images (WSI), showcasing a positive impact on the environment and healthcare efficiency. By automating the detection and classification of steatotic hepatocytes in liver tissue slides, the model reduces the dependence on manual, time-intensive annotation by healthcare professionals, streamlining the diagnostic process and minimizing resource-intensive manual labor.

The algorithm achieves a remarkable accuracy of 91.9%, coupled with a low classification error of 8.1%, indicating its reliability in identifying and differentiating steatotic areas[26] . This high precision is crucial for medical applications, promising more accurate diagnoses and potentially reducing the need for redundant or unnecessary tests, thereby contributing to a more sustainable healthcare system.

The steatosis quantification algorithm identifies steatotic hepatocytes based on white color, specific size, and round shape. Using color thresholds in the HSB color space, it distinguishes potential hepatocytes, addressing the challenge of underestimating surface area. A statistical classifier, employing logistic regression, refines identification by considering size and roundness, ensuring accurate detection amid diverse tissue elements.

IV. COMPARISON

A. AI1 service of Zebra medical vision

Advantage:
- Zebra Medical Vision's AI streamlines diagnostics, enhancing radiologists' focus and efficiency.
- It reduces paper use, promoting eco-friendly medical workflows and efficiency.
- Its initiative promotes global accessibility, ensuring affordable healthcare solutions worldwide.
- It emphasizes early detection, improving timely diagnosis for better patient outcomes.

Disadvantage:
- Heavy reliance on AI in diagnostics may raise concerns about human oversight.
- Using AI with medical data raises privacy worries, necessitating strong safeguards.
- Merging AI into healthcare faces challenges like compatibility, training, and resistance.

B. AI approach of Google Deep Mind

Advantage:
- CoDoC reduces human involvement, lowering potential carbon emissions intelligently.
- CoDoC's 25% false positive reduction aids accurate diagnoses, cutting emissions.
- CoDoC's easy deployment streamlines processes, contributing to reduced emissions.

Disadvantage:
- Limited CoDoC details may hinder transparent, sustainable practices in training.
- AI ethical concerns, including CoDoC, may impact privacy, increasing emissions.
- CoDoC's validation uncertainty may lead to increased emissions in implementation.

C. AI-integrated telemedicine for a lower carbon footprint in the healthcare sector

Advantage:
- It minimizes tests, lowers emissions, and aligns with sustainability goals.
- It cuts vehicle emissions, promoting a healthier, eco-friendly environment.
- Telehealth curtails healthcare infrastructure, fostering sustainable practices, and reducing carbon emissions.
- It expands global access, reducing the environmental impact of medical travel.

Disadvantage:
- Telehealth's digital reliance may heighten energy use, especially from non-renewables.
- Its tech advances may accelerate e-waste, raising environmental concerns.
- Its infrastructure may carry a higher carbon footprint during its lifecycle."
- Telehealth's exam constraints may increase in-person visits, raising transport emissions.

***D.* Autonomous predictive maintenance in Healthcare**

Advantage:
- Reduce the system's carbon footprint, combining choices for ecological sustainability and emission reduction.
- Boosting energy productivity reduces carbon emissions, enhancing responsible resource use."
- Eco-friendly waste management and sustainable construction ensure a viable economy, reducing environmental impact.
- Commits to environmental accountability, improving brand reputation, and clarifying trust among stakeholders.

Disadvantage:
- Carbon assessments rely on assumptions, risking neglect and varying results.
- Variation in methods leads to unreliable findings in carbon emissions.
- Carbon evaluation is resource-intensive; inadequate data compromises assessment reliability.
- Decision-makers navigate complexity in choosing carbon reduction measures, considering potential environmental outcomes.

E. AlphaFold2

Advantage:

- AlphaFold2 Uses an end-to-end deep neural network for streamlined predictions.
- Innovative Designs as it Combines alignments and pairwise features for versatile predictions.
- Consists of a Special Attention Model that Enhances focus, refining predictions for increased accuracy.
- Masked MSA Loss Enables simultaneous training with structural information, improving performance.

Disadvantage:
- AlphaFold2's computational requirements may hinder accessibility for researchers with limited resources.
- A lack of detailed training insights may challenge reproducibility and modification for researchers.
- AlphaFold2's performance may vary across protein families, presenting challenges in predicting structures for unique or less-studied proteins.

F. AI and ML algorithm by Evinova

Advantage:
- Evinova aims to address diverse healthcare needs, providing a holistic approach for professionals, regulators, and patients.
- Evinova's goal is to bring healthcare closer to patients, promoting accessibility and potentially minimizing the need for extensive travel.

- Features like automatic cost analysis and carbon footprint estimation demonstrate a commitment to reducing the ecological impact of healthcare practices.
- Evinova's focus on digital remote patient monitoring aligns with the trend of reducing the carbon footprint associated with patient travel, contributing to environmental sustainability.

Disadvantage:
- Integrating AI and ML algorithms into study design may pose implementation, training, and adoption challenges.
- Lack of discussion on user adoption challenges, particularly among healthcare professionals, may hinder successful implementation.
- The use of advanced technologies like AI and ML raises concerns about data security and privacy, necessitating robust measures.

G. CNN model based on Deep Learning

Advantage:
- Efficient CNN implementation reduces the carbon footprint, enhancing accessibility for facilities.
- AI models, like CNNs, are ethically tuned and contribute to emissions reduction and improved efficiency.
- CNN models' streamlined operation enhances energy efficiency, aiding transparent interpretation, and potentially lowering emissions.

Disadvantage:
- CNN's resource-demanding implementation may increase carbon emissions, limiting accessibility.
- Algorithmic bias in AI, including CNNs, poses ethical concerns, impacting efficiency.
- CNN's 'black-box' nature increases energy use, hindering transparent interpretation, and potentially raising emissions.

H. ML in Liver Histopathology

Advantage:
- Reduces tests, fostering sustainable healthcare by minimizing procedures and resource use.
- Automated pathology minimizes environmental impact, optimizing chemical use for sustainability.
- Aids hepatic steatosis studies, offering insights for therapeutic advancements in related conditions.
- Early detection via automation supports timely interventions in managing liver-related conditions.

Disadvantage:
- The model's effectiveness hinges on the quality and diversity of the training dataset.
- AI in healthcare demands adherence to ethical guidelines, addressing concerns about patient privacy, consent, and impact on human decision-making.
- The algorithm's accuracy may suffer from poor image quality or artifacts in H&E-stained liver tissue slides.

We condense the advantages and disadvantages of each sustainable AI approach outlined above into a concise and comprehensive comparison table as shown in Table 1, enhancing clarity and understanding.

Parameter / AI Technique	Zebra Medical Vision	Google Deep Mind	Telemedicine	Predictive Analysis	AlphaFold2	Evinova	CNN Model	Liver Histopathology
Data Base	✓	✓	✗	✓	✓	✓	✓	✓
Early detection	✓	✓	✗	✗	✗	✗	✗	✓
Sustainable practices	✓	✓	✓	✓	✓	✓	✓	✓
Deep neural network	✗	✓	✗	✗	✓	✗	✓	✗
Lowering emission	✓	✓	✓	✓	✓	✓	✓	✓
Remote Patient Monitoring	✗	✗	✓	✗	✗	✓	✗	✗
Eco-friendly	✓	✗	✓	✓	✗	✓	✓	✓
Energy efficient	✓	✓	✓	✓	✓	✓	✓	✓
User-friendly	✗	✓	✗	✗	✓	✗	✓	✗
Ethically Safe	✓	✗	✓	✓	✓	✗	✗	✗

Table 1. Comparison Table

V. CONCLUSION

The comparative exploration of sustainable AI approaches in healthcare highlights a complex landscape. The sustainable AI techniques, including the AI service of Zebra Medical Vision, Google DeepMind AI, AI-integrated telemedicine, Autonomous Predictive Maintenance, AlphaFold2, Evinova, CNN models, and ML in liver histopathology, showcase a dual nature of advancing efficiency, reducing environmental impact, and improving patient outcomes. Simultaneously, they experience inherent challenges such as privacy concerns, ethical considerations, and implementation hurdles. This comprehensive review illuminates the mutual relation between innovation and challenges in the search for sustainable and impactful AI applications within the healthcare domain, offering valuable insights for future developments and considerations in this evolving field.

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