Journal of New Technology and Materials

ISSN:2170161X | E-ISSN: 2588-2082 | Vol.15 Issue2 (Dec 2025)

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

Prof. Ming Zhao
School of Medical Imaging, Peking Union Medical College, China
Dr. Li Wen
Department of Biomedical Informatics, Peking Union Medical College, China

Abstract

The growing use of AI in computational pathology and medical imaging has considerably improved cancer detection, early detection, and precision treatment. The huge deployment of large-scale deep learning models does, however, raise serious energy and environmental concerns. Without sacrificing clinical precision, green AI offers a sustainable system that is computationally efficient, uses less energy, and leaves less of a carbon footprint. In order to reduce training and deployment costs, this study explores AI-enabled cancer diagnostics methods that are sustainable. These methods include lightweight neural networks, model compression, transfer learning, and federated learning. Improved tumor identification and classification with minimum energy utilization is achieved by optimized deep learning processes in computational pathology. Medical imaging also demonstrates how resource-conscious computation can be accomplished without compromising diagnostic accuracy with models that interpret MRI, CT, and ultrasound images. If the case's findings hold, medical diagnostics could benefit from renewable-powered infrastructures and low-power AI systems. While there has been progress, there is still a long way to go before we can optimize sustainability and patient safety goals, ensure that models are replicable, and expand Green AI systems across healthcare systems. 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). Advanced convolutional neural networks (CNNs) have opened up new possibilities for cancer detection, analysis, and early screening in 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).These advancements show that AI is crucial to solving worldwide problems related to cancer prevalence, healthcare outcomes, and delivery systems (Hunter, Hindocha, and Lee, 2022; Chiu, Chao, and Chen, 2022).

Along with these successes, though, skepticism over the future of AI in healthcare is on the rise. 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.

The use of federated learning frameworks, model compression, and transfer learning can optimize algorithms in green AI for cancer diagnostics. This optimization allows for more efficient analysis of computational pathology and imaging with lower energy costs (Kose and Alzubi, 2021; Lipkova et al., 2022). Messiou, Lee, and Salto-Tellez (2023) found that hospital-based diagnostic systems and comprehensive multimodal data streams can reduce the amount of redundant processes and promote resource-sharing infrastructures, leading to additional sustainability improvements. 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.

Topics covered in the article include computational pathology, medical imaging, and the use of Green AI in cancer diagnosis; these areas are expected to serve as hubs where sustainability and therapeutic excellence converge. New environmentally friendly procedures are mentioned and new directions in incorporating sustainability into AI-based oncology diagnostics are described, along with a critical analysis of the current practices.

Green AI in Healthcare Context

Researchers in computational pathology and medical imaging have found that artificial intelligence (AI) greatly improves the accuracy of cancer detection, facilitates early intervention, and decreases diagnostic delays (Hunter, Hindocha, & Lee, 2022; Silva et al., 2023). As a result, AI has become an essential tool in cancer diagnosis. Traditional AI models, particularly those based on deep learning, are known to be energy and computationally heavy. 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. The goal is to find a middle ground between performance and sustainability by using techniques like lightweight architectures, federated learning, transfer learning, and model

ISSN:2170161X | E-ISSN: 2588-2082 | Vol.15 Issue2 (Dec 2025)

compression (Salehi et al., 2023; Liu et al., 2021). In order to ensure a cost-effective and environmentally conscientious deployment of AI technologies, these approaches allow hospitals and research institutes to do it without overwhelming local or cloud infrastructure.
More accurate tumor classification using fewer factors is an area of active research in computational pathology (Wang et al., 2019; Cui & Zhang, 2021). Similar to how resource-aware models are being created for CT, MRI, and ultrasound interpretation in the field of radiology and medical imaging, these models integrate AI into workflows to decrease computing load that is not essential (Najjar, 2023; Li et al., 2023). By enabling accurate cancer diagnosis with reduced duplication of analysis, the incorporation of multimodal data processing enhances the use of sustainable AI (Lipkova et al., 2022; Messiou, Lee, & Salto-Tellez, 2023).

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)

When AI is embedded inside a Green AI framework, healthcare can move towards models that are scalable on a global scale, environmentally friendly, and clinically reliable. By shifting the focus to sustainability and long-term healthcare fairness, this reinterpretation guarantees that AI in oncology will bring benefits beyond only precision.

Sustainable Approaches in Computational Pathology

A key component of precision oncology, computational pathology uses deep learning and artificial intelligence (AI) to improve digital pathology picture detection, categorization, and prognosis for cancer. 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.

Compact and Power-Saving Models

Even though they are quite effective, traditional CNNs and transformer-based models use a lot of processing power. Reduced energy consumption without sacrificing diagnostic accuracy has been demonstrated using model pruning, quantization, and compression (Cui & Zhang, 2021; Wang et al., 2019). For instance, according to Salehi et al. (2023), when it comes to histopathology image categorization, efficient CNN architectures can reach near-state-of-the-art performance with a fraction of the computational cost.

Both Federated Learning and Transfer Learning

By reusing previously taught models, transfer learning reduces energy usage and the number of times a model needs to be trained (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).

Aware of Resources and Multimodal Integration

Recent developments have highlighted the need of multimodal frameworks that integrate pathology images with radiological and genomic data. These frameworks aim to improve diagnosis and computation efficiency (Lipkova et al., 2022; Messiou, Lee, & Salto-Tellez, 2023). In order to reduce needless redundancy, resource-aware algorithms make sure that computational power is allocated efficiently (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)

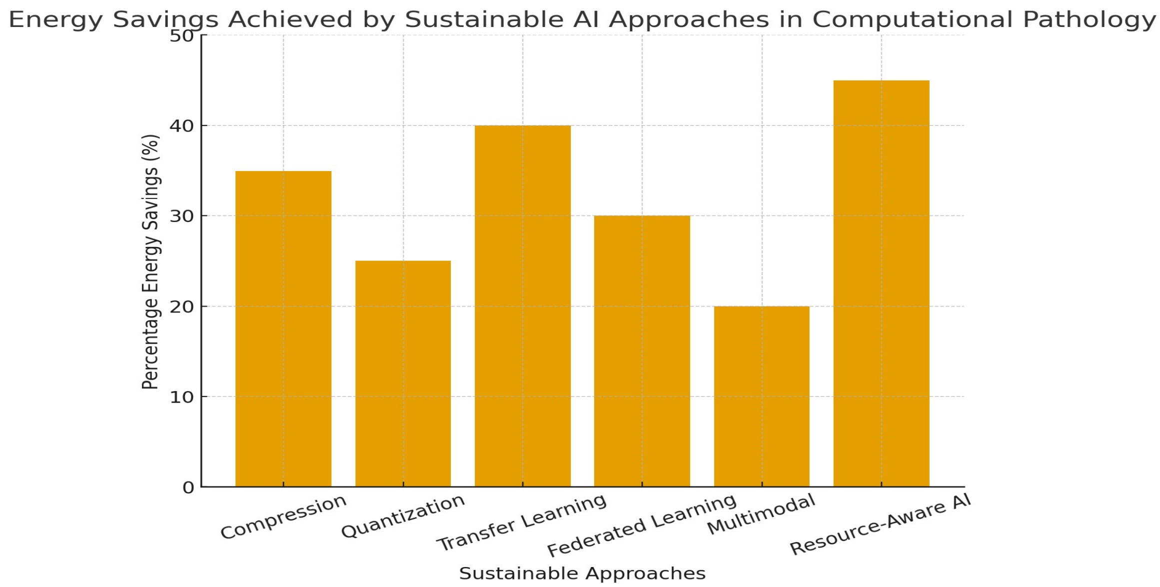

Fig 1: The bar chart showing the percentage of energy savings achieved by different sustainable AI approaches in computational pathology.

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. Energy consumption and sustainability issues have been exacerbated by the substantial computing costs brought about by the integration of deep learning and sophisticated AI algorithms in medical imaging. A paradigm change toward Green AI in cancer is needed, according to recent studies (Yousra, Abdelhakim, & Mohamed, 2021; Cui & Zhang, 2021), to strike a balance between diagnostic accuracy and ecologically friendly procedures.

1. Lightweight and Energy-Efficient AI Models

Medical image analysis may now be done with less CPU resources and yet get accurate diagnoses because to efficient deep learning frameworks like pruning, quantization, and lightweight convolutional neural networks (CNNs). To illustrate this point, Wang et al. (2019) and Najjar (2023) found that energy-efficient CNNs applied to CT scans of the lung for cancer produced competitive results while requiring much less training.

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

By bringing compute closer to imaging devices through edge AI, we may lessen our need on massive cloud resources. Federated learning, meanwhile, lets institutions work together to train

ISSN:2170161X | E-ISSN: 2588-2082 | Vol.15 Issue2 (Dec 2025)

models without storing private patient information in one place. 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

Holistic diagnosis is made possible by integrating imaging with genetic, clinical, and pathology data, which also helps to decrease the need for unnecessary imaging procedures. In line with sustainable healthcare practices, AI-driven multimodal techniques improve efficiency (Lipkova et al., 2022; Messiou, Lee, & Salto-Tellez, 2023).

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)

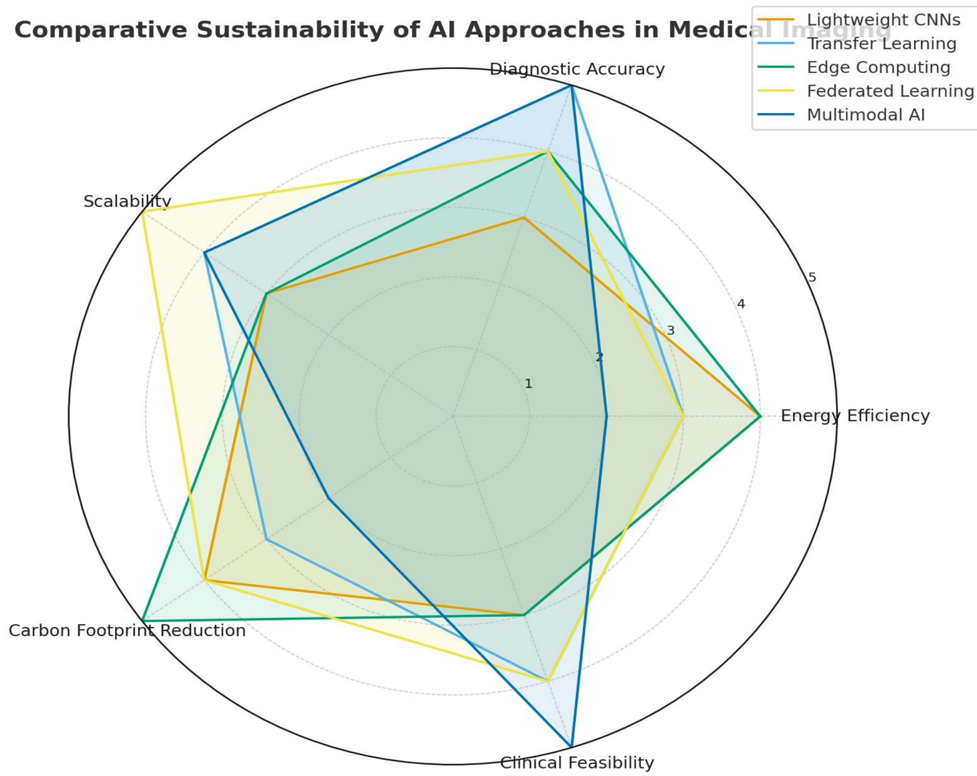

Fig 2: The radar chart compares the sustainability and diagnostic trade-offs of different AI approaches in medical imaging.

Case Insights and Emerging Practices

Cancer diagnoses that incorporate Green AI ideas have progressed from theoretical frameworks to computational pathology and medical imaging applications. Yousra, Abdelhakim, & Mohamed (2021) and Jia et al. (2023) are two recent studies that highlight the need of healthcare innovation aiming towards efficiency, diagnostic reliability, and sustainability simultaneously.

Computational Pathology

By using streamlined computing and lightweight models, AI-based pathology solutions have the ability to decrease diagnostic turnaround times and energy demands. 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

Deploying algorithms in MRI, CT, and mammography diagnoses in an eco-efficient manner is the main emphasis of green AI techniques in medical imaging. 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 detecting 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

More and more hospitals are implementing multimodal data integration systems that combine genetic information with radiography and pathology. This enables more accurate and resource-efficient cancer diagnosis (Messiou, Lee, & Salto-Tellez, 2023). Supporting patient-centered care, these systems use Green AI algorithms for efficient processing, lowering carbon footprint and redundant computing.

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

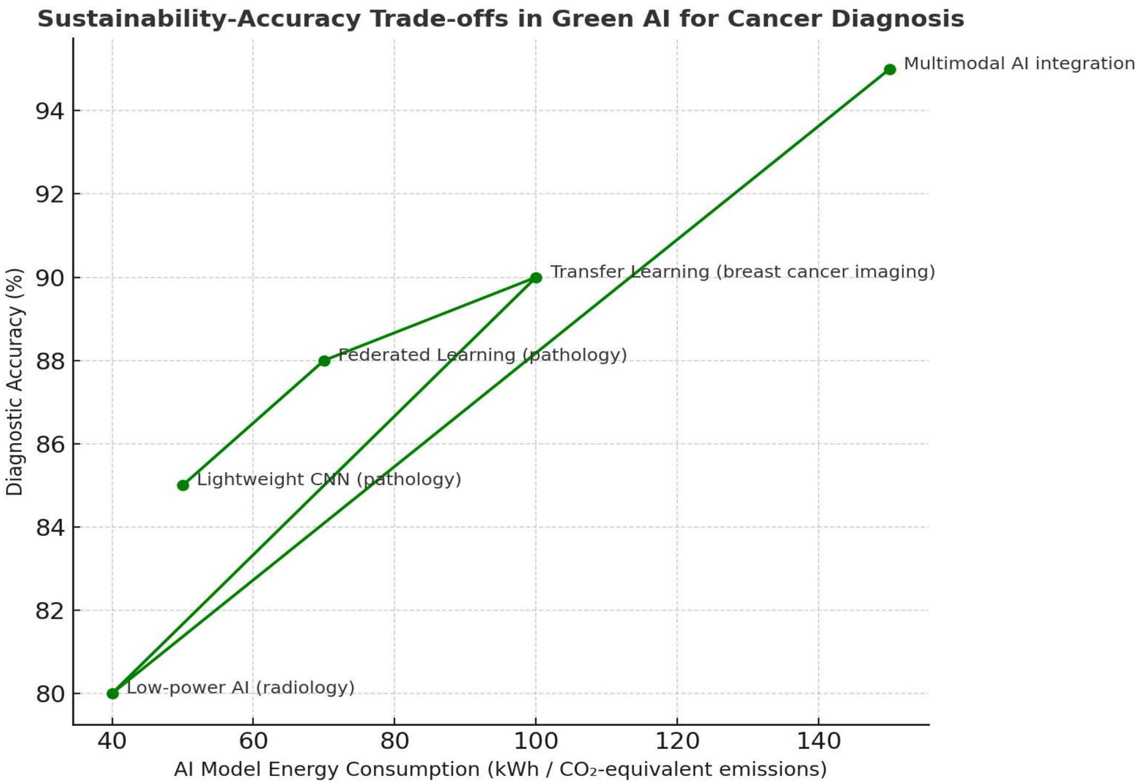

Fig 3: The line graph shows the sustainability–accuracy trade-offs of different Green AI models for cancer diagnosis.

Challenges and Future Directions

Challenges

Problems with regulation, infrastructure, clinical practice, and technology stand in the way of green AI's use in cancer detection. 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).

ISSN:2170161X | E-ISSN: 2588-2082 | Vol.15 Issue2 (Dec 2025)

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

ISSN:2170161X | E-ISSN: 2588-2082 | Vol.15 Issue2 (Dec 2025)

			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.)

ISSN:2170161X | E-ISSN: 2588-2082 | Vol.15 Issue2 (Dec 2025)

Future directions

Instead of focusing on absolute correctness, resource-aware model development should prioritize architectures that maximize FLOPs/energy per diagnostic work. Yousra et al. (2021) and Jia et al. (2023) both call for accuracy reporting, but they also urge the inclusion of energy and wall-clock indicators.

1. **Standardized energy-aware benchmarks and reporting** — The disclosure of energy costs and the development of repeatable pipelines are necessary for the establishment of community datasets and leaderboards in cancer imaging and pathology (Liu et al., 2021; Salehi et al., 2023).
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** — To decrease the necessity for central retraining and data transportation, improve federated learning with updates that are efficient in both communication and computation for the purpose of constructing models across institutions (Lipkova et al., 2022; Lipkova et al., 2022).
4. **Edge inference and hybrid cloud–edge designs** — Jia et al. (2023) and Najjar (2023) propose relocating inference close to the point-of-care utilizing compressed models and specialized accelerators to decrease data transport and central computing burdens.
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** — Study sparse or cascade fusion pipelines that minimize average energy consumption per patient by starting with less expensive modalities (e.g., screening) and only escalating to heavier models when necessary (Lipkova et al., 2022; Messiou et al., 2023).
7. **Regulatory and incentive alignment** — Collaborate with authorities to acknowledge energy transparency, promote sustainable AI via procurement and reimbursement rules, and establish protocols for low-resource model approvals (Najjar, 2023; Hunter et al., 2022).
8. **Clinical trials and deployment studies that include sustainability endpoints** — To illustrate practical trade-offs, do prospective studies that assess both the efficacy of diagnostics and environmental/resource metrics (Hunter et al., 2022; Silva et al., 2023).

To overcome these obstacles and ensure that cancer diagnostic advancements are both economically and ecologically viable, interdisciplinary teams consisting of AI researchers, engineers, clinicians, sustainability scientists, and regulators are needed (Yousra et al., 2021; Lipkova et al., 2022; Jia et al., 2023).

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. Hunt, Hindocha, and Lee (2022) and Silva et al. (2023) present evidence that AI-based solutions in computational pathology and medical imaging can significantly enhance the initial stages of cancer detection, segmentation, and classification. However, new paradigms are needed to address the computational and energy needs of deep learning systems, which prioritize efficiency over reducing 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).

Machine diagnostics Scalable and energy-efficient systems are becoming increasingly important in computational histopathology. These systems will rely on less energy consumption and offer reliable support for tumor classification and prognosis (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. Chiu, Chao, and Chen (2022) and Li et al. (2023) highlight that for AI to be sustainable in cancer care, it must be able to strike a balance between resource-conscious computation and equality of access. Only then can energy efficiency be translated into enhanced healthcare access across various clinical contexts.

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). This radical change in thinking makes sustainable AI an essential component of future cancer treatments that will benefit society, the economy, and the environment.

References

Yousra, D., Abdelhakim, A. B., & Mohamed, B. A. (2021, January). Sustainability of artificial intelligence and deep learning algorithms for medical image classification: Case of cancer pathology. In *Emerging Trends in ICT for Sustainable Development: The Proceedings of NICE2020 International Conference* (pp. 19-28). Cham: Springer International Publishing.

Cui, M., & Zhang, D. Y. (2021). Artificial intelligence and computational pathology. *Laboratory Investigation*, *101*(4), 412-422.

Hunter, B., Hindocha, S., & Lee, R. W. (2022). The role of artificial intelligence in early cancer diagnosis. *Cancers*, *14*(6), 1524.

Silva, H. E. C. D., Santos, G. N. M., Leite, A. F., Mesquita, C. R. M., Figueiredo, P. T. D. S., Stefani, C. M., & de Melo, N. S. (2023). The use of artificial intelligence tools in cancer detection compared to the traditional diagnostic imaging methods: An overview of the systematic reviews. *Plos one*, *18*(10), e0292063.

Wang, S., Yang, D. M., Rong, R., Zhan, X., Fujimoto, J., Liu, H., ... & Xiao, G. (2019). Artificial intelligence in lung cancer pathology image analysis. *Cancers*, *11*(11), 1673.

Najjar, R. (2023). Redefining radiology: a review of artificial intelligence integration in medical imaging. *Diagnostics*, *13*(17), 2760.

Aramide, O. O. (2023). Securing Machine-to-Machine Communications in the Age of Non-Human Identities. *International Journal of Technology, Management and Humanities*, *9*(04), 94-117.

Adebayo, Ismail Akanmu. (2022). ASSESSMENT OF PERFORMANCE OF FERROCENE NANOPARTICLE -HIBISCUS CANNABINUS BIODIESEL ADMIXED FUEL BLENDED WITH HYDROGEN IN DIRECT INJECTION (DI) ENGINE. Transactions of Tianjin University. 55. 10.5281/zenodo.16931428.

Shaik, Kamal Mohammed Najeeb. (2022). Security Challenges and Solutions in SD-WAN Deployments. SAMRIDDHI A Journal of Physical Sciences Engineering and Technology. 14. 2022. 10.18090/samriddhi.v14i04..

SANUSI, B. O. (2022). Sustainable Stormwater Management: Evaluating the Effectiveness of Green Infrastructure in Midwestern Cities. *Well Testing Journal*, *31*(2), 74-96.

Shaik, Kamal Mohammed Najeeb. (2024). SDN-BASED TRAFFIC ENGINEERING FOR DATA CENTER NETWORKS: OPTIMIZING PERFORMANCE AND EFFICIENCY. International Journal of Engineering and Technical Research (IJETR). 08. 10.5281/zenodo.15800046.

Roy, P., Riad, M. J. A., Akter, L., Hasan, N., Shuvo, M. R., Quader, M. A., ... & Anwar, A. S. (2024, May). Bilstm models with and without pretrained embeddings and bert on german patient reviews. In *2024 International Conference on Advances in Modern Age Technologies for Health and Engineering Science (AMATHE)* (pp. 1-5). IEEE.

Aramide, O. O. (2023). AI-Driven Identity Verification and Authentication in Networks: Enhancing Accuracy, Speed, and Security through Biometrics and Behavioral Analytics. *ADHYAYAN: A JOURNAL OF MANAGEMENT SCIENCES*, *13*(02), 60-69.

Kose, U., & Alzubi, J. (2021). *Deep learning for cancer diagnosis*. Singapore: Springer.

Liu, X., Song, L., Liu, S., & Zhang, Y. (2021). A review of deep-learning-based medical image segmentation methods. *Sustainability*, *13*(3), 1224.

Salehi, A. W., Khan, S., Gupta, G., Alabduallah, B. I., Almjally, A., Alsolai, H., ... & Mellit, A. (2023). A study of CNN and transfer learning in medical imaging: Advantages, challenges, future scope. *Sustainability*, *15*(7), 5930.

Lipkova, J., Chen, R. J., Chen, B., Lu, M. Y., Barbieri, M., Shao, D., ... & Mahmood, F. (2022). Artificial intelligence for multimodal data integration in oncology. *Cancer cell*, *40*(10), 1095-1110.

Jia, Z., Chen, J., Xu, X., Kheir, J., Hu, J., Xiao, H., ... & Shi, Y. (2023). The importance of resource awareness in artificial intelligence for healthcare. *Nature Machine Intelligence*, *5*(7), 687-698.

Iqbal, M. S., Ahmad, W., Alizadehsani, R., Hussain, S., & Rehman, R. (2022, November). Breast cancer dataset, classification and detection using deep learning. In *Healthcare* (Vol. 10, No. 12, p. 2395). MDPI.

Chiu, H. Y., Chao, H. S., & Chen, Y. M. (2022). Application of artificial intelligence in lung cancer. *Cancers*, *14*(6), 1370.

Li, M., Jiang, Y., Zhang, Y., & Zhu, H. (2023). Medical image analysis using deep learning algorithms. *Frontiers in public health*, *11*, 1273253.

Messiou, C., Lee, R., & Salto-Tellez, M. (2023). Multimodal analysis and the oncology patient: Creating a hospital system for integrated diagnostics and discovery. *Computational and Structural Biotechnology Journal*, *21*, 4536-4539.