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(Review Article)

Machine learning in personalized cancer treatment: Implications for global public health

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Abstract

Cancer remains a leading cause of mortality worldwide, posing a significant challenge to global public health. Traditional approaches to cancer treatment often adopt a "one-size-fits-all" strategy, which may not be effective for every patient due to the complex and heterogeneous nature of the disease. Personalized cancer treatment aims to tailor therapeutic interventions to the individual characteristics of each patient, enhancing the efficacy and reducing adverse effects. In recent years, machine learning (ML) has emerged as a powerful tool in personalized cancer care, offering the potential to revolutionize diagnosis, prognosis, and treatment by leveraging vast amounts of biomedical data. This review explores the current landscape of machine learning applications in personalized cancer treatment, including its role in imaging, genomics, and drug discovery. We provide an overview of key machine learning techniques, highlight successful case studies from both developed and developing nations, and examine the challenges and limitations associated with the integration of these technologies into clinical practice. Furthermore, we discuss the implications of machine learning-driven personalized cancer care for global public health, emphasizing its potential to address disparities in access to healthcare and improve outcomes in resource-limited settings. Finally, we offer insights into future research directions and policy considerations that could accelerate the adoption of machine learning in global cancer treatment, fostering a more equitable and effective healthcare ecosystem.

Keywords: Machine Learning; Personalized; Cancer Treatment; Implications; Global; Public Health

1. Introduction

1.1. Overview of Cancer as a Global Health Challenge

Cancer represents a significant and growing global health issue, responsible for millions of deaths annually. In 2013, there were approximately 8.2 million cancer-related deaths and 14.9 million new cases, highlighting its severe burden across the world, particularly in developing nations where healthcare systems are often inadequate (Fitzmaurice et al., 2015). The rise in cancer cases can be attributed to various factors including aging populations, lifestyle changes, and persistent exposure to modifiable risk factors such as smoking, poor diet, and lack of physical activity (Thun et al., 2009; Idoko et al., 2024).

Figure 1 illustrates various types of cancer, each represented by an icon of the affected organ or system. There are 15 types of cancer displayed, including lung, gastric (stomach), brain, breast, kidney, pancreatic, prostate, leukemia (blood), liver, colorectal, cervical, uterine, ovarian, skin, and bladder cancer. Each icon uses simple graphics and a highlighted

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circular marker to denote the cancer's location within the organ, providing a clear visual reference for commonly diagnosed cancers across different parts of the body.

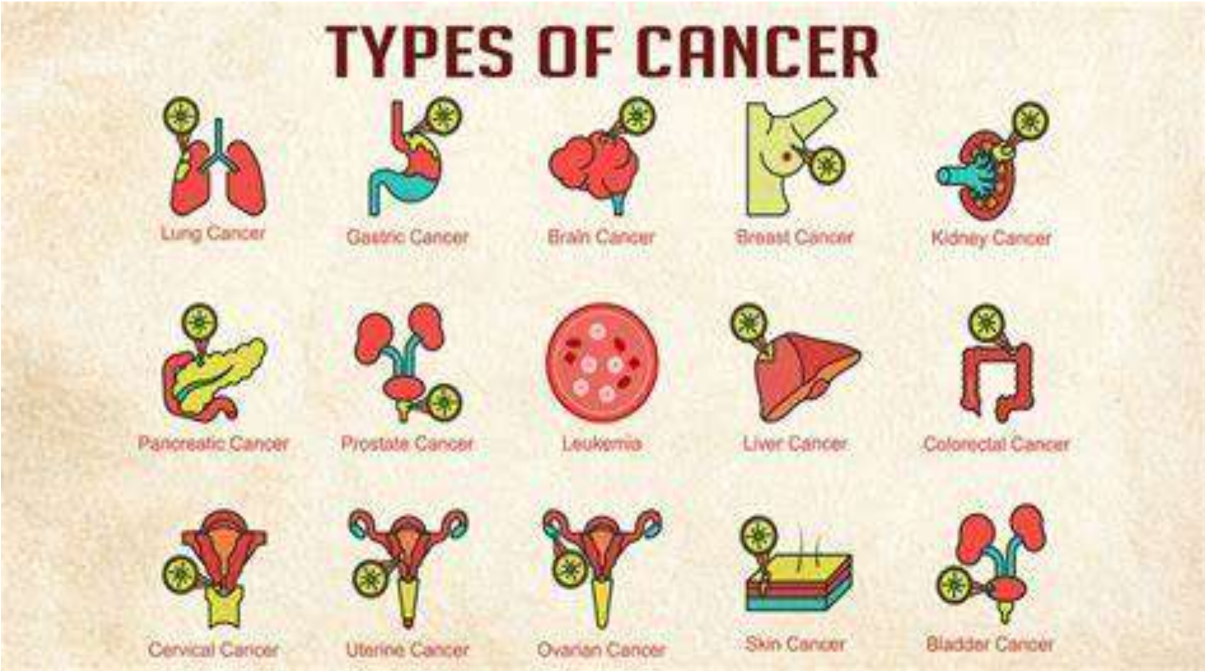

Figure 1 Common Types of Cancer and Affected Organs (Health Results Blog, 2020)

Developing countries, which account for more than 60% of global cancer deaths, are expected to see a significant increase in cancer incidence by 2030 due to rapid urbanization, increased life expectancy, and ongoing challenges in healthcare infrastructure (Torre et al., 2015; Idoko et al., 2024). Additionally, these nations face unique challenges including a high prevalence of cancers linked to infections, such as cervical and liver cancers, which are less common in developed regions (Jemal et al., 2010).

The projected global cancer burden underscores the urgent need for comprehensive strategies in prevention, early detection, and treatment, especially in low- and middle-income countries. Without effective intervention, the global incidence of cancer is expected to rise to 21.4 million new cases and 13.2 million deaths annually by 2030, placing an immense strain on global health systems (Mattiuzzi & Lippi, 2019; Idoko et al., 2024). Therefore, addressing cancer as a global health challenge necessitates coordinated efforts across governments, healthcare providers, and the research community.

Figure 1 presents an overview of cancer incidence and mortality rates worldwide, categorized by region. In 2018, there were 18.1 million new cancer cases globally, with Asia accounting for the highest proportion at 48.4%, followed by Europe at 23.4%, and the Americas at 21.0%. Africa and Oceania had lower incidences, representing 5.8% and 1.4% of cases, respectively. In terms of mortality, there were 9.6 million cancer deaths worldwide, with Asia again showing the highest share at 57.3%, followed by Europe at 20.3% and the Americas at 14.4%. Africa and Oceania contributed 7.3% and 0.7% of cancer deaths, respectively. This data encompasses all ages and both sexes and includes all cancers except non-melanoma skin cancer.

1.2. The Need for Personalized Cancer Treatment

The heterogeneous nature of cancer makes personalized treatment approaches essential to improving patient outcomes. Unlike traditional therapies, which often adopt a generalized approach, personalized cancer treatment focuses on tailoring interventions to the unique molecular and genetic profile of each patient's tumor. This method aims to enhance treatment efficacy while minimizing adverse effects, representing a paradigm shift in oncology (Jackson & Chester, 2015). By identifying specific biomarkers and genetic mutations, personalized therapies can precisely target cancer cells, sparing healthy tissues and improving the quality of life for patients.

Advancements in molecular diagnostics have paved the way for the development of personalized medicine strategies across various cancer types. For example, in breast cancer treatment, the identification of genetic markers has enabled the selection of therapies that are more likely to be effective for specific subtypes, reducing the likelihood of resistance and recurrence (Chan et al., 2017; Idoko et al., 2024). Similarly, in non-small cell lung cancer, the use of biomarkers to guide treatment decisions has significantly improved the success rate of targeted therapies, providing a more tailored approach compared to traditional chemotherapy (Mascaux et al., 2017; Idoko et al., 2024).

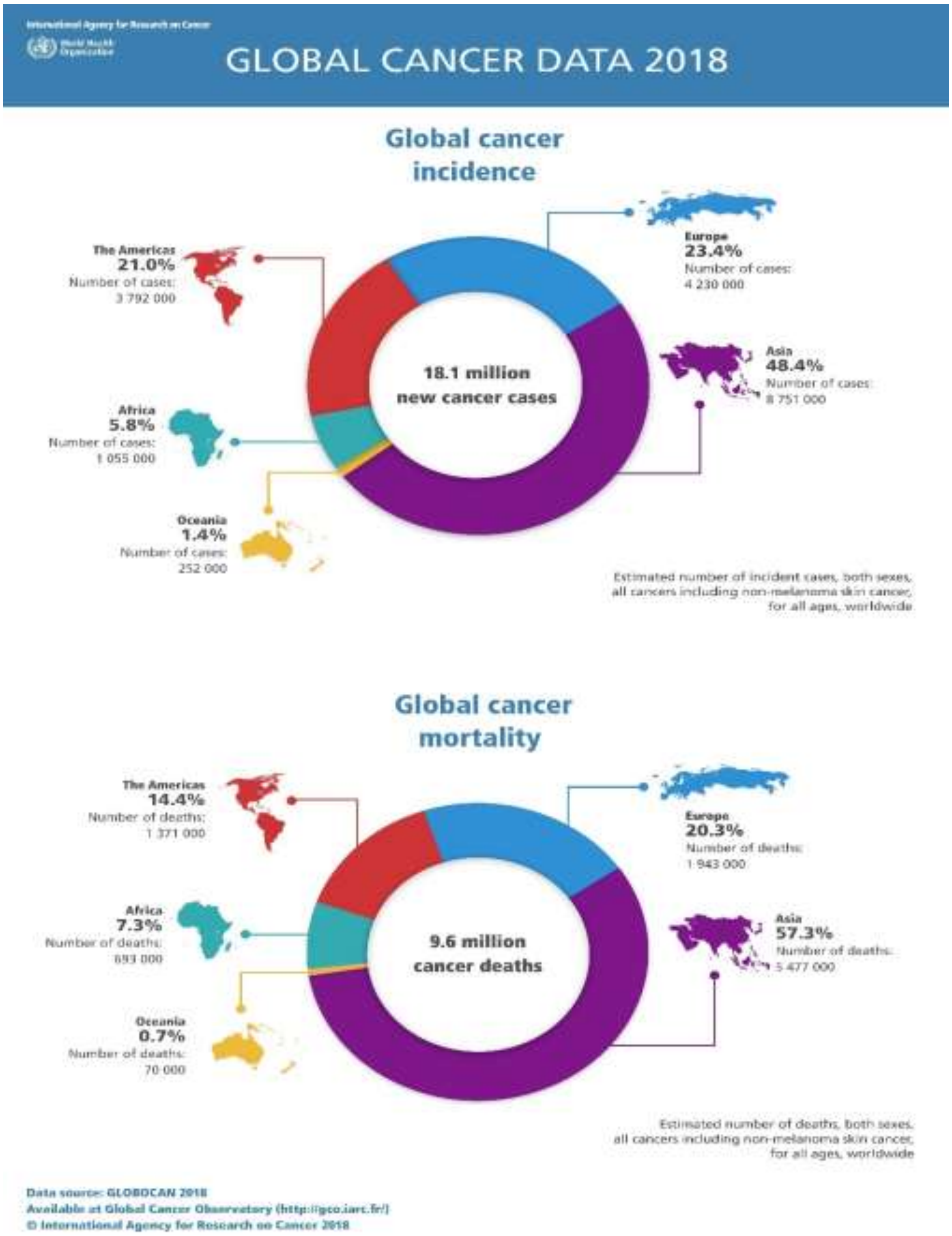

Figure 2 Global Cancer Data 2018 (International Agency for Research on Cancer, 2018)

Table 1 outlines the essential aspects, benefits, mechanisms, and challenges associated with personalized cancer treatment. Unlike traditional therapies, personalized treatment is designed to address the heterogeneous nature of cancer by tailoring interventions to the unique molecular and genetic profiles of individual tumors, which enhances treatment effectiveness and minimizes side effects. Key mechanisms involve using biomarkers and genetic mutations to target cancer cells while sparing healthy tissues, improving patients' quality of life. Examples in breast and lung cancer demonstrate how specific biomarkers and genetic markers guide therapy selection, reducing recurrence and increasing success rates in targeted treatments. Advancements in molecular diagnostics and genomic technologies support the growth of personalized medicine across various cancers. However, challenges such as the high cost of genetic testing and the need for advanced healthcare infrastructure remain, underscoring the importance of addressing these barriers to make personalized cancer treatment widely accessible.

Table 1 Key Aspects of Personalized Cancer Treatment: Benefits, Mechanisms, and Challenges

Aspect	**Details**
Need for Personalized Treatment	Cancer's heterogeneity requires personalized treatments to improve outcomes, differing from traditional generalized therapies.
Goal of Personalized Treatment	To enhance treatment effectiveness and reduce side effects by tailoring therapies to the unique molecular and genetic profile of each patient's tumor.
Mechanism	Uses specific biomarkers and genetic mutations to precisely target cancer cells, sparing healthy tissues and improving the patient's quality of life.
Example in Breast Cancer	Identification of genetic markers helps select effective therapies for specific subtypes, reducing resistance and recurrence (Chan et al., 2017).
Example in Lung Cancer	Biomarkers in non-small cell lung cancer guide treatment, improving targeted therapy success over traditional chemotherapy (Mascaux et al., 2017).
Advancements Supporting It	Molecular diagnostics and genomic technologies have facilitated the growth of personalized medicine strategies for various cancers.
Challenges	High costs of genetic testing and the need for advanced healthcare infrastructure limit the global scalability of personalized cancer treatments.
Importance of Overcoming Challenges	Addressing cost and infrastructure challenges is essential for making personalized cancer treatment a standard, accessible approach across diverse healthcare systems.

The increasing adoption of personalized cancer treatment is driven by the growing understanding of tumor biology and the availability of advanced genomic technologies. However, there remain challenges, including the high cost of genetic testing and the need for robust healthcare infrastructure to support precision oncology on a global scale. Addressing these challenges is crucial to ensuring that personalized treatment becomes a standard care approach, accessible to patients across diverse healthcare settings.

1.3. Emergence of Machine Learning in Healthcare

The integration of machine learning (ML) into healthcare has brought transformative changes, offering new approaches for diagnosis, treatment, and patient management. Over the past decade, ML algorithms have demonstrated the ability to analyze vast datasets, enabling the identification of patterns that can improve clinical decision-making and enhance personalized care. This shift marks a departure from traditional methods, facilitating more accurate and faster diagnoses, which are crucial for effective treatment outcomes (Javaid et al., 2022). For instance, in fields like oncology, ML models can process medical images and genomic data to detect early signs of cancer, thereby increasing the chances of successful treatment.

Despite its potential, the application of machine learning in healthcare is accompanied by challenges, such as data integration, algorithm transparency, and ethical considerations. Machine learning systems, while powerful, often function as "black boxes," making it difficult for clinicians to interpret how specific decisions are made, which raises concerns about trust and accountability in clinical settings (Cabitza et al., 2017; Idoko et al., 2024). Addressing these concerns requires collaboration between data scientists, healthcare professionals, and policy makers to ensure that ML technologies are both effective and ethically sound.

The future of ML in healthcare looks promising, with ongoing advancements poised to improve patient outcomes across various medical specialties. The continuous development of algorithms capable of learning from patient data in real time will further enhance the ability to provide personalized treatment plans. However, achieving widespread implementation will necessitate strategic investments in technology infrastructure and workforce training to fully harness the potential of machine learning in healthcare (Darcy et al., 2016; Idoko et al., 2024).

Table 2 provides an overview of the transformative role of machine learning (ML) in healthcare, highlighting its benefits, applications, challenges, and future outlook. Machine learning enables new methods for diagnosis, treatment, and patient management by analyzing large datasets and identifying patterns, thus supporting faster and more accurate clinical decision-making. Key applications, particularly in oncology, include early cancer detection through medical imaging and genomic data analysis, which increases the likelihood of successful treatment. However, ML in healthcare also faces significant challenges, such as data integration, transparency in algorithmic decisions, and ethical concerns around accountability. The future of ML in healthcare appears promising, with advancements aimed at enabling real-time personalized treatment plans and improving patient outcomes across various medical fields. To fully realize this potential, strategic investments in infrastructure, interdisciplinary collaboration, and workforce training are essential.

Table 2 The Role of Machine Learning in Transforming Healthcare: Benefits, Applications, Challenges, and Future Prospects

Aspect	Description	Applications	Challenges	Future Outlook
Transformation in Healthcare	ML offers new methods for diagnosis, treatment, and patient management, enhancing clinical decision-making.	Oncology: ML for early cancer detection via image and genomic data analysis.	Data integration, algorithm transparency, and ethical concerns like accountability.	Promising advancements to improve patient outcomes across specialties, with potential for real-time learning.
Benefits of ML in Healthcare	Enables analysis of vast datasets, identifying patterns for accurate and faster diagnoses.	Personalized care, early diagnosis, and improved treatment outcomes.	Clinician trust issues due to "black box" nature of some ML systems.	Requires collaboration among data scientists, healthcare professionals, and policymakers.
Examples of ML Use	Oncology field uses ML to detect early signs of cancer, increasing treatment success rates.	Oncology, radiology, genomics.	Interdisciplinary collaboration needed for effective and ethical ML deployment.	Investments in infrastructure and training essential for broader ML adoption.
Challenges with ML Adoption	Complex data handling and lack of transparency make ML implementation difficult in clinical settings.	Addressing algorithm interpretability for clinician trust.	Ethical issues regarding decision-making transparency in clinical use.	Strategic investments required in technology and workforce development for ML's full potential.
Long-Term Potential	Ongoing advancements in ML aim to improve real-time, personalized treatment plans for patients.	Enhanced patient outcomes, personalization.	Ethical and technical challenges must be overcome.	Achieving widespread adoption depends on infrastructure, training, and policy support.

1.4. Objectives of the Review

The primary objective of this review is to provide a comprehensive analysis of the role of machine learning in advancing personalized cancer treatment and its implications for global public health. By examining the current state of machine learning applications in oncology, this paper aims to highlight the potential benefits of integrating these technologies into clinical practice, particularly in the context of personalized care. The review also seeks to explore the challenges and limitations that may hinder the adoption of machine learning in healthcare settings, with a focus on issues such as data privacy, algorithmic transparency, and the need for robust healthcare infrastructure.

Additionally, this paper aims to identify emerging trends and future directions in the application of machine learning for personalized cancer therapy. By drawing on case studies from both high-resource and low-resource settings, the review will evaluate how machine learning can contribute to reducing healthcare disparities and improving patient outcomes on a global scale. Ultimately, the goal is to provide insights that can inform future research, policy development, and the strategic implementation of machine learning technologies in cancer treatment.

1.5. Structure of the Paper

This paper is organized into several sections, each addressing key aspects of machine learning in personalized cancer treatment. The introduction provides an overview of the global cancer burden, the need for personalized approaches, and the role of emerging technologies in addressing these challenges. Following this, the review explores various machine learning techniques used in oncology, highlighting their applications in cancer diagnosis, prognosis, and treatment personalization.

The subsequent sections present case studies that demonstrate the real-world impact of machine learning in personalized cancer care, with examples drawn from both developed and developing nations. These case studies illustrate successful implementations, as well as the obstacles encountered, offering a balanced perspective on the adoption of these technologies across diverse healthcare systems.

A detailed discussion on the implications of machine learning for global public health follows, examining how these technologies can help bridge healthcare disparities, improve accessibility to personalized treatments, and address ethical and policy considerations. The paper concludes with insights into future research directions, recommendations for overcoming current barriers, and reflections on the potential for machine learning to transform cancer care on a global scale.

2. Machine learning techniques in personalized cancer treatment

2.1. Overview of Machine Learning Algorithms in Healthcare

Machine learning (ML) algorithms have significantly advanced the field of healthcare, particularly in oncology, by enabling more precise and personalized diagnostic and treatment approaches. These algorithms can analyze complex and large datasets, uncovering patterns that might not be immediately apparent to human clinicians. Commonly used ML algorithms in healthcare include supervised learning methods like Support Vector Machines (SVM), Random Forests, and Artificial Neural Networks (ANNs). These approaches are applied to tasks ranging from disease diagnosis and patient risk stratification to predicting treatment outcomes and detecting anomalies in medical imaging.

Figure 3 illustrates key fields of application for machine learning in healthcare, presented in a circular layout around the central theme. These fields include "Diseases Identification and Diagnosis," "Medical Imaging," "Drug Discovering and Manufacturing," "Personalized Medical Treatment," "Smart Health Records," and "Disease Prediction." Each application area highlights how machine learning can support various healthcare processes, from identifying diseases and managing health records to enhancing personalized treatments and advancing drug discovery. This visual emphasizes the broad potential of machine learning to transform and improve healthcare services.

In oncology, ML algorithms have proven to be particularly effective in enhancing diagnostic accuracy. For instance, computer-aided diagnosis systems using neural networks have demonstrated the ability to process medical images and identify malignant tumors with high precision. These systems can improve early cancer detection, thereby increasing the likelihood of successful treatment (Iqbal et al., 2021). Furthermore, algorithms like Random Forests and Gradient Boosting Machines have been utilized for predicting patient survival rates and treatment responses, offering clinicians valuable insights to personalize therapy plans.

Despite the successes, the integration of ML in healthcare presents challenges, including the need for vast amounts of high-quality data and the complexities involved in ensuring algorithm transparency and interpretability. Effective implementation of ML in clinical settings requires robust frameworks that support not only the deployment of these algorithms but also continuous learning and adaptation to new data. As the technology evolves, the focus remains on refining these algorithms to enhance their predictive capabilities and to support more accurate and individualized treatment plans across various medical disciplines (Hsu et al., 2021; Benbrahim et al., 2019; Idoko et al., 2024).

Figure 3 Applications of Machine Learning in Healthcare (Bayes 2020)

2.2. Key Applications in Cancer Diagnosis and Treatment

Machine learning (ML) has brought significant advancements to cancer diagnosis and treatment by enhancing the precision and efficiency of traditional methods. In cancer diagnostics, ML algorithms are applied to analyze complex datasets, including medical images, genomic sequences, and clinical records. Deep learning models, for example, have improved the accuracy of detecting various types of cancers by facilitating better image segmentation and classification. These techniques allow for earlier detection of malignancies, which is crucial for improving patient outcomes (Saba, 2020; Idoko et al., 2024). Furthermore, ML algorithms can identify subtle patterns in genomic data, which helps in understanding the genetic mutations driving cancer progression, aiding in personalized treatment strategies.

Another critical application of ML in oncology is in drug discovery and development. Traditional drug discovery is time-consuming and expensive, often taking years of research and testing. Machine learning accelerates this process by analyzing vast amounts of biochemical data to identify potential drug candidates and predict their effectiveness. For instance, ML models can simulate how a drug interacts with specific proteins or cancer cells, allowing researchers to prioritize compounds that are more likely to succeed in clinical trials (Iqbal et al., 2021; Forood 2024). Moreover, ML techniques are also employed in developing personalized treatment plans, where they help predict how a patient will respond to a specific therapy based on their unique genetic and molecular profile.

ML's ability to analyze data from various sources has also contributed to identifying biomarkers that are essential for developing targeted therapies. These biomarkers enable clinicians to choose treatments that are more likely to be effective for individual patients, thereby reducing the risk of adverse effects. The integration of ML into cancer care exemplifies the shift towards more personalized and precise medicine, enhancing the ability to manage the disease more effectively (Painuli et al., 2022).

Table 3 outlines the key applications of machine learning (ML) in cancer diagnosis and treatment, highlighting how ML enhances precision and efficiency in oncology. ML is used in cancer diagnostics to analyze complex datasets, such as medical images and genomic sequences, enabling early and accurate detection through techniques like deep learning and image segmentation. In genomic analysis, ML helps identify genetic mutations driving cancer, supporting personalized treatment strategies. Additionally, ML accelerates drug discovery by analyzing biochemical data to identify promising drug candidates, reducing the time and cost of development. Personalized treatment planning is another critical area, where ML predicts patient responses to therapies based on individual genetic and molecular profiles, increasing treatment effectiveness. Finally, ML aids in biomarker identification, enabling clinicians to select targeted therapies that are more likely to be effective. Together, these applications demonstrate the transformative impact of ML in creating more personalized and effective cancer care.

Table 3 Key Applications of Machine Learning in Cancer Diagnosis and Treatment

Application Area	Description	ML Techniques Used	Benefits
Cancer Diagnostics	ML algorithms analyze complex datasets like medical images and genomic sequences for cancer detection.	Deep learning, image segmentation, classification	Early and accurate cancer detection
Genomic Analysis	ML identifies patterns in genomic data, understanding mutations driving cancer, aiding personalized treatment.	Pattern recognition, data mining	Supports personalized treatment strategies
Drug Discovery and Development	ML accelerates drug discovery by analyzing biochemical data to identify potential candidates.	Predictive modeling, data simulation	Reduces time and cost in drug development
Personalized Treatment Planning	ML predicts patient responses to therapies based on genetic and molecular profiles.	Predictive analytics, personalized modeling	Improves treatment effectiveness
Biomarker Identification	ML helps identify biomarkers essential for developing targeted therapies.	Data analysis, biomarker discovery algorithms	Enables targeted and effective treatments
Overall Impact	Enhances personalized and precise medicine in oncology, improving cancer management.	Various ML algorithms	Reduces adverse effects and improves outcomes

2.3. Challenges and Limitations of Implementing Machine Learning in Cancer Care

Despite the potential benefits of machine learning (ML) in cancer care, there are significant challenges and limitations that impede its widespread adoption. One of the primary issues is the need for vast amounts of high-quality data to train ML models. In cancer care, data is often fragmented across different institutions and lacks standardization, which can lead to inconsistencies in model performance. Moreover, many ML models require extensive retraining when new data becomes available, complicating their deployment in clinical settings. This issue is further compounded by the challenges of model validation, particularly in ensuring that algorithms perform accurately across diverse patient populations (Sendak et al., 2019 Ijiga et al., 2024).

Figure 4 Data Challenges in Implementing AI and Machine Learning in Cancer Care (Aldoseri et al., 2023)

Figure 4 highlights six data challenges crucial to implementing AI and machine learning in cancer care. Ensuring data quality is essential, as high-quality, consistent data across institutions is necessary to train reliable AI models for accurate diagnoses. Data volume is also a major concern, as cancer care relies on large datasets to identify complex patterns, like genetic mutations and tumor markers, which are critical for precise diagnosis and treatment planning. Data privacy and security is paramount in this field, given the sensitivity of patient information, and compliance with regulations is necessary to maintain patient trust. Additionally, bias and fairness in AI models are important to prevent inequities in treatment recommendations, particularly for underrepresented patient groups. Interpretability and explainability of AI models are essential for clinicians, as they need to understand and trust AI-generated insights to make informed patient care decisions. Finally, a lack of technical expertise poses a barrier, as deploying and maintaining these complex AI systems requires specialized skills. Addressing these challenges is vital for the safe and effective integration of AI in cancer care, ensuring improvements in diagnosis, treatment, and overall patient outcomes.

Another critical limitation lies in the "black box" nature of many ML algorithms, particularly deep learning models. While these models can achieve high accuracy, their decision-making processes are often opaque, making it difficult for clinicians to interpret and trust their recommendations. This lack of transparency poses a significant barrier to clinical adoption, as healthcare professionals need to understand how a model arrives at its conclusions, especially when making decisions that could impact patient outcomes. Additionally, ethical and privacy concerns around data collection and usage remain unresolved, which further limits the integration of ML technologies in healthcare settings (Jarrett et al., 2019; Ijiga et al., 2024).

Figure 5 outlines major challenges encountered during the training and validation of machine learning models, specifically highlighting issues such as insufficient training data, poor data quality, overfitting, underfitting, and the presence of unrelated or irrelevant features. In the context of cancer care, these challenges can significantly impact the effectiveness of AI models. For instance, not enough training data can lead to underfitting, where the model fails to capture complex patterns necessary for accurately identifying cancerous cells or predicting patient outcomes. Poor quality data may introduce noise, further complicating model reliability and leading to inaccurate diagnoses. Overfitting can occur when models are too tailored to the training data, potentially limiting their generalization to new patient cases. Underfitting, on the other hand, can result from simplistic models that overlook subtle cancer indicators. Finally, unrelated or irrelevant features can mislead the model, reducing its predictive accuracy in identifying cancer types or treatment responses. Addressing these challenges is essential to ensure that AI models in cancer care are both accurate and reliable, enhancing early diagnosis and personalized treatment.

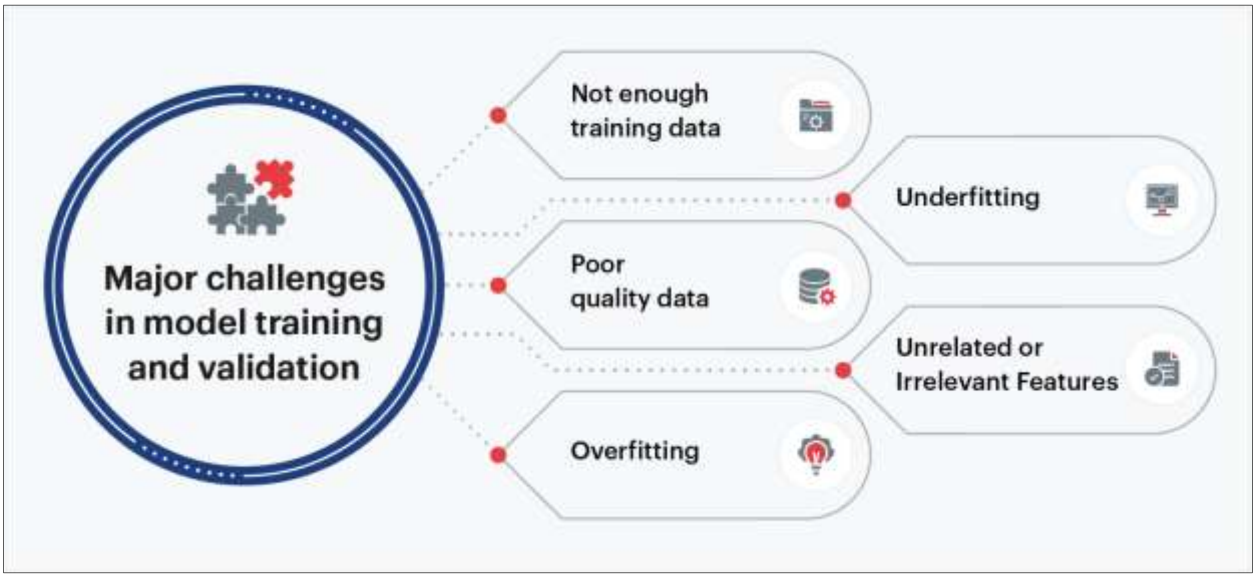

Figure 5 Challenges in Model Training and Validation for AI in Cancer Care (Sigmoid 2024)

Finally, there are practical and logistical challenges related to integrating ML systems into existing healthcare infrastructure. Many healthcare institutions lack the computational resources and technical expertise required to implement and maintain these systems effectively. Successful integration of ML into cancer care demands strategic investments in technology, workforce training, and cross-disciplinary collaboration to bridge the gap between data science and clinical practice. Without these structural changes, the full potential of ML to improve cancer care remains underutilized (Cruz & Wishart, 2006; Ijiga et al., 2024).

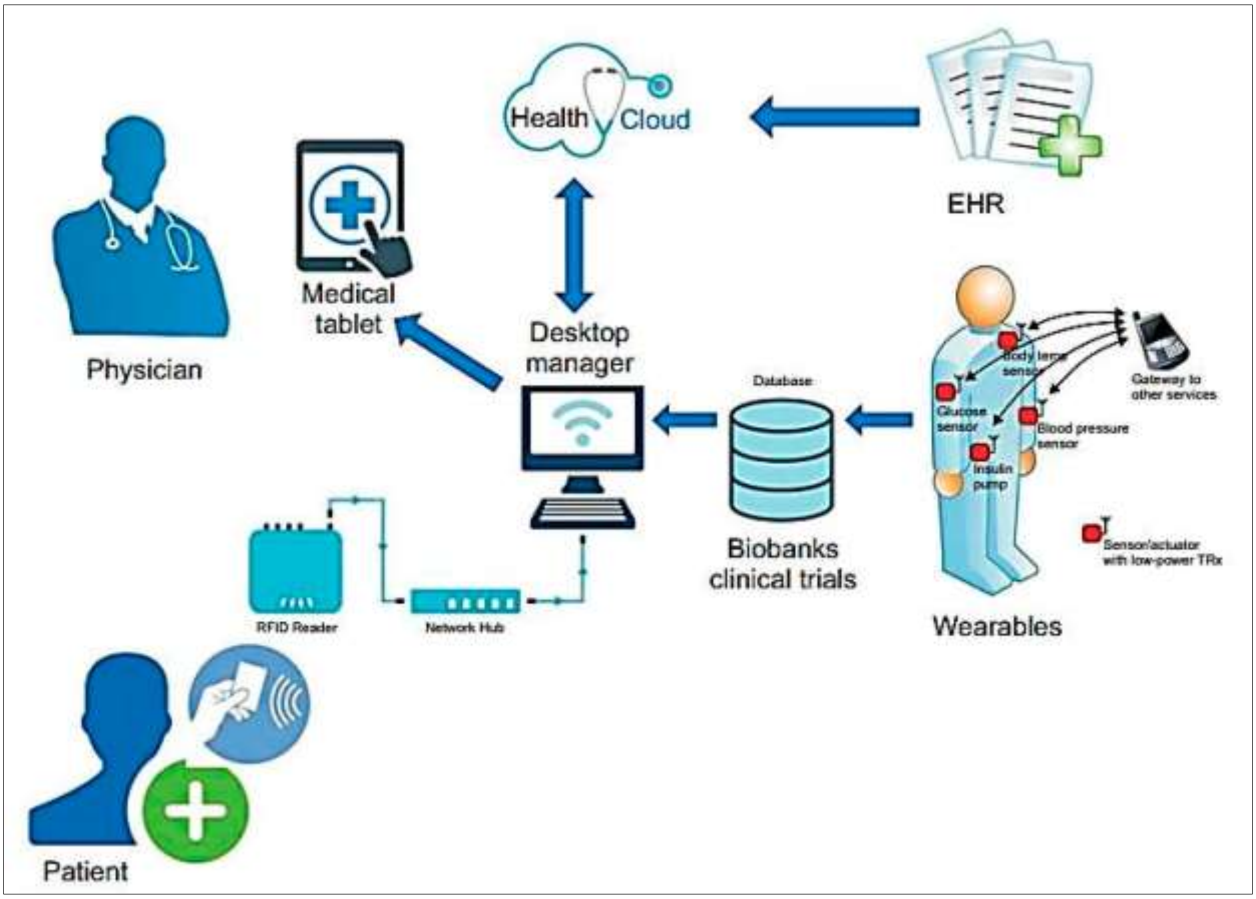

Figure 6 Practical and Logistical Challenges of Integrating Machine Learning Systems into Healthcare Infrastructure (Kumar et al, 2023)

Table 4 Challenges and Limitations of Machine Learning Implementation in Cancer Care

Challenge	Description	Limitations	References
Data Quality and Availability	High-quality, standardized data is essential for ML training, but cancer data is often fragmented and inconsistent.	Leads to inconsistencies in model performance and retraining needs.	Sendak et al., 2019
Model Validation	Ensuring ML models perform accurately across diverse patient populations is challenging.	Complicates deployment in clinical settings.	Sendak et al., 2019
Lack of Transparency	Many ML models, especially deep learning, function as "black boxes," making decision-making processes opaque.	Limits clinician trust and interpretability.	Jarrett et al., 2019
Ethical and Privacy Concerns	Issues around data collection and usage in healthcare raise privacy and ethical concerns.	Restricts integration of ML in clinical practice.	Jarrett et al., 2019
Infrastructure Limitations	Many healthcare institutions lack resources and expertise for ML implementation.	Requires investment in technology, training, and collaboration.	Cruz & Wishart, 2006
Need for Structural Changes	Integrating ML into healthcare requires bridging gaps between data science and clinical practice.	Without changes, ML's potential remains underutilized.	Cruz & Wishart, 2006

Table 4 highlights the main challenges and limitations in implementing machine learning (ML) in cancer care, which hinder its widespread adoption despite its potential benefits. One significant challenge is the need for high-quality, standardized data, as cancer data is often fragmented and inconsistent across institutions, affecting model performance and necessitating frequent retraining. Model validation across diverse patient populations remains complex, making clinical deployment difficult. Additionally, the "black box" nature of many ML models, particularly deep learning, limits transparency, leading to a lack of clinician trust. Ethical and privacy concerns around data collection further restrict ML integration in clinical settings. Infrastructure limitations, including a lack of computational resources and technical expertise in healthcare institutions, also pose barriers. Addressing these challenges requires structural changes, investment in technology, workforce training, and stronger collaboration between data scientists and clinicians to fully harness ML's potential in cancer care.

3. Case studies of machine learning in cancer treatment

3.1. Success Stories from Developed Nations

Machine learning (ML) has been successfully integrated into cancer treatment protocols across developed nations, leading to improvements in diagnostic accuracy and treatment personalization. In the United States, one notable application involved a machine learning model that enhanced treatment decisions for head and neck cancer. The study demonstrated that the model could effectively recommend chemoradiation for a substantial percentage of patients, leading to a measurable survival benefit. This approach not only optimized patient outcomes but also underscored the potential of ML in refining treatment selection for complex cancers (Howard et al., 2020).

In Europe, ML has made significant strides in breast cancer management. A recent case study demonstrated the application of machine learning to predict treatment responses post-neoadjuvant chemotherapy. By analyzing extensive datasets from clinical records, the model could accurately identify patients likely to experience tumor recurrence, helping clinicians adjust treatment plans proactively. This approach is particularly valuable in improving prognostic accuracy, offering a personalized strategy to manage breast cancer patients and mitigate risks of relapse (Jin et al., 2023; Ijiga et al., 2024).

Furthermore, ML has been leveraged to enhance cancer diagnosis, particularly in complex cases where traditional methods fall short. In a UK-based study, ML algorithms showed higher accuracy in identifying oesophago-gastric cancer patients compared to existing clinical risk assessment tools. The advanced analytical techniques employed by these models could detect 11-25% more cancer cases without significantly increasing false positives, thereby facilitating earlier diagnosis and improving survival rates. This success underscores the role of machine learning in revolutionizing cancer diagnostics by offering more precise and efficient screening methods (Briggs et al., 2022; Ijiga et al., 2024).

Table 5 Impact of Machine Learning on Cancer Care: Diagnostic and Treatment Innovations Across Regions

Region	ML Application in Cancer Care	Cancer Type	Outcome/Benefit	Reference
United States	ML model to recommend chemoradiation treatment	Head and neck cancer	Improved survival benefits by optimizing treatment decisions for a significant percentage of patients.	Howard et al., 2020
Europe	ML model to predict treatment response post-neoadjuvant chemotherapy	Breast cancer	Enhanced prognostic accuracy; allowed clinicians to proactively adjust treatment to reduce recurrence risks.	Jin et al., 2023
United Kingdom	ML algorithms for improved cancer diagnosis	Oesophago-gastric cancer	Detected 11-25% more cases than traditional methods, facilitating earlier diagnosis and improved survival rates.	Briggs et al., 2022

Table 5 highlights the transformative role of machine learning (ML) in cancer care by showcasing its regional applications in diagnostics and treatment personalization. The title reflects how ML has been integrated into healthcare protocols in the United States, Europe, and the United Kingdom, each region contributing unique advancements in cancer care. In the U.S., ML optimizes treatment recommendations, especially for complex cancers like head and neck cancer. In Europe, it enhances prognostic accuracy for breast cancer patients post-chemotherapy, while in the U.K., it improves diagnostic precision for oesophago-gastric cancer. This title encapsulates the global perspective on ML-driven innovations in cancer management, emphasizing the enhanced accuracy, personalization, and early detection these technologies bring to patient care.

3.2. Emerging Applications in Low- and Middle-Income Countries

In low- and middle-income countries (LMICs), machine learning (ML) is emerging as a vital tool to improve cancer care, particularly in settings where resources are limited, and access to specialized healthcare is often challenging. One of the notable applications is in the early diagnosis of cervical cancer, which remains a significant health burden in many LMICs. ML algorithms, particularly classifiers like Random Forest, have been employed to predict cervical cancer risk among women, offering a cost-effective method for early detection. This approach has been particularly effective in communities where regular screening might not be feasible, thereby helping to bridge the gap in cancer prevention and management (Namalinzi et al., 2024).

Another area where ML has shown promise is in enhancing the accuracy and efficiency of cancer diagnostics through automated image processing. For instance, in Honduras, researchers developed an ML-based tool for leukemia diagnosis that significantly reduces the time needed for analysis by utilizing automated image processing algorithms. This innovation not only accelerates the diagnostic process but also ensures that patients receive timely and accurate diagnoses, which is critical for initiating early treatment, especially in resource-limited settings where delays can be life-threatening (Cerrato, 2020).

Moreover, ML's potential extends to addressing global disparities in cancer care by enabling affordable and scalable solutions for complex treatments. An example is the development of point-of-care technology (POCT) that integrates ML for better data management and treatment monitoring. This technology has been adapted to resource-limited settings, improving patient care by facilitating real-time monitoring and decision-making without the need for extensive infrastructure. Such innovations are crucial for enhancing cancer care in LMICs, offering hope for more equitable health outcomes across diverse global regions (Silas et al., 2019).

Table 6 highlights the role of machine learning (ML) as a transformative tool in improving cancer care within low- and middle-income countries (LMICs). ML offers innovative solutions to healthcare challenges in resource-limited settings, where access to specialized care and diagnostic resources is often constrained. For instance, ML classifiers like Random Forest aid in the early diagnosis of cervical cancer, providing a cost-effective and accessible alternative to regular screenings. Additionally, automated image processing tools speed up leukemia diagnoses, ensuring that patients receive timely and accurate results. ML-driven point-of-care technology (POCT) further supports real-time monitoring and treatment management without requiring extensive infrastructure. Together, these applications demonstrate ML's potential to bridge healthcare gaps in LMICs, promoting equitable access to quality cancer care and improving patient outcomes in underserved communities.

Table 6 Harnessing Machine Learning for Cancer Care in Low- and Middle-Income Countries: Emerging Applications and Impact

Application Area	ML Use Case	Cancer Type	Benefits	Reference
Early Diagnosis	ML classifiers like Random Forest for cervical cancer risk prediction	Cervical cancer	Provides a cost-effective early detection method, bridging gaps in regular screening in LMICs.	Namalinzi et al., 2024
Automated Diagnostics	ML-based tool for leukemia diagnosis with automated image processing	Leukemia	Reduces diagnostic time, ensuring timely and accurate diagnoses critical for early treatment in LMICs.	Cerrato, 2020
Point-of-Care Technology (POCT)	POCT integrated with ML for real-time monitoring and data management	Various cancers	Facilitates decision-making and treatment monitoring without extensive infrastructure, enhancing patient care.	Silas et al., 2019

3.3. Lessons Learned and Future Directions

The application of machine learning (ML) in cancer care has highlighted several key lessons and pointed toward future opportunities to enhance patient outcomes. One important lesson learned is the need for robust validation of ML models. While many studies have demonstrated the potential of ML to improve cancer prediction and prognosis, issues related to model validation have surfaced repeatedly. Inadequate validation can lead to overfitting and reduced generalizability, which undermines the practical application of these technologies in clinical settings. Moving forward, efforts must focus on developing more interpretable and validated ML models that can be trusted by clinicians for routine use (Cruz & Wishart, 2006).

Additionally, successful integration of ML in healthcare requires collaboration across multiple disciplines. Effective implementation involves not just data scientists but also clinicians, healthcare administrators, and policymakers. Addressing technical, ethical, and infrastructural challenges demands coordinated efforts that include investment in technology infrastructure and workforce training. Partnerships between clinical researchers and machine learning experts are essential for building solutions that are both technologically sound and clinically relevant, ensuring that ML tools are seamlessly integrated into existing workflows (Sendak et al., 2019).

Looking to the future, initiatives like the Cancer Moonshot have emphasized the importance of leveraging data to drive innovation in cancer care. One of the major takeaways from these efforts is the need to create a national learning healthcare system where data from diverse sources can be shared and analyzed. By pooling data, researchers can uncover new insights into cancer biology and treatment, ultimately leading to more personalized and effective therapies. Future directions should prioritize data accessibility, privacy, and the continuous development of ML algorithms capable of learning from real-world clinical data to improve care outcomes across various cancer types (Hsu et al., 2017).

Table 7 summarizes important lessons and future directions for applying machine learning (ML) in cancer care, based on past experiences and current challenges. One major lesson learned is the need for robust model validation; inadequate validation can lead to overfitting, reducing the reliability of ML models in clinical settings. The future direction for this area is to create more interpretable and validated models that clinicians can confidently use. Another critical insight is the importance of cross-disciplinary collaboration, as effective ML integration requires teamwork among data scientists, clinicians, administrators, and policymakers. Future efforts should emphasize partnerships and investments in infrastructure and workforce training to streamline implementation. Finally, there is a call for data sharing and the development of a national healthcare system to enable pooled data analysis, which can foster more personalized cancer treatments. Moving forward, establishing a learning healthcare system that prioritizes data accessibility and privacy is essential for advancing ML-driven innovations in cancer care.

Table 7 Key Insights and Future Directions for Machine Learning in Cancer Care

Key Lessons Learned	Description	Future Directions	References
Need for Robust Model Validation	Inadequate validation leads to overfitting and reduced generalizability, limiting clinical application.	Develop more interpretable and validated ML models trusted by clinicians.	Cruz & Wishart, 2006
Importance of Cross-Disciplinary Collaboration	Successful ML integration requires teamwork among data scientists, clinicians, administrators, and policymakers.	Foster partnerships and invest in technology infrastructure and workforce training for effective implementation.	Sendak et al., 2019
Data Sharing and National Healthcare System	Leveraging pooled data can drive innovation in personalized cancer therapies.	Build a national learning healthcare system to ensure data accessibility, privacy, and algorithm development.	Hsu et al., 2017

4. Implications for global public health

4.1. Addressing Inequalities in Access to Personalized Cancer Care

Machine learning (ML) has the potential to revolutionize personalized cancer care by enabling precise treatment strategies tailored to individual patient characteristics. This approach could help mitigate disparities in healthcare access by making advanced diagnostics and treatment more broadly available. For instance, ML can standardize the processing of patient data, ensuring that individuals receive consistent information and care recommendations, regardless of their location. This ability to democratize access to personalized treatment can be particularly beneficial for underserved communities where healthcare resources are often limited (Brant, 2019).

Despite its potential, there are significant challenges to overcome to ensure that ML does not inadvertently exacerbate existing inequalities. One major concern is the potential for biases in machine learning algorithms, particularly those trained on electronic health records (EHRs). Studies have shown that biases can emerge when algorithms rely on data that reflects existing socioeconomic disparities, leading to unequal care recommendations. Addressing these biases requires careful consideration in the design and implementation of ML models to prevent them from amplifying health inequities, ensuring that advances in technology truly benefit all patient populations (Gianfrancesco et al., 2018).

Moreover, the effective deployment of ML in personalized cancer care depends on the availability of high-quality, diverse datasets. Currently, many ML models are developed using data primarily from well-resourced healthcare systems, which may not represent the diverse genetic, environmental, and socioeconomic factors found in broader populations. Efforts must be made to collect and incorporate data from a wide range of demographics to ensure that ML algorithms can provide equitable care. Future strategies should focus on collaboration between healthcare providers, data scientists, and policy makers to address these barriers and foster a more inclusive approach to cancer treatment (William et al., 2023).

Table 8 highlights the opportunities and challenges of using machine learning (ML) to promote equitable access to personalized cancer care. ML has the potential to standardize data processing, enabling consistent diagnostics and treatment recommendations for patients, regardless of location—a benefit particularly impactful for underserved communities with limited healthcare resources. However, there are challenges to address, such as algorithmic bias in ML models trained on electronic health records (EHRs), which may inadvertently reflect existing socioeconomic disparities. Ensuring fairness requires careful model design and implementation to avoid amplifying health inequities. Another critical issue is data diversity; many ML models are developed using data from well-resourced systems, which limits their applicability across diverse populations. Enhancing data collection from varied demographics is essential for equitable care. Collaborative efforts between healthcare providers, data scientists, and policymakers are necessary to overcome these barriers and realize the potential of ML in creating a more inclusive approach to cancer treatment.

Table 8 Addressing Inequalities in Personalized Cancer Care Through Machine Learning

Challenge	ML Role in Personalized Cancer Care	Potential Solution	Reference
Standardizing Access to Care	ML can standardize data processing, ensuring consistent diagnostics and treatment recommendations.	Democratizes access, particularly benefiting underserved communities with limited healthcare resources.	Brant, 2019
Addressing Algorithmic Bias	Biases in ML algorithms may result in unequal care recommendations, particularly with EHR-based models.	Design and implement ML models carefully to prevent amplifying existing health inequities.	Gianfrancesco et al., 2018
Data Diversity and Representation	Many ML models rely on data from well-resourced systems, lacking diversity.	Increase data collection from diverse populations to ensure equitable care across various demographics.	William et al., 2023
Collaborative Efforts	Effective ML implementation in cancer care requires cross-sector collaboration.	Foster partnerships among healthcare providers, data scientists, and policymakers to address barriers.	William et al., 2023

4.2. Potential of Machine Learning to Bridge Gaps in Resource-Limited Settings

Machine learning (ML) has emerged as a promising tool to bridge healthcare gaps in resource-limited settings by enhancing the accessibility and accuracy of cancer diagnostics and treatment. One of the significant advantages of ML is its ability to improve diagnostic capabilities where traditional healthcare infrastructure may be lacking. For example, a deep learning model for breast cancer diagnosis has been developed to enhance the accuracy of early detection in regions that might not have consistent access to specialists. By utilizing advanced techniques, the model compensates for data scarcity and supports healthcare providers in making accurate diagnoses, thereby improving patient outcomes in under-resourced areas (Zakareya et al., 2023; Manuel et al., 2024).

Moreover, ML can standardize health information and make it accessible to patients and healthcare professionals regardless of geographical constraints. This is particularly beneficial for delivering personalized cancer care in settings where access to specialized treatment options is often limited. By automating the analysis of complex datasets, ML enables the development of tailored treatment plans based on individual patient data, which can help reduce disparities in care and ensure that patients receive optimal therapy, even in settings with limited medical infrastructure (Brant, 2019; Manuel et al., 2024).

Additionally, ML's capacity to process diverse data sources allows it to address issues related to healthcare disparities. For instance, the integration of demographic, biological, and risk data through ML has facilitated earlier detection and pre-screening of cancers, such as in the case of breast cancer. This approach provides a non-invasive and affordable alternative to traditional screening methods, making it easier to implement in low-resource environments. By leveraging demographic and clinical data, ML-driven solutions can significantly reduce the burden on healthcare systems while enabling earlier and more accurate diagnoses, ultimately improving cancer care in resource-constrained regions (Gonzales Martinez & van Dongen, 2023; Onuh et al., 2024).

This table highlights the transformative potential of machine learning (ML) to bridge healthcare gaps in resource-limited settings, particularly in cancer diagnostics and treatment. ML enhances diagnostic accuracy through models like deep learning for breast cancer, which can aid early detection even in regions lacking specialist access. Additionally, ML facilitates standardized health information and automates complex data analyses to offer personalized treatment plans, ensuring that patients receive appropriate care across geographic barriers. The integration of demographic and clinical data for non-invasive cancer screening is particularly beneficial, providing affordable and accessible pre-screening methods suited to low-resource environments. By addressing these areas, ML can reduce healthcare disparities and enhance cancer care accessibility and effectiveness in underserved regions.

Table 9 Leveraging Machine Learning to Improve Cancer Care in Resource-Limited Settings

ML Application	Use Case	Benefits	Examples	Reference
Enhanced Diagnostics	Deep learning for breast cancer diagnosis in resource-limited areas	Improves diagnostic accuracy and supports healthcare providers in regions with limited specialists.	Early breast cancer detection	Zakareya et al., 2023
Standardized Health Information	Automated analysis for personalized treatment across geographic barriers	Ensures consistent and accessible personalized care, reducing disparities in regions with limited infrastructure.	Tailored treatment plans	Brant, 2019
Non-Invasive Screening	Integration of demographic and clinical data for early cancer detection	Provides affordable, non-invasive screening alternatives, enabling earlier diagnoses in low-resource settings.	Pre-screening for breast cancer	Gonzales Martinez & van Dongen, 2023

4.3. Ethical and Policy Considerations in Global Health Context

The integration of machine learning (ML) into cancer care raises critical ethical and policy issues, particularly concerning the fair and equitable use of technology in global health. One of the primary ethical considerations involves the potential for ML to amplify existing health inequities. If algorithms are trained on biased data that reflect systemic disparities, they may perpetuate or even exacerbate these issues. To mitigate such risks, it is essential to design ML systems that prioritize fairness, ensuring that they are aligned with principles of social justice and equity. Addressing biases early in the development process and employing causal inference methods to understand health disparities can help create more equitable solutions that benefit diverse populations globally (Chen et al., 2020).

Another ethical concern is the transparency and accountability of ML algorithms. Many ML models operate as "black boxes," making it difficult for clinicians and patients to understand how decisions are made. This opacity raises questions about moral responsibility and informed consent, particularly when applying ML to life-altering decisions, such as cancer treatment. Ethical frameworks in healthcare emphasize the need for transparency, ensuring that patients are fully informed about how ML is being used in their care. This includes clear communication about the limitations of these technologies and the potential risks associated with automated decision-making (Grote & Berens, 2019).

In addition to these ethical considerations, policy frameworks must address data privacy and security issues. The use of large datasets, often containing sensitive patient information, necessitates stringent data governance policies to protect individuals' rights. Moreover, creating policies that foster patient engagement, transparency, and accountability can enhance trust in ML applications, making them more widely accepted in healthcare systems worldwide. The Learning Health Care System model, which emphasizes these ethical obligations, could serve as a blueprint for integrating ML into cancer care in a manner that respects patient autonomy and promotes global health equity (Kass & Faden, 2018).

Table 10 outlines key ethical and policy considerations necessary for the responsible integration of machine learning (ML) in cancer care on a global scale. Ensuring health equity is vital, as ML models can unintentionally amplify existing disparities if trained on biased data; therefore, designing fair algorithms and using causal inference can help address these inequities. Transparency and accountability are also essential, as the "black box" nature of many ML models limits patient understanding and informed consent in critical healthcare decisions. Additionally, data privacy and security require strong governance policies to protect sensitive patient information, building trust in ML's application in healthcare. Embracing a global health equity approach, such as the Learning Health Care System model, can guide ethical ML integration, making advanced cancer care accessible and fair for diverse populations worldwide.

Table 10 Ethical and Policy Considerations for Integrating Machine Learning in Global Cancer Care

Consideration	**Description**	**Ethical/Policy Focus**	**Approach**	**Reference**
Health Equity	Potential for ML to amplify health inequities if trained on biased data.	Fairness, social justice, and equity	Design ML systems with fairness and use causal inference to address disparities.	Chen et al., 2020
Transparency and Accountability	Lack of transparency in "black box" ML models raises questions on decision-making accountability and informed consent.	Moral responsibility and informed consent	Ensure transparent communication on ML limitations and risks to inform patient decisions.	Grote & Berens, 2019
Data Privacy and Security	Large, sensitive datasets require stringent data governance to protect patient information.	Privacy, data governance, and patient rights	Implement data privacy policies fostering engagement, transparency, and accountability.	Kass & Faden, 2018
Global Health Equity	Ensuring ML benefits are accessible to diverse populations across healthcare systems globally.	Accessibility and inclusion in healthcare systems	Adopt Learning Health Care System model to promote equitable and respectful ML integration.	Kass & Faden, 2018

5. Summary

The integration of machine learning (ML) into personalized cancer treatment has led to significant advancements in improving diagnosis, prognosis, and therapy selection. One of the key strengths of ML lies in its ability to process large and complex datasets, allowing for more accurate predictions of cancer susceptibility, recurrence, and mortality. Studies have demonstrated that ML can enhance predictive accuracy by 15-25%, contributing to the development of personalized predictive medicine. This capability supports clinicians in identifying high-risk patients and tailoring treatment approaches that improve overall patient outcomes (Cruz & Wishart, 2006).

Moreover, ML has facilitated the identification of genetic mutations and biomarkers that are crucial for developing individualized treatment regimens. By analyzing diverse data sources, such as genomic sequences and clinical records, ML algorithms can pinpoint the genetic drivers of cancer, leading to more precise and effective therapeutic interventions. This approach has opened new avenues in precision medicine, where patients receive treatment strategies based on their specific tumor characteristics, thereby addressing the challenge of therapy resistance and improving survival rates (Iqbal et al., 2021).

Despite these promising advancements, the practical implementation of ML in clinical settings remains a challenge. Issues such as data scarcity, algorithm interpretability, and the need for robust pharmacogenomic data limit the clinical applicability of these technologies. Ongoing research aims to develop clinically viable models that can bridge these gaps, ensuring that ML-driven solutions are not only effective but also accessible to diverse patient populations globally. Addressing these challenges will be essential for realizing the full potential of ML in transforming cancer care and advancing personalized treatment (Rafique et al., 2021).

5.1. Recommendations for Future Research and Policy

To fully harness the potential of machine learning (ML) in personalized cancer treatment, future research should focus on developing more interpretable and robust algorithms that can be validated across diverse clinical settings. Current ML models often face challenges with generalizability due to limitations in training data, which may not represent all patient demographics. Therefore, future research should prioritize the inclusion of diverse datasets to improve model accuracy and ensure broader applicability. This approach will help address discrepancies in treatment outcomes and improve the overall efficacy of personalized cancer care (Cruz & Wishart, 2006; Ayoola et al., 2024).

Additionally, there is a critical need for further exploration of how ML can be integrated with real-world learning systems (RLSs) to optimize treatment strategies based on real-time data. By leveraging ML to analyze vast amounts of clinical data, RLSs can provide evidence-based insights that help clinicians make more informed decisions tailored to individual patient needs. Enhancing these decision-support systems can significantly improve clinical outcomes, but it requires ongoing research to refine ML models and integrate them seamlessly into healthcare infrastructure (Finlayson et al., 2016).

From a policy perspective, it is essential to establish frameworks that address the ethical implications of using ML in healthcare. Privacy concerns, data security, and algorithmic transparency must be considered when implementing ML-based solutions. Policy initiatives should also encourage the development of standardized protocols for data collection, sharing, and analysis to facilitate collaboration across institutions and enhance the reliability of ML models in clinical practice. Moreover, investing in training programs to equip healthcare professionals with the necessary skills to interpret and utilize ML technologies will be crucial for the successful integration of these tools in routine cancer care (Dubey et al., 2023).

5.2. Final Thoughts on the Future of Machine Learning in Global Cancer Treatment

The future of machine learning (ML) in personalized cancer treatment is poised to revolutionize the field by enabling more accurate and timely diagnoses, predicting therapeutic responses, and enhancing individualized treatment plans. By leveraging complex datasets, ML can identify patterns in genomic and clinical data that are often missed by traditional methods, facilitating early detection and precise therapeutic interventions. The integration of ML into oncology has already demonstrated success in predicting cancer susceptibility, recurrence, and mortality, underscoring its transformative potential in global cancer care (Cruz & Wishart, 2006).

However, the path forward is not without challenges. One of the key areas that requires further research is the development of clinically viable models that can be seamlessly integrated into existing healthcare systems. Despite the promising advancements, there is still a need for robust pharmacogenomic data to improve predictive accuracy and address the issue of therapy resistance. Additionally, future research should focus on developing algorithms that can learn from real-time clinical data, allowing for adaptive treatment strategies that respond to the evolving nature of cancer within each patient (Rafique et al., 2021).

For ML to truly enhance global cancer treatment, it is essential to address disparities in healthcare access. This includes creating models that are inclusive of diverse populations to ensure that the benefits of ML are equitably distributed.

Policy initiatives must also focus on data privacy, ethical considerations, and infrastructural support to foster a healthcare environment where ML can thrive. With continued investment in research and development, along with strategic policy frameworks, ML has the potential to significantly improve patient outcomes and pave the way for a more equitable and effective global health landscape (William et al., 2023).

6. Conclusion

Machine learning (ML) is rapidly transforming the landscape of personalized cancer treatment by offering innovative solutions that can analyze complex datasets, identify patterns, and provide tailored therapeutic strategies. The integration of ML into oncology has enabled significant advancements in early diagnosis, treatment planning, and prognosis, leading to more precise and effective care. By leveraging diverse data sources, including genomic profiles, medical imaging, and clinical records, ML facilitates the development of personalized treatment plans that address the unique needs of each patient, ultimately improving survival rates and quality of life.

Despite the remarkable progress, several challenges must be addressed to realize the full potential of ML in cancer care. Issues such as data privacy, algorithmic transparency, and the need for robust, diverse datasets are critical to ensuring that ML models are accurate, reliable, and free from biases. Furthermore, the successful integration of these technologies requires strategic investments in healthcare infrastructure, as well as comprehensive training programs to equip clinicians with the necessary skills to interpret and apply ML insights effectively.

Future research and policy initiatives must focus on fostering collaboration between data scientists, healthcare professionals, and policymakers to create a robust framework that supports the ethical and widespread use of ML in cancer care. Addressing these challenges will be crucial to making personalized cancer treatment accessible globally, particularly in low- and middle-income countries, where disparities in healthcare continue to be a significant concern. With continued innovation, strategic planning, and investment, machine learning has the potential to revolutionize global cancer treatment, making precision medicine a reality for all patients.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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