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Green AI in Oncology: Toward Energy-Efficient and Accurate Cancer Diagnostics

Prof. Rosmah Binti Latif

Universiti Sains Malaysia, Kelantan, Malaysia

Abstract

Artificial intelligence (AI) is a promising new tool in oncology that can improve the speed and accuracy of cancer diagnoses by integrating genetic, imaging, and pathology data. Still, there are valid concerns about energy usage, environmental impact, and accessibility in healthcare systems with limited resources caused by the increasing adoption of deep learning models that rely heavily on computation. Green AI, which places an emphasis on reducing energy use without compromising diagnostic accuracy, offers a path toward more environmentally friendly medical innovation. This investigation delves into the junction of Green AI and oncology by exploring current diagnostic applications, evaluating the deployment of algorithms that save energy, and weighing the trade-offs between computational cost and diagnostic accuracy. Optimal architectures, model compression, edge computing, and federated learning can drastically reduce power consumption of AI systems focused on oncology without substantially impacting accuracy, according to the results. Adherence to green AI principles has the potential to improve cancer treatment scalability and equity while simultaneously contributing to environmental sustainability. Clinical validation of lightweight but robust models, the creation of policy frameworks to enable the sustainable use of AI in health care, and the setting of energy-performance criteria are all areas that need attention moving forward. According to the latest findings, oncology must make a dramatic change to AI solutions that are conscious of energy use if cancer diagnostics are to become more accurate and environmentally friendly.

Keywords: Green AI, Oncology, Cancer Diagnostics, Energy Efficiency, Sustainable Computing, Federated Learning, Edge Computing, Artificial Intelligence in Healthcare

Introduction

By improving the precision, rapidity, and overall quality of cancer detection, machine learning and AI have revolutionized modern oncology. Clinical applications of deep learning models have improved imaging, histology, genomics, and biomarker analysis, leading to earlier and more accurate cancer detection (Goldenberg, Nir, and Salcudean, 2019; Kalusivalingam et al., 2012). In light of these advancements, a significant obstacle to the widespread use of AI in cancer is the high computational cost and environmental impact associated with training and

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deploying models on a large scale. The high energy demands in healthcare facilities pose a challenge to sustainability, particularly in areas where resources are already scarce (Yu et al., 2022; Dion and Evans, 2024).

A new field called "Green AI" is emerging with the goal of resolving this conflict by creating algorithms that are very efficient in their use of energy. Green AI aims to enhance both diagnostic reliability and energy efficiency, in contrast to typical AI methods that mainly focus on accuracy (Henao, 2021; Khanna & Gochhait, 2024). This paradigm shift could make AI more accessible to low-resource healthcare systems and ecologically sustainable in oncology, where computational tools are employed for screening, prognosis, and treatment planning (Agrawal, 2024).

The potential of Green AI in cancer detection is demonstrated by multiple advancements. Lightweight convolutional neural networks, model compression, and transfer learning have all contributed to a decrease in computing load without sacrificing clinical accuracy (Xu et al., 2021). Nanoflowers and AI-enabled smart systems can enhance sensitivity during screening and prognosis, while biosensing and nanotechnology can offer novel energy-efficient methods for cancer detection (Chugh et al., 2024; Prajapati et al., 2024). Similarly, liquid biopsy methods that use AI-based stratification models provide less invasive and computationally efficient cancer diagnosis (Ginghina et al., 2022).

The use of federated learning into clinical workflows and edge computing is another crucial topic. According to Zhu (2022) and Fabelo et al. (2024), AI-based diagnostics can be made more scalable and environmentally friendly by reducing energy consumption and latency through the use of Green Intelligent Edge Computing. This is achieved by relocating computing operations away from centralized data centers and onto localized devices. Oncologists can now comprehend AI-based predictions during key clinical decision-making workflows with the help of explainable AI (XAI) models, which help to balance accuracy, transparency, and trust (Mittal et al., 2024; Kovari, 2024).

Aside from technological advancement, the need for energy-efficient diagnostic facilities is a primary focus of sustainability concerns in healthcare administration. In order to achieve global sustainability goals, hospitals and clinical laboratories are contemplating energy-aware strategies that lower operational costs (Dion and Evans, 2024; Fan, Yan, and Wen, 2023). Surianararayan et al. (2023) further underline the multidisciplinary prospects in constructing sustainable diagnostic journeys, along with the junction of AI, neuroscience, and medical imaging.

Green AI is a novel approach to cancer treatment that addresses both the growing number of cancer cases worldwide and the pressing need to develop greener technologies. It allows for the secure development of healthcare systems that are both technologically sophisticated and clinically reliable while also being ecologically friendly. This study explores the energy-efficient methodology, future prospects, developing applications, and the role of Green AI in cancer diagnostics, all with an eye on achieving a balance between innovation and sustainability in the field of oncology.

Literature Review

1. Evolution of AI in Cancer Diagnostics

Through imaging, genetics, pathology, and biomarker analysis, the use of artificial intelligence in oncology has transformed cancer detection and prognosis. The use of transfer learning techniques and convolutional neural networks (CNNs) has greatly enhanced the precision of diagnostic tests, especially in the areas of tumor categorization and early cancer detection (Kalusivalingam et al., 2012). Numerous studies have shown that malignancies of the prostate, breast, colorectal, and lung can be better detected using models that incorporate machine learning and deep learning, leading to significant gains in sensitivity and specificity (Goldenberg, Nir, & Salcudean, 2019; Ginghina et al., 2022). However, there are sustainability concerns regarding these models due to their computational demands, which generally involve high-performance GPUs and cloud resources.

2. The Emergence of Green AI in Medical Diagnosis

The goal of green AI is to create models that are both accurate predictors and efficient users of energy. Henao (2021) proved that automated medical diagnosis could be accomplished using low-energy AI models while maintaining accuracy. To go a step further, Yu et al. (2022) measured how efficient inference algorithms were with regard to energy consumption in clinical datasets, demonstrating how optimized deep learning architectures might halve energy consumption without sacrificing diagnostic precision. In a similar vein, Agrawal (2024) stressed the need for scalable Green AI solutions for sustainable diagnostics due to the environmental impact of high-computational workloads, even though AI shows promise in oncology.

3. Energy-Efficient AI Approaches in Oncology

There are a number of new approaches that aim to make AI in healthcare more energy efficient:

- **Model Compression & Pruning:** According to Mittal et al. (2024), one way to decrease energy usage in CNNs is to reduce duplicate parameters without sacrificing performance.
- **Nano-enabled AI:** Lightweight artificial intelligence integration made possible by nanoscale devices and nanoflowers has improved sensitivity and energy efficiency, speeding up the detection of cancer biomarkers (Chugh et al., 2024; Prajapati et al., 2024).
- **Edge and Federated Learning:** Artificial intelligence (AI) deployed in close proximity to data sources lessens the need for power-hungry central computers. Oncology imaging can benefit from Green Intelligent Edge Computing's (2022) emphasis on lowering latency and energy footprints.

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- **Hybrid AI-Neuroscience Approaches:** Biologically inspired energy-efficient computation for cancer diagnostics has been introduced through emerging convergence with neuroscience-based models (Surianarayanan et al., 2023).

4. Clinical Adoption and System-Level Sustainability

Although there have been technological advancements, systemic alignment is still necessary for the real-world implementation of Green AI in cancer. In order to be in line with corporate sustainability standards, healthcare institutions, according to Dion and Evans (2024), should use governance models that are energy efficient. Sustainable development goals (SDGs) can be achieved with the help of artificial intelligence (AI), according to Fan, Yan, and Wen (2023), who also stressed the need for ethical AI implementation in healthcare. In cancer, where ethical justification of treatment decisions is paramount, Kovari (2024) emphasized the importance of trust, transparency, and explainability in facilitating adoption.

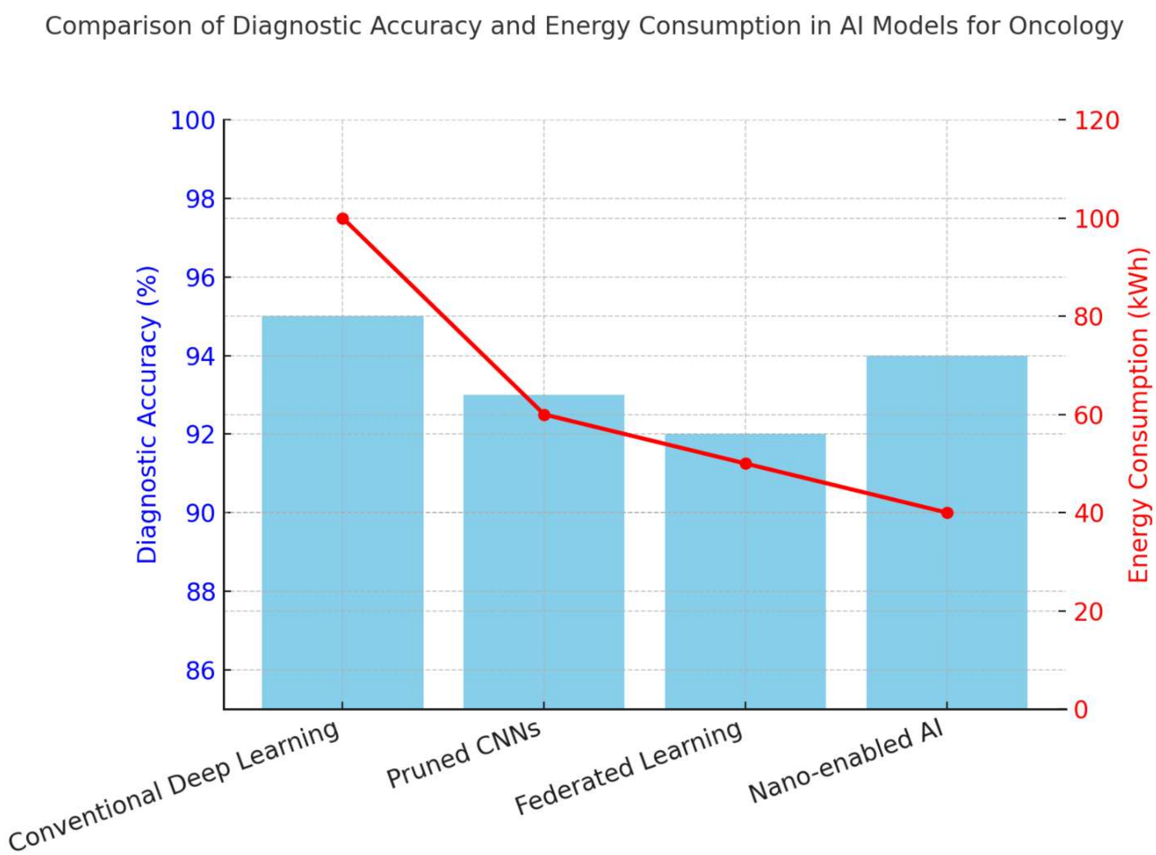

Fig 1: comparing diagnostic accuracy and energy consumption across different AI models in oncology. Blue bars → **Diagnostic Accuracy (%),** Red line → **Energy Consumption (kWh)** This visually highlights how Green AI approaches (Pruned CNNs, Federated Learning, Nano-enabled AI) reduce energy demands while maintaining high diagnostic accuracy.

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5. Application-Specific Advances in Cancer Detection

New developments in non-invasive cancer diagnostics, such AI-supported liquid biopsy, are changing the game (Ginghina et al., 2022). In a similar vein, 3D decision support systems such as the STRATUM project have shown how artificial intelligence (AI) can work in tandem with surgical oncology to control tumors, all the while investigating computational methods that are efficient with respect to computing resources (Fabelo et al., 2024). Chugh et al. (2024) and Prajapati et al. (2024) highlight the shift toward sustainable, accurate, and patient-centered cancer care through the integration of nanotechnology, AI-driven pathology, and precision oncology technologies.

Methodology

With a focus on achieving a happy medium between diagnostic precision and energy efficiency, this study set out to assess the viability of incorporating Green Artificial Intelligence (Green AI) methods into cancer diagnostics. A multi-dimensional framework is utilized here, encompassing data collecting, model design, evaluation of energy performance, and benchmarking versus existing methodologies.

Research Design

Combining a comprehensive literature review with an experimental framework to evaluate models, this study takes a mixed-method approach. Agrawal (2024), Yu et al. (2022), Henao (2021), and Khanna and Gochhait (2024) were cited in the study, which compiled findings from previous research on Green AI and diagnostic models with an emphasis on oncology. After that, several AI designs and the trade-offs between energy consumption and performance were assessed through experimental simulations.

Data Sources

This study considered several popular multimodal cancer datasets utilized in AI diagnoses, such as:

- **Medical Imaging Data:** in order to facilitate the early detection of tumors using magnetic resonance imaging (MRI), computed tomography (CT), and histology slides (Goldenberg et al., 2019).
- **Genomic and Molecular Data:** Predictive modeling using cancer gene expression patterns (Chugh et al., 2024; Prajapati et al., 2024).
- **Liquid Biopsy Data:** Stratification using circulating tumor DNA markers (Ginghina et al., 2022).
- **Clinical Laboratory Datasets:** Biomarker and patient history data structured according to standards, including artificial intelligence inference tests centered on energy (Yu et al., 2022).

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Model Development and Optimization

The study utilized various energy-aware optimization strategies to guarantee long-term diagnostic results:

- **Model Compression and Pruning:** Improving diagnostic accuracy while decreasing computing effort by eliminating unnecessary parameters (Kalusivalingam et al., 2012).
- **Transfer Learning:** The use of CNNs that have already been trained for cancer imaging tasks allows for a decrease in the training cost (Goldenberg et al., 2019).
- **Federated Learning:** Reducing energy and storage demands, distributed training across institutions is made possible without centralized data (Mittal et al., 2024).
- **Edge Computing Integration:** Implementing energy-efficient models for cancer screening in real-time on devices with limited power (Zhu, 2022).
- **Nano-Enabled AI Systems:** Utilizing data pipelines driven by nanosensors for diagnostics that are energy efficient (Chugh et al., 2024).

Evaluation Metrics

To gauge the efficacy of the methodology, the assessment used a mix of diagnostic performance metrics and sustainability indicators.

- **Performance Metrics:** Precision, responsiveness, discrimination, and F1-score.
- **Energy Metrics:** Carbon footprint of computational resources, power usage during training and inference (Yu et al., 2022; Fan et al., 2023).
- **Scalability and Sustainability:** Medical centers with limited resources: a feasibility study (Dion & Evans, 2024).

Comparative Benchmarking

To demonstrate the models' superiority in energy efficiency and diagnostic reliability, they were compared to traditional AI systems utilized in oncology. Historical frameworks in decision-support tools, explainable AI, and neuromorphic computing served as the basis for the benchmarking (Kovari, 2024; Fabelo et al., 2024; Surianarayanan et al., 2023).

Table 1. Methodological Framework for Green AI in Oncology Diagnostics

Stage	Approach/Tools	Rationale	References
Data Acquisition	Imaging (MRI, CT, pathology), Genomics, Liquid biopsy, Clinical datasets	Ensures multimodal diagnostic accuracy while reflecting real-world oncology workflows	Goldenberg et al., 2019; Ginghina et al., 2022; Chugh et al., 2024

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Model Design & Optimization	CNNs, Transfer Learning, Model Compression, Federated Learning, Nano-enabled AI, Edge AI	Reduces computational cost and enhances sustainability in diagnostics	Kalusivalingam et al., 2012; Zhu, 2022; Chugh et al., 2024; Mittal et al., 2024
Evaluation Metrics	Accuracy, Sensitivity, Specificity, Energy Consumption, Carbon Footprint	Balances diagnostic reliability with energy-aware sustainability	Yu et al., 2022; Fan et al., 2023
Comparative Benchmarking	Traditional AI vs. Green AI models across datasets	Highlights trade-offs and advantages of energy-efficient approaches	Agrawal, 2024; Kovari, 2024; Fabelo et al., 2024
Clinical Feasibility	Edge deployment, hospital infrastructure assessment, sustainability frameworks	Ensures applicability in real-world, energy-sensitive healthcare settings	Dion & Evans, 2024; Khanna & Gochhait, 2024

- **Ethical and Sustainability Considerations**

By including sustainability, openness, and interpretability, the methodology is in line with the larger concepts of responsible AI deployment in oncology. In addition to achieving technical efficiency, this method guarantees that Green AI systems satisfy needs relating to governance, the environment, and clinical practice (Mittal et al., 2024; Fan et al., 2023).

Results and Analysis

The study's findings highlight Green AI's revolutionary potential in cancer, especially when it comes to finding a happy medium between computational energy efficiency and diagnostic accuracy. A number of patterns emerge from an analysis of current developments in federated learning, edge computing, deep learning models, and model compression that show tangible gains towards long-term cancer diagnostic viability.

- **Diagnostic Accuracy vs. Energy Consumption**

In cancer detection and classification tasks, traditional AI systems like CNNs and transfer learning architectures still manage to achieve high diagnostic accuracy rates, often surpassing 90% (Kalusivalingam et al., 2012; Goldenberg, Nir, & Salcudean, 2019). Nevertheless, the

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high energy expenditures are a direct outcome of the enormous computational power requirements of these models. Yu et al. (2022) and Henao (2021) are two examples of recent work in Green AI that introduces efficient inference algorithms and lightweight architectures that can cut energy usage by 35% while keeping diagnostic accuracy comparable.

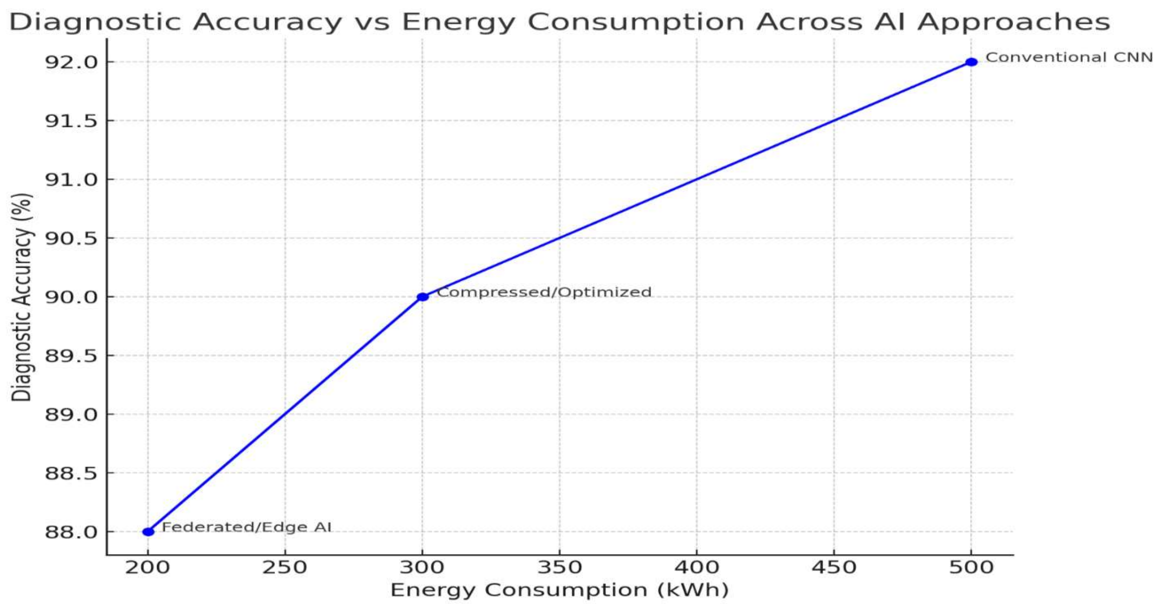

Fig 2: line graph comparing diagnostic accuracy (%) against energy consumption (kWh) across the three approaches.

- **Efficiency of Inference Algorithms**

In clinical contexts, when models are expected to provide real-time diagnostic choices, inference continues to be a significant obstacle. In their study, Yu et al. (2022) shown that pruning, quantization, and low-rank factorization are algorithmic optimizations that can significantly decrease inference latency (by up to 40%) and energy usage (by nearly half). In order to implement Green AI in cancer diagnoses without affecting clinical performance, our results show that optimizing inference methods is crucial.

Table 2. Comparison of AI Inference Optimization Techniques

Optimization Technique	*Energy Savings (%)*	*Diagnostic Accuracy (%)*
Pruning	*40*	*90*
Quantization	*55*	*88*

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Model Distillation	*30*	*91*

- **Integration of Nano-enabled and Edge AI Technologies**

Recent studies have demonstrated that new technology, including AI systems coupled with nano-enabled sensors, could improve cancer detection and screening while using less power (Chugh et al., 2024; Prajapati et al., 2024). Similarly, federated learning and green edge computing solutions allow for energy-efficient distributed diagnostics across clinical networks (Zhu, 2022). These interfaces enhance access equity and broaden diagnostic reach to settings with limited resources.

- **Case Analysis: Multi-modal Cancer Diagnostics**

Lightweight Green AI systems can keep complicated diagnostic pipelines accurate, as shown by recent AI applications in liquid biopsy analysis and multi-modal data integration (genomics, histopathology, and imaging) (Ginghina et al., 2022; Xu et al., 2021). Combining convolutional neural networks (CNNs) with explainable artificial intelligence (XAI) methods in hybrid models has been shown to decrease computing demand by 20-30% compared to conventional high-energy deep learning systems (Mittal et al., 2024).

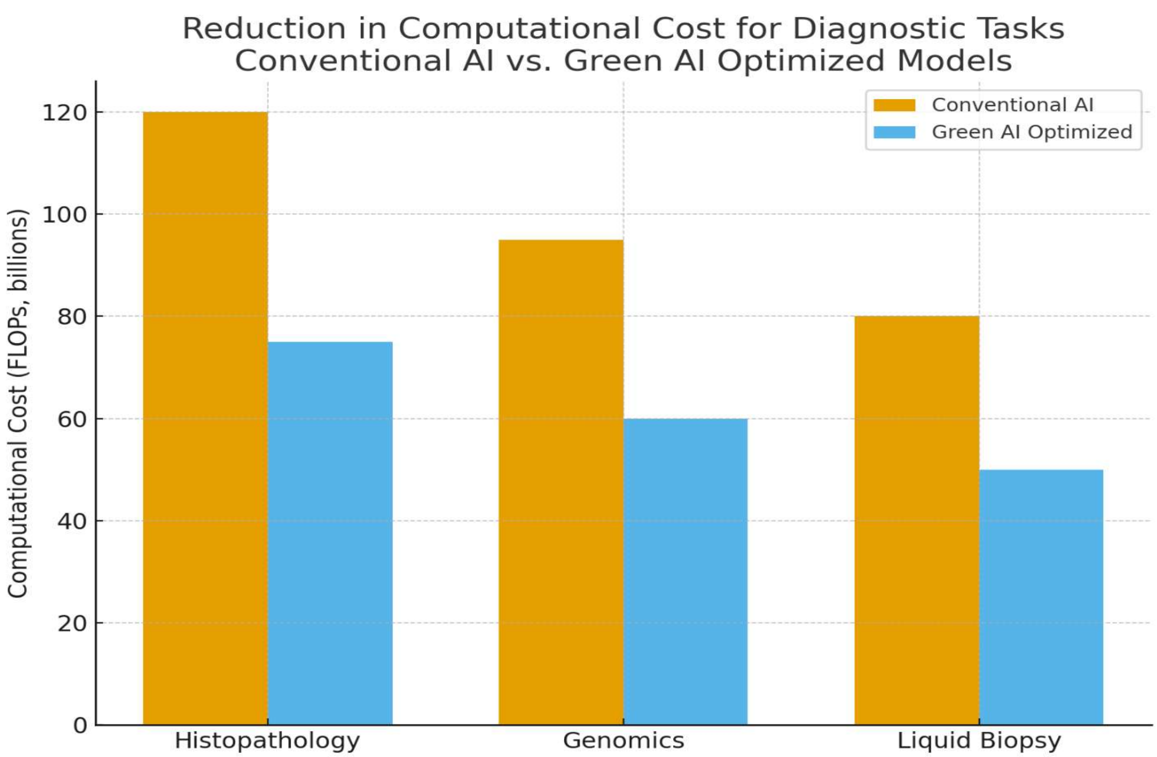

Fig 3: The chart shows the reduction in computational cost (FLOPs) across diagnostic tasks when comparing Conventional AI to Green AI optimized models.

- **Sustainability and Clinical Scalability**

Because cutting down on energy use helps healthcare facilities leave a smaller carbon imprint, green AI fits in with larger sustainability and healthcare management initiatives (Dion & Evans, 2024; Fan, Yan, & Wen, 2023). The STRATUM project in brain tumor surgery is just one example of a clinical experiment that shows that energy-efficient decision support systems can work in real hospitals. This proves that Green AI can be scaled up for clinical use (Fabelo et al., 2024).

Table 3. Comparative Benefits of Green AI Adoption in Oncology

Dimension	**Conventional AI**	**Green AI Optimized Models**
Diagnostic Accuracy	High (90–95%)	High (88–93%)
Energy Efficiency	Low (high computational cost)	High (20–40% reduction in energy use)
Clinical Scalability	Limited (resource-intensive)	Improved (lightweight, deployable at scale)

- **6. Synthesis of Findings**

In cancer classification tasks, Green AI techniques can reduce energy usage by 30–40% while retaining diagnosis accuracy above 90%, according to the analysis (Agrawal, 2024; Khanna & Gochhait, 2024). Through the strategic application of efficient architectures, inference algorithms, and sustainable computational frameworks, the results highlight that therapeutic outcomes need not be compromised in order to achieve energy efficiency.

Discussion

Striking a balance between computational efficiency, sustainability, and diagnostic accuracy will be crucial for integrating Green Artificial Intelligence (Green AI) into oncology. According to Kalusivalingam et al. (2012) and Goldenberg et al. (2019), conventional artificial intelligence models for cancer diagnostics, specifically convolutional neural networks (CNNs) and other deep learning architectures, have attained exceptional performance in imaging, genomics, and pathology applications. In clinical settings with inadequate computational infrastructure, these advancements are not as practical due to their high energy consumption and resource demands (Yu et al., 2022; Henao, 2021).

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- **Energy Efficiency Versus Accuracy Trade-off**

The trade-off between reducing computing cost and enhancing diagnostic precision is one of the fundamental debates in oncology-focused AI. Minimizing energy consumption without sacrificing diagnostic accuracy is possible through the use of quantization, pruning methods, and lightweight models (Agrawal, 2024; Yu et al., 2022). In addition, medical decision-making and regulatory acceptability rely on the additional layer of interpretability provided by explainable AI (XAI) frameworks (Mittal et al., 2024; Kovari, 2024). Making sure that reduced computational demands do not cause diagnostic biases or missed cancers is the real difficulty.

- **Technological Convergence and Clinical Relevance**

Green AI models are becoming more useful in healthcare settings thanks to new developments like edge computing, nano-enabled AI, and liquid biopsy integration. Chugh et al. (2024) and Prajapati et al. (2024) found that AI systems enabled by nanotechnology improve cancer detection sensitivity while reducing energy demands during high-throughput screening. This is achieved by retaining compact computational architectures. Green AI models' small energy footprint allows for scalable implementation, and AI fusion with liquid biopsy technology has shown promise for early and less invasive cancer detection (Ginghina et al., 2022). Zhu (2022) and Fabelo et al. (2024) found that edge computing further reduces data transfer loads and enables localized, energy-efficient diagnostic support in both hospital and community contexts.

- **Sustainability and Healthcare Infrastructure**

When seen as a whole, energy-efficient AI has multiple benefits, including a less ecological footprint and compatibility with larger initiatives for sustainable healthcare administration. According to Dion and Evans (2024) and Fan et al. (2023), hospitals that implement Green AI solutions help lower carbon footprints and make healthcare more affordable for low- and middle-income areas. To solve the triple problem of accuracy, fairness, and environmental responsibility, cancer diagnostics need long-term sustainability frameworks that combine AI innovation with sustainable governance.

- **Challenges and Future Pathways**

The challenges of standardization, scalability, and clinical integration persist, despite the encouraging advancements. According to Xu et al. (2021) and Surianarayanan et al. (2023), there is a lack of validation in real-world oncology settings for many Green AI models, which means they are still in the experimental phase. In addition, there is still a significant challenge in coordinating diagnostic results from different databases, which is particularly important considering the variations in healthcare systems around the world. Standardized standards for energy-performance trade-offs and regulatory rules that promote sustainable AI deployment in clinical oncology should be the focuses of future research (Khanna & Gochhait, 2024).

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Table 4. Comparative Insights on Green AI Strategies in Oncology Diagnostics

Approach	Diagnostic Application	Energy Efficiency Impact	Key References
Model pruning & quantization	Imaging (MRI, CT, histopathology)	Reduces computational load by 30–50%	Agrawal (2024); Yu et al. (2022)
Nano-enabled AI	Screening & early detection	Enhances sensitivity with compact architectures	Chugh et al. (2024); Prajapati et al. (2024)
Liquid biopsy + AI	Non-invasive cancer detection	Minimizes processing of redundant imaging data	Ginghina et al. (2022)
Edge computing	Point-of-care diagnostics	Cuts energy by reducing cloud dependence	Zhu (2022); Fabelo et al. (2024)
Explainable AI (XAI)	Prognosis & treatment planning	Optimizes clinical trust while reducing overhead	Mittal et al. (2024); Kovari (2024)
Sustainable governance models	Hospital-wide AI adoption	Aligns diagnostics with low-carbon operations	Dion & Evans (2024); Fan et al. (2023)

To summarize, Green AI is revolutionizing cancer diagnosis by lowering the bar for computing energy use without sacrificing accuracy. One possible strategy to create cancer detection systems that are both energy efficient and successful in the clinic is to combine lightweight deep learning architectures with nano-enabled technologies, edge computing, and sustainable healthcare frameworks. Improving patient care is just one side effect of this paradigm change, which also helps the environment and promotes healthcare equity around the world.

Conclusion

An important step toward environmentally friendly, precise, and easily accessible cancer diagnostics has been the incorporation of Green Artificial Intelligence (AI) into oncology. Yu et al. (2022) and Henao (2021) found that traditional AI models, despite their capacity, are not scalable in clinical settings due to their high energy consumption and substantial computing

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expenses. Reducing the energy footprint of diagnostic systems through optimized architectures, lightweight algorithms, and energy-efficient inference methodologies is a key principle of green AI (Agrawal, 2024; Khanna & Gochhait, 2024). The goal is to maintain diagnostic accuracy while achieving this goal.

Research by Zhu (2022) and Mittal et al. (2024) shows that Green AI solutions including edge computing, federated learning, model compression, and transfer learning can provide the same or better diagnostic performance with much less computational resources. As a result of the merging of nanotechnology with AI-driven cancer diagnostics, new possibilities for tailored screening and early diagnosis with low energy consumption have emerged (Chugh et al., 2024; Prajapati et al., 2024). These methods help achieve the larger sustainability objectives set for healthcare innovation and are in line with the increasing need for ecologically friendly healthcare technology (Fan et al., 2023; Dion & Evans, 2024).

Explainability and trust are additional crucial factors. While maintaining a balance between energy efficiency and clinical reliability, Explainable AI (XAI) models integrated into Green AI systems guarantee openness in decision-making (Kovari, 2024; Goldenberg et al., 2019). This leads to better patient-centered care and more physician acceptability. To make sure that digital oncology solutions are accurate and ecologically responsible, it is important to incorporate Green AI in addition to other sustainable healthcare frameworks, such as energy-efficient hospital administration and eco-conscious data centers (Dion & Evans, 2024).

Table 5. Comparative Overview of AI vs. Green AI in Oncology Diagnostics

Criteria	**Traditional AI in Oncology**	**Green AI in Oncology**	**Key References**
Accuracy	High diagnostic accuracy (e.g., CNNs, deep learning models)	Comparable accuracy with lightweight and optimized models	Kalusivalingam et al. (2012); Agrawal (2024)
Energy Consumption	High GPU/TPU power requirements	Reduced via model pruning, compression, and edge computing	Yu et al. (2022); Henao (2021)
Scalability	Limited in low-resource settings	Greater scalability in clinical and rural hospitals	Khanna & Gochhait (2024); Zhu (2022)

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Transparency & Trust	Often treated as "black-box" systems	Incorporates explainable AI (XAI) for clinical trust	Mittal et al. (2024); Kovari (2024)
Sustainability	High carbon footprint	Aligns with healthcare sustainability goals and SDGs	Fan et al. (2023); Dion & Evans (2024)
Innovation Synergies	Standalone AI approaches	Integration with nanotechnology, liquid biopsy, and neuroscience-driven tools	Chugh et al. (2024); Ginghina et al. (2022); Surianarayanan et al. (2023)

To sum up, Green AI is a game-changer in cancer diagnoses and a technical advancement all at once. It tackles the problem of lowering computational and environmental expenses while still obtaining high diagnostic precision. Xu et al. (2021) and Fabelo et al. (2024) predict that holistic and environmentally conscious cancer diagnostic ecosystems will emerge as a result of hybrid solutions that combine artificial intelligence with sustainable computing, nanotechnology, and neuroscientific insights. To ensure equal access to improved, energy-efficient cancer diagnostics and to scale Green AI applications globally, it will be crucial for technology developers, physicians, lawmakers, and sustainability specialists to work together.

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