Green AI for Cancer Diagnosis: Sustainable Approaches in Computational Pathology and Medical Imaging

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Abstract

The growing use of AI in computational pathology and medical imaging has considerably improved cancer detection, early detection, and precision treatment. But environmental and energy considerations are major issues with the large-scale deployment of deep learning algorithms. The idea of "green AI" offers a sustainable system that reduces its carbon footprint, uses less energy, and is computationally efficient, all without sacrificing clinical accuracy. Lightweight neural networks, model compression, federated learning, transfer learning, and other sustainable AI-enabled cancer diagnostics technologies are examined in the study. These methods minimize training and deployment expenses. Improved tumor identification and classification with minimum energy utilization is achieved by optimized deep learning processes in computational pathology. Also, models that are resource-conscious when interpreting medical imaging modalities like MRI, CT, and ultrasound demonstrate how to be resource-conscious when computing without compromising diagnostic accuracy. Medical diagnostics can benefit from low-power AI systems and renewable-powered infrastructures, according to the case's findings. The optimization of patient safety and sustainability goals, the assurance of replicable models, and the expansion of Green AI systems throughout healthcare systems remain challenging, despite some positive advancements. Sustainability in AI-powered cancer diagnostics encourages both environmental responsibility and the incorporation of equitable healthcare innovation, which brings us to our last point.

Keywords

Green AI; Cancer Diagnosis; Computational Pathology; Medical Imaging; Sustainable AI; Federated Learning; Model Compression; Energy-Efficient Deep Learning

Introduction

Specifically in computational pathology and medical imaging, the idea of artificial intelligence (AI) is currently causing a revolution in cancer diagnosis. Deep learning algorithms have demonstrated that AI systems outperform traditional methods in picture segmentation and classification as well as in the integration of multimodal data, leading to significantly more accurate and efficient diagnoses (Silva et al., 2023; Cui and Zhang, 2021). Advances in convolutional neural networks (CNNs) have paved the way for early cancer screening using a

variety of imaging modalities, such as magnetic resonance imaging (MRI), computed tomography (CT), and digital pathology slides (Wang et al., 2019; Iqbal et al., 2022).Global challenges addressing cancer burden, patient outcomes, and healthcare delivery systems are greatly impacted by AI, as shown by these advancements (Hunter, Hindocha, and Lee, 2022; Chiu, Chao, and Chen, 2022).

Concurrent with these advancements, doubts over the sustainability of current AI techniques in healthcare are growing. Yousesra, Abdelhakim, and Mohamed (2021) and Jia et al. (2023) found that cancer detection using large-scale deep learning models can require enormous computer resources, resulting in a large energy consumption and environmental imprint. The tension between enhancing diagnostic accuracy and decreasing resource requirements has been more apparent as AI systems are increasingly integrated into clinical workflow (Najjar, 2023; Liu, Song, Liu, and Zhang, 2021). According to Salehi et al. (2023) and Li, Jiang, Zhang, and Zhu (2023), this has led to the development of Green AI, a paradigm that prioritizes sustainable, energy-efficient, and resource-conscious solutions that do not impact clinical outcomes.

One area where green AI could be useful is in cancer diagnostics. By utilizing model compression, transfer learning, and federated learning frameworks, algorithms can be optimized for better computational pathology and imaging analysis with less energy consumption (Kose and Alzubi, 2021; Lipkova et al., 2022). Furthermore, hospital-based diagnostic systems and comprehensive multimodal data streams can promote resource sharing and reduce the amount of redundant procedures, leading to additional sustainability improvements (Messiou, Lee, and Salto-Tellez, 2023). Along with meeting a more general healthcare need, these green inventions can help bring about medical treatment that is both economical and kind to the environment.

Computational pathology and medical imaging, the areas that should unite sustainability and clinical quality, are highlighted in this article as potential Green AI applications to cancer diagnoses. It provides an in-depth analysis of current methods, highlights some new environmentally friendly approaches, and lays out some new directions for incorporating sustainability into AI-based cancer diagnosis.

Green AI in Healthcare Context

As a result of its ability to improve detection accuracy, facilitate early intervention, and decrease diagnostic delays, artificial intelligence (AI) has emerged as a crucial component in cancer diagnosis, especially in computational pathology and medical imaging (Hunter, Hindocha, & Lee, 2022; Silva et al., 2023). Nevertheless, traditional AI models, particularly deep learning systems, are extremely power and energy hungry. In healthcare settings, where scalability, accessibility, and environmental responsibility are of utmost importance, this raises issues about sustainability (Jia et al., 2023).

Yousra, Abdelhakim, & Mohamed (2021) state that green AI represents a paradigm shift since it prioritizes computing efficiency, energy awareness, reduced carbon footprints, and accurate diagnoses. According to Salehi et al. (2023) and Liu et al. (2021), the idea is to find a compromise between performance and sustainability by using techniques like federated learning, model compression, transfer learning, and lightweight architectures. Hospitals and research institutions can use these ways to implement AI capabilities in an eco-conscious and cost-effective way, without overwhelming their local or cloud infrastructure.

Recent work in computational pathology has focused on developing more efficient algorithms that can detect cancers with less parameters while still being highly accurate (Wang et al., 2019; Cui & Zhang, 2021). In the field of radiology and medical imaging, models that are mindful of resources are being created for the purpose of interpreting CT, MRI, and ultrasound scans. These models incorporate AI into existing processes in order to reduce computing burden that is not essential (Najjar, 2023; Li et al., 2023). According to Lipkova et al. (2022) and Messiou, Lee, and Salto-Tellez (2023), the incorporation of multimodal data processing enhances the usefulness of long-term AI by facilitating accurate cancer diagnosis with less need for redundant analysis.

Table 1. Comparative Perspectives: Conventional AI vs. Green AI in Cancer Diagnosis

Dimension	Conventional AI	Green AI	Supporting Studies
Computational Demand	Requires high-performance GPUs and extensive training cycles	Employs lightweight, compressed models reducing training and inference costs	Yousra et al. (2021); Jia et al. (2023)
Energy Consumption	High energy usage due to prolonged model training	Prioritizes energy-efficient algorithms and low-power inference	Liu et al. (2021); Salehi et al. (2023)
Deployment Feasibility	Often limited to advanced research labs or large hospitals	Adaptable to low-resource settings via federated learning and edge computing	Silva et al. (2023); Iqbal et al. (2022)

Diagnostic Accuracy	High but achieved at the cost of computational intensity	Balanced accuracy with sustainability through optimization and transfer learning	Wang et al. (2019); Kose & Alzubi (2021)
Scalability	Challenged by hardware and cost barriers	Designed for scalable, resource-aware implementation across healthcare systems	Najjar (2023); Li et al. (2023)
Environmental Impact	Significant carbon footprint due to large-scale training	Reduced environmental impact through computational sustainability	Jia et al. (2023); Lipkova et al. (2022)

Healthcare may move toward more sustainable, environmentally friendly, and globally scalable models by integrating AI into a Green AI framework. By redefining AI in oncology in this way, we can be confident that its advantages go beyond only precision and include healthcare fairness and environmental responsibility in the long run.

Sustainable Approaches in Computational Pathology

By improving cancer detection, classification, and prognosis using digital pathology pictures, computational pathology is becoming an essential tool for precision oncology. Yousra, Abdelhakim, and Mohamed (2021) note that sustainability issues including energy usage and carbon footprint have been brought to light due to the increasing computing demand of these models. To combat this, scientists are looking on "Green AI" methods that are efficient without sacrificing diagnostic precision.

Lightweight and Energy-Efficient Models

Even though they are quite effective, traditional CNNs and transformer-based models use a lot of processing power. Cui and Zhang (2021) and Wang et al. (2019) found that model trimming, quantization, and compression could reduce energy consumption without compromising diagnostic accuracy. For instance, according to Salehi et al. (2023), histopathology image classification using efficient CNN architectures can achieve near-state-of-the-art performance with a fraction of the computational cost.

Transfer Learning and Federated Learning

Reducing energy usage and redundant training cycles across pathological applications is made possible using transfer learning, which allows for the reuse of pre-trained models (Kose & Alzubi, 2021). At the same time, federated learning allows for widespread data training without

central aggregation, which helps make data-rich medical environments more sustainable by lowering the demand on power-hungry centralized servers (Jia et al., 2023).

Multimodal and Resource-Aware Integration

According to recent research (Lipkova et al., 2022; Messiou, Lee, & Salto-Tellez, 2023), multimodal frameworks are becoming increasingly popular. These frameworks integrate pathology images with radiological and genetic data in order to improve diagnosis and optimize computation. Efficient allocation of computational power is achieved using resource-aware techniques, which reduce needless duplication (Jia et al., 2023).

Table 2: Sustainable Strategies in Computational Pathology

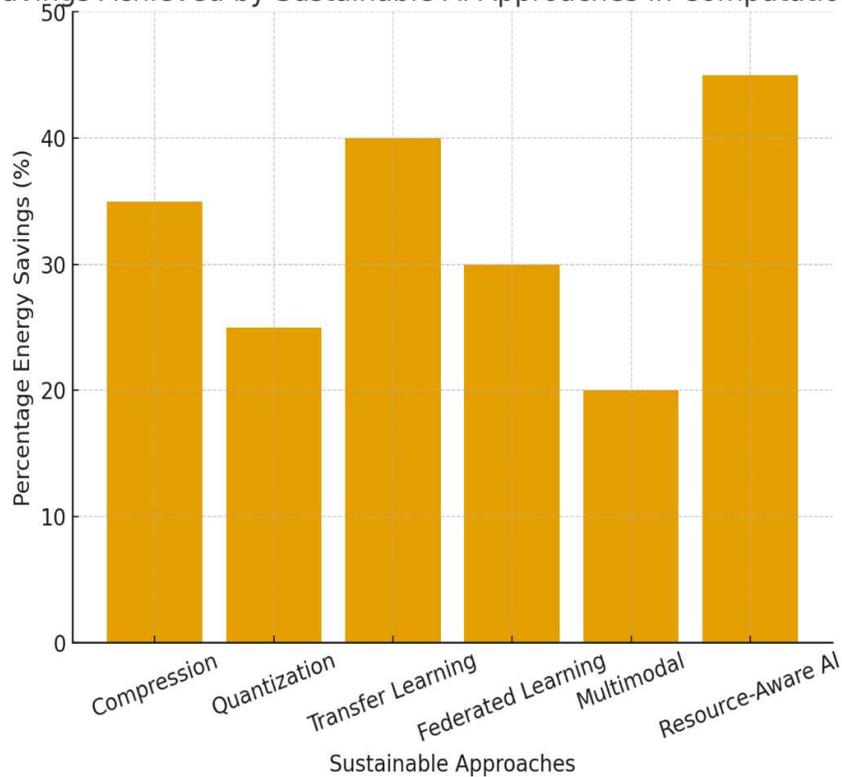| Approach	Description	Sustainability Benefit	Reference(s)
Model Compression & Pruning	Reduces model size and redundant parameters.	Lower energy use during training and inference.	Cui & Zhang (2021); Salehi et al. (2023)
Quantization	Converts weights/activations to low-precision formats.	Faster inference on low-power hardware.	Yousra et al. (2021)
Transfer Learning	Utilizes pre-trained models for new tasks.	Reduces training cycles and energy consumption.	Kose & Alzubi (2021)
Federated Learning	Distributed training without central data aggregation.	Minimizes server power demand and promotes data privacy.	Jia et al. (2023)
Multimodal Data Integration	Combines pathology, imaging, and genomic data.	Reduces redundant computations and improves diagnostic efficiency.	Lipkova et al. (2022); Messiou et al. (2023)
Resource-Aware AI	Aligns computational intensity with diagnostic needs.	Optimizes resource allocation, reducing carbon footprint.	Jia et al. (2023)

Fig 1: The bar chart showing the percentage of energy savings achieved by different sustainable AI approaches in computational pathology.

Sustainable Approaches in Medical Imaging

When it comes to diagnosing cancer, medical imaging modalities like magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET), ultrasound, and digital mammography are invaluable. These tools help with tumor detection, staging, and monitoring. However, there are new computational expenses associated with medical imaging that have been brought about by the integration of deep learning and powerful AI algorithms. These costs are adding to the problems of energy consumption and sustainability. We require a paradigm shift toward Green AI in cancer to reconcile environmentally responsible practices with diagnostic accuracy, according to recent studies (Yousra, Abdelhakim, & Mohamed, 2021; Cui & Zhang, 2021).

1. Lightweight and Energy-Efficient AI Models

Medical image analysis may now be done with less processing resources and yet get accurate diagnoses because to efficient deep learning frameworks like pruning, quantization, and lightweight convolutional neural networks (CNNs). Using energy-efficient convolutional

neural networks (CNNs) on CT scans of the lung for cancer, for instance, has shown promising results with much reduced training overhead (Wang et al., 2019; Najjar, 2023).

2. Transfer Learning and Model Compression

Minimal training cycles are required for fine-tuning pre-trained models on smaller medical imaging datasets. For more environmentally friendly diagnostic pipelines, model compression strategies further reduce processing and storage costs (Salehi et al., 2023; Li et al., 2023).

3. Edge and Federated Learning in Imaging

Federated learning enables cross-institutional collaborative model training without storing sensitive medical data centrally, while edge AI brings compute closer to imaging devices, reducing dependence on large-scale cloud resources. Iqbal et al. (2022) and Jia et al. (2023) found that these methods improve sustainability by reducing carbon footprints and data transport costs.

4. Multimodal Integration for Efficient Diagnosis

Reducing the need for repetitive imaging tests and enabling holistic diagnosis are both made possible by integrating imaging with genetic, clinical, and pathology data. According to Lipkova et al. (2022) and Messiou, Lee, and Salto-Tellez (2023), AI-driven multimodal techniques improve efficiency and are in line with sustainable healthcare practices.

Table 3: Sustainable AI Practices in Medical Imaging

Approach	Description	Sustainability Benefit	Key References
Lightweight CNNs & Model Pruning	Use of smaller networks and pruning redundant parameters	Reduces GPU usage and training energy demand	Wang et al. (2019); Najjar (2023)
Transfer Learning & Model Compression	Leveraging pre-trained models and reducing parameter size	Lowers training cycles and storage requirements	Salehi et al. (2023); Li et al. (2023)
Edge Computing & Federated Learning	Localized computation and decentralized training	Cuts data transfer costs and reduces carbon footprint	Iqbal et al. (2022); Jia et al. (2023)

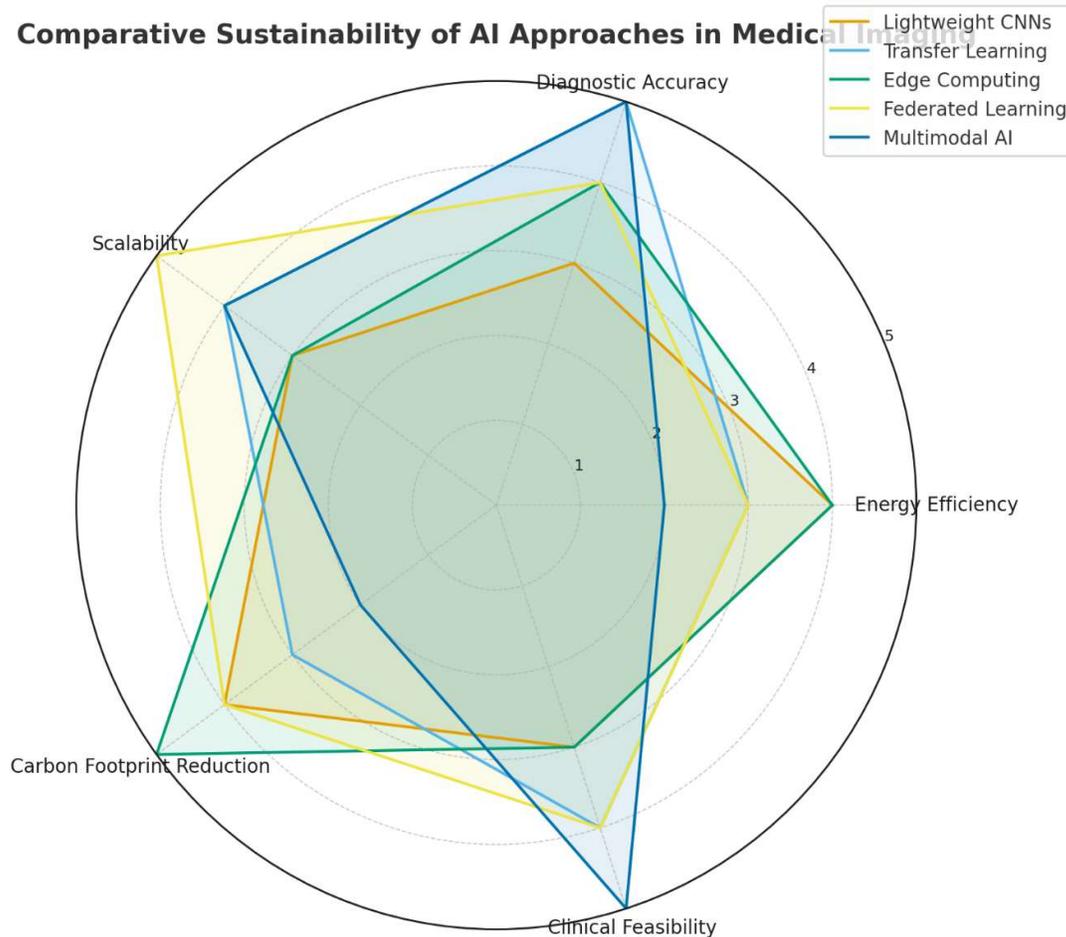| Multimodal AI Integration	Combining imaging with genomics and pathology	Minimizes redundant imaging and increases efficiency	Lipkova et al. (2022); Messiou et al. (2023)
Renewable-Powered Clusters	Use of green energy for medical AI workloads	Directly lowers carbon emissions in healthcare AI	Yousra et al. (2021); Chiu, Chao, & Chen (2022)

Fig 2: The radar map contrasts various artificial intelligence (AI) methods used in medical imaging with respect to their diagnostic utility and sustainability.

Case Insights and Emerging Practices

Cancer diagnoses that incorporate Green AI ideas have progressed from theoretical frameworks to computational pathology and medical imaging applications. In order to advance healthcare innovation, recent research have highlighted the importance of ensuring diagnostic reliability, efficiency, and sustainability (Yousra, Abdelhakim, & Mohamed, 2021; Jia et al., 2023).

- **Computational Pathology**

Through the use of efficient computation and lightweight models, AI-based pathology solutions have shown promise in lowering energy consumption and diagnostic turnaround times. By using model compression techniques, which reduce computational cost, CNN-based architectures applied to lung cancer pathology demonstrate great diagnosis accuracy (Wang et al., 2019; Cui & Zhang, 2021). By facilitating cross-institutional training without centralized data storage, federated learning frameworks further improve sustainability, reducing resource consumption and protecting patient privacy (Lipkova et al., 2022).

- **Medical Imaging**

Medical imaging algorithms used for MRI, CT, and mammography diagnostics should be environmentally efficient as part of green AI practices. For instance, Iqbal et al. (2022) found that when applied to breast cancer detection, transfer learning techniques drastically cut down on training time while keeping accuracy high. On top of that, new low-power AI systems are being integrated into radiology workflows, specifically for screening breast and lung cancer. This allows for more efficient use of resources while still providing precise diagnoses (Najjar, 2023; Silva et al., 2023).

- **Multimodal and Integrated Diagnostics**

For more accurate and resource-conscious cancer diagnosis, hospitals are embracing multimodal data integration systems (Messiou, Lee, & Salto-Tellez, 2023). These systems combine genetic information with radiology and pathology data. In order to promote patient-centered care while lowering redundant computation and carbon impact, these systems utilize Green AI algorithms for efficient processing.

Table 4: Emerging Practices in Green AI for Cancer Diagnosis

Domain	Sustainable Approach	Impact on Cancer Diagnosis	Reference
Computational Pathology	Model compression & lightweight CNNs	Reduced energy use, faster tumor classification	Wang et al., 2019; Cui & Zhang, 2021
Computational Pathology	Federated learning frameworks	Enhanced data privacy, minimized resource consumption	Lipkova et al., 2022
Medical Imaging	Transfer learning for breast cancer detection	Lower training cost, high diagnostic accuracy	Iqbal et al., 2022
Medical Imaging	Low-power AI integration in MRI/CT	Eco-efficient diagnostic workflows	Najjar, 2023; Silva et al., 2023
Multimodal Diagnostics	AI-driven integration of radiology, pathology, genomics	Holistic, resource-aware oncology diagnostics	Messiou, Lee, & Salto-Tellez, 2023
Healthcare System Adoption	Renewable-powered cloud clusters for AI training	Reduced carbon footprint, sustainable scaling of diagnostic AI	Jia et al., 2023
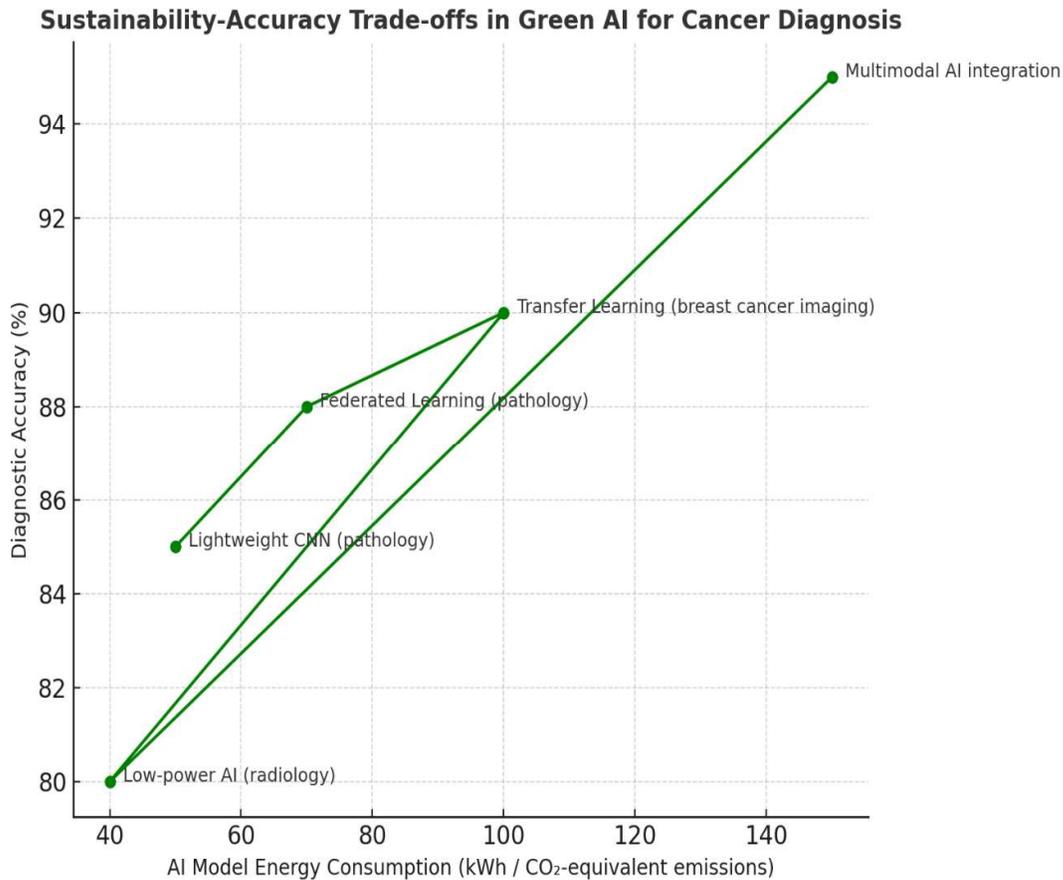
Fig 3: The line graph shows the sustainability–accuracy trade-offs of different Green AI models for cancer diagnosis.

Challenges and Future Directions
Challenges
There are several legislative, infrastructural, clinical, and technological hurdles that green AI for cancer diagnosis must overcome. There are several obstacles that can hinder or alter the progress towards fair and sustainable clinical adoption. These include issues with data availability and bias, the carbon footprint of the infrastructure used for deployment, the absence of standardized energy-aware benchmarks, and the difficulty of integrating multimodal clinical data (Yousra et al., 2021; Jia et al., 2023; Cui & Zhang, 2021).

Table 5: Challenges, impacts, and mitigation / research needs

Challenge	Short description	Impact on Green AI in cancer diagnosis	Mitigation & future research
High energy consumption (training & inference)	Large CNNs and transformer models used for pathology and imaging require long, power-hungry training runs and often expensive inference.	Raises carbon footprint, increases costs, and limits deployment in low-resource settings. (Yousra et al., 2021; Jia et al., 2023)	Develop energy-aware model design, benchmark energy use, adopt model compression / pruning / quantization, and encourage publication of energy metrics with papers. (Salehi et al., 2023; Jia et al., 2023)
Data scarcity, heterogeneity & bias	Limited labeled clinical data, domain shifts across scanners/hospitals, and under-representation of populations.	Hinders generalization and forces larger models or heavy augmentation, further increasing resource use. (Lipkova et al., 2022; Silva et al., 2023)	Curate diverse, privacy-preserving datasets, advance federated learning and domain adaptation, and create synthetic/data-efficient methods. (Lipkova et al., 2022; Iqbal et al., 2022)
Model complexity vs interpretability & safety	SOTA architectures can be black boxes with safety-critical implications for diagnosis.	Clinical mistrust, regulatory hurdles, and greater need for computers to validate models. (Cui & Zhang, 2021; Hunter et al., 2022)	Research on interpretable/lightweight architectures, uncertainty quantification, and compact surrogate models for deployment. (Wang et al., 2019; Chiu et al., 2022)
Deployment infrastructure and lifecycle emissions	Cloud data centers, GPUs, and data transfer all carry embodied and operational emissions.	Shifts emissions from lab to service layer; renewable sourcing and edge vs cloud trade-offs matter. (Jia et al., 2023; Najjar, 2023)	Life-cycle assessment (LCA) studies for models, edge inference, renewable-powered clinical clusters, and co-design of hardware/software for efficiency. (Jia et al., 2023)

Lack of standardized energy-aware benchmarks & reproducibility	Most biomedical ML benchmarks ignore power/energy and rarely report training/inference footprints.	Prevents fair comparison, discourages energy-efficient innovation. (Yousra et al., 2021; Liu et al., 2021)	Create community benchmarks that include compute/energy metrics, plus reproducibility requirements and public code/weights. (Liu et al., 2021; Salehi et al., 2023)
Multimodal integration cost & complexity	Combining histopathology, radiology, genomics, and EHRs multiplies data processing and compute needs.	Greater resource demand and challenging privacy/coordination across data sources. (Lipkova et al., 2022; Messiou et al., 2023)	Research efficient multimodal fusion, sparse/attention-based fusion, and privacy-preserving distributed systems. (Lipkova et al., 2022)
Regulatory, ethical, clinical-workflow barriers	Certification, medico-legal risk, and clinician acceptance slow translation.	Delays deployment of even energy-efficient models; may push institutions to retain older, less efficient tools. (Najjar, 2023; Hunter et al., 2022)	Co-design with clinicians, regulatory science research on low-resource AI validation, and policy frameworks that incentivize energy disclosure. (Najjar, 2023)

(References in table reflect core literature on sustainability, computational pathology, and medical imaging listed below.)

Future directions

When building models, keep resources in mind. Rather than focusing on absolute correctness, prioritize designs that maximize FLOPs and energy efficiency per diagnostic work. In addition to accuracy, it is recommended that energy and wall-clock measures be reported (Yousra et al., 2021; Jia et al., 2023).

1. **Standardized energy-aware benchmarks and reporting** — Liu et al. (2021) and Salehi et al. (2023) recommend disclosing energy costs and creating replicable workflows in order to put up community datasets and leaderboards for cancer imaging and pathology.
2. **Data-efficient learning strategies** — Increase the use of efficient augmentation, transfer learning, and semi-supervised and self-supervised learning techniques to reduce the number of epochs and labeled sets needed by models (Salehi et al., 2023; Iqbal et al., 2022).

3. **Federated and privacy-preserving approaches** — Maximize the benefits of federated learning by minimizing the need for central retraining and data migration through efficient communication and computation during cross-institutional model construction (Lipkova et al., 2022; Lipkova et al., 2022).

4. **Edge inference and hybrid cloud–edge designs** — Reducing data transit and central computing demands, move inference closer the point-of-care utilizing compressed models and specialized accelerators (Jia et al., 2023; Najjar, 2023).

5. **Life-cycle assessment and green procurement** — Recommend software and hardware stacks with little embodied carbon to clinical procurement and incorporate life cycle assessment into model evaluation (Jia et al., 2023).

6. **Multimodal, compute-efficient fusion** — Lipkova et al. (2022) and Messiou et al. (2023) propose sparse or cascade fusion pipelines that minimize average energy consumption per patient by starting with inexpensive modalities (e.g., screening) and only escalating to heavier models when necessary.

7. **Regulatory and incentive alignment** — Collaborate with authorities to acknowledge energy transparency, promote sustainable AI via procurement and reimbursement rules, and establish approval paths for models with limited resources (Najjar, 2023; Hunter et al., 2022).

8. **Clinical trials and deployment studies that include sustainability endpoints** — To show real-world trade-offs, develop prospective studies that assess both the efficacy of diagnostics and environmental/resource indicators (Hunter et al., 2022; Silva et al., 2023).

According to Yousra et al. (2021), Lipkova et al. (2022), and Jia et al. (2023), AI researchers, clinicians, engineers, sustainability scientists, and regulators must work together to address these challenges and co-design solutions that are both clinically effective and environmentally and economically sustainable in cancer diagnosis.

Conclusion

If we are serious about finding a way to reconcile the need for cutting-edge medical technology with the need for environmentally responsible cancer diagnostic research, then we must embrace green AI. According to recent research (Hunter, Hindocha, and Lee, 2022; Silva et al., 2023), AI-based solutions in computational pathology and medical imaging have demonstrated an extraordinary capacity to enhance the initial identification, segmentation, and classification of cancer. Still, new paradigms are needed to address the energy and computing needs of deep learning systems, which necessitate efficiency rather than a decrease in diagnostic accuracy. To reduce environmental impact while preserving clinical performance, recent research has focused on practices such as resource-aware model design, lightweight

convolutional neural networks, transfer learning, and yousera, abdelhakim, and Mohamed (2021), salehi et al. (2023), and Jia et al. (2023).

Pathology through computation Supporting tumor classification and prognosis with smaller energy footprints, computational histopathology is presently aiming at scalable and energy-efficient systems (Cui and Zhang, 2021; Wang et al., 2019; Kose and Alzubi, 2021). Similarly, radiology (Najjar, 2023; Lipkova et al., 2022; Messiou, Lee, and Salto-Tellez, 2023) demonstrates how AI may streamline multimodal image interpretation, integrating MRI, CT, and molecular imaging to enhance the diagnostic depth and add to the sustainability agenda. The capacity to strike a balance between resource-conscious computing and equality of access is crucial for the long-term viability of AI in cancer care, as this will guarantee that energy efficiency translates into improved healthcare access across various clinical contexts (Chiu, Chao, and Chen, 2022; Li et al., 2023).

Ultimately, the use of Green AI in cancer diagnostics has the potential to improve both precision oncology and the moral imperative to guarantee that healthcare innovation does not compromise environmental stewardship. Artificial intelligence (AI) in oncology has the potential to save lives while minimizing harm to the environment if sustainability is considered throughout algorithm design, infrastructure decisions, and deployment strategies (Liu et al., 2021; Iqbal et al., 2022). Because of this sea change, sustainable AI will be an integral part of cancer treatments in the future, which will benefit society, the economy, and the environment.

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