

A Comprehensive Review of GAN, DL and Gen AI application in Spinal Cord Cancer Detection

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Abstract: Spinal cord cancer, although relatively rare, poses significant diagnostic challenges that often result in delayed treatment and poor patient outcomes. This comprehensive literature review aims to synthesize the latest advancements in the detection of spinal cord neoplasms, underscoring innovative methodologies that incorporate sophisticated deep learning techniques, the application of generative Artificial Intelligence (AI), and the utilization of Generative Adversarial Networks (GANs). By analyzing recent studies, this review highlights the transformative potential of these technologies in enhancing diagnostic accuracy and efficiency. GANs, with their ability to generate synthetic medical images, can augment training datasets, thereby improving the performance of machine learning models. Furthermore, deep learning techniques, particularly convolutional neural networks (CNNs), have shown promise in automating image analysis and identifying malignancies with minimal human intervention. The integration of generative AI applications in clinical workflows is also discussed, emphasizing their role in personalized medicine and predictive analytics. This comprehensive examination not only underscores the importance of these innovative approaches in spinal cord cancer detection but also identifies avenues for future research and development, ultimately aiming to improve patient outcomes and advance the field of oncology.

Keywords: Machine Learning; Deep Learning; Spinal Cord Cancer; Convolutional Neural Networks; Generative Artificial Intelligence; Diagnostic Accuracy; Predictive Analytics; Generative Adversarial Networks;

Introduction

Spinal cord cancer is relatively rare disease, poses significant challenges for both patients and healthcare professionals. Unlike other types of cancer, spinal cord tumors can lead to debilitating symptoms and difficulties that severely affect an individual's quality of life. These tumors can find in the spinal cord itself (primary tumors) or metastasize from other parts of the body (secondary tumors) [1], [2]. The complexity of identifying spinal cord cancer is further compounded by the various range of symptoms that can mimic other neurological circumstances, emphasizing the critical need for advanced imaging techniques and artificial intelligence to improve detection accuracy and treatment outcomes [3], [4].

The significance of spinal cord cancer cannot be overstated, as prompt identification and accurate diagnosis are essential for effective treatment and enhanced patient prognoses. Early detection of spinal

cord cancer is paramount. Symptoms often begin subtly, such as localized pain, weakness, or sensory changes, which can easily be attributed to less severe conditions [1]. Consequently, many patients may experience delays in diagnosis, leading to disease progression and a more complicated treatment landscape.

An Artificial Intelligence (AI) and advances in medical imaging have surfaced as crucial tools in enhancing the accuracy and speed of diagnosis, thereby improving the chances of successful intervention [5]. Technological advancements in medical imaging, including Magnetic Resonance Imaging (MRI), and Computed Tomography (CT) scans, have revolutionized the way spinal cord tumors are detected. These imaging modalities provide detailed insights into the structural and functional changes within the spinal column, allowing for better visualization of tumors [6]. Moreover, the integration of AI in medical imaging has opened new frontiers in early detection. AI algorithms can analyze massive amount of imaging data, discerning patterns and irregularities that may be overlooked by the human eye. This capability not only aids in diagnosis but also helps in predicting the progression of the disease, thereby informing treatment strategies [7], [8].

The objective of this systematic review is to investigate the current state of spinal cord cancer detection and diagnosis, focusing on the role of technological advancements in medical imaging and AI. By examining recent developments and their implications for clinical practice, this paper aims to highlight the significance of quick detection in improving patient prognoses and to underscore the potential of emerging technologies in the fight against spinal cord cancer.

Through a comprehensive analysis, we aim to deepen the understanding of how these innovations can shape the future of spinal cord cancer diagnosis and management. This exploration will delve into specific imaging modalities such as MRI and CT scans, in conjunction with the incorporation of AI algorithms that augment diagnostic precision and operational efficiency. The synergy between advanced imaging techniques and AI not only facilitates more precise identification of tumors but also enables personalized treatment plans, ultimately leading to improved survival rates for patients affected by spinal cord cancer.

Spinal Cord Cancer: An Overview

Spinal cord neoplasms, despite their infrequent occurrence, present considerable difficulties in both diagnostic evaluation and therapeutic intervention. This manuscript seeks to elucidate the various classifications of spinal cord tumors, the clinical manifestations that accompany them, the diagnostic hurdles encountered, and the contemporary diagnostic methodologies employed in clinical settings.

Spinal cord neoplasms can be categorized into two principal divisions: primary neoplasms and metastatic neoplasms [9], [10].

1. **Primary Neoplasms:** These neoplasms originate within the spinal cord or in the adjacent anatomical structures, such as the meninges or nerve roots. They can be further classified into benign and malignant variants. Notable primary neoplasms encompass: Astrocytomas, Ependymomas and Meningiomas. Astrocytomas that develop from astrocytes, the star-shaped glial cells institute in the crucial nervous structure, containing the brain and spinal cord. – Ependymomas originate from

ependymal cells that are situated along the epithelial lining of the brain's ventricles and the central canal of the spinal cord. Meningiomas that originate from the meninges, the protective membranes encasing the spinal cord and brain.

2. Metastatic Neoplasms: These neoplasms represent secondary malignancies that have disseminated to the spinal cord from other regions of the body, such as the pulmonary, mammary, or prostatic tissues. Metastatic neoplasms are more prevalent than primary neoplasms and frequently signify advanced pathological conditions.

The symptoms of spinal cord cancer can be diverse and may vary subject to the tumor's size, location, and type. Common indications comprise pain, neurological deficits, loss of coordination, bowel or bladder dysfunction. Diagnosing spinal cord cancer presents several challenges. Symptoms can mimic those of other conditions, leading to potential misdiagnosis. Moreover, the location of the tumor may complicate the evaluation of symptoms, necessitating a thorough medical history and physical examination.

Spinal cord malignancy constitutes a complex clinical entity that necessitates a comprehensive, multidisciplinary strategy for its precise diagnosis and effective management. In order to accurately delineate the diagnosis of spinal cord tumors, healthcare professionals utilize a spectrum of diagnostic methodologies. A diverse array of imaging modalities, encompassing X-ray imaging, MRI, and Computed CT scans, are routinely employed in clinical practice. MRI is acknowledged as the utmost sensitive imaging modality for the detection and classification of spinal cord neoplasms. This imaging technique enables the acquisition of detailed representations of soft tissue structures, thereby facilitating the assessment of tumor size, anatomical positioning, and potential effects on surrounding tissues [11]. CT imaging is often employed in conjunction with MRI, particularly for the evaluation of bony structures or in instances when MRI is not feasible. Biopsy represents another critical method, wherein a sample of the tumor is obtained for histopathological evaluation. This procedure may be executed through needle biopsy or during surgical resection[7] .

Deep Learning in Medical Imaging

Deep learning, a specialized domain within the broader field of machine learning, has fundamentally transformed numerous disciplines by facilitating the capability of computers to derive insights from extensive datasets via neural networks. This innovative technology emulates the intricate architecture of interrelated neurons in the human brain, thereby enabling the autonomous identification of sophisticated patterns and characteristics within data [12]. In the domain of medical imaging, deep learning has arisen as a transformative tool, significantly enhancing diagnostic accuracy and efficiency. As healthcare professionals increasingly rely on imaging modalities such as X-rays, MRI, and CT scans, as discussed earlier in this paper, the integration of deep learning algorithms can enable quick investigation of diseases, improve treatment planning, and eventually enhance patient prognosis [13],[14].

The relevance of deep learning in medical imaging lies in its capability to analyze and process huge datasets rapidly, which is particularly crucial in a field where timely diagnosis can be life-saving. By

harnessing deep learning, practitioners can leverage advanced algorithms to detect subtle anomalies that may be elude by the human observations, thereby augmenting the diagnostic capabilities of radiologists and pathologists. This technological advancement is particularly significant in the detection of complex conditions such as spinal cord cancer, where early intervention is critical.

At the core of deep learning applications within the domain of medical imaging lies the Convolutional Neural Network (CNN), an architecture meticulously crafted for the analysis of structured grid data, such as images. Convolutional Neural Networks operate through the implementation of convolutional layers that autonomously acquire spatial hierarchies of characteristics, thereby enabling the identification of edges, textures, and more complex patterns within visual data. This hierarchical learning process is particularly effective in medical imaging, where different layers of the network can learn to identify various anatomical structures and pathological changes. The architecture of a CNN consists of several integral layers that collaboratively extract and learn features from input images as shown in Figure 1. The method starts at the input layer, where image data is characterized as multi-dimensional ranges of pixel values. Convolutional layers follow, applying filters to perform convolution operations, producing feature maps that focus on essential attributes like boundaries and textures.

The Rectified Linear Unit (ReLU) which is an activation functions, used to apply non-linearity, enabling the network to grasp complex patterns. Pooling layer helps in reducing model overfitting by diminishing the spatial dimensions of feature maps. This will help to reduce the computational load of the model. Fully connected layers then combine the features learned earlier to make predictions. Finally, the output layer produces the final results, often using a softmax function for classification tasks. Techniques like dropout and batch normalization are employed to enhance training stability and prevent overfitting.

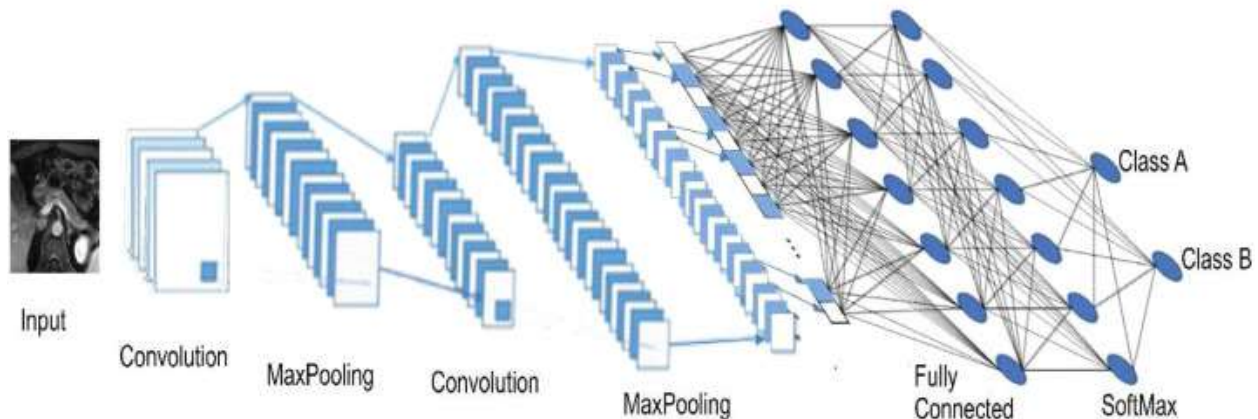


Figure 1: General architecture of CNN

In the context of spinal cord cancer detection, CNNs have shown remarkable promise. They can be trained on huge datasets of labeled medical images to identify the unique characteristics of tumors, such as their size, shape, and location. Applications of CNNs extend beyond mere detection; they also play a vital role in segmentation, where the network delineates tumor boundaries, and classification, where it categorizes tumors based on their malignancy [15], [16]. Furthermore, CNNs can assist in

predicting treatment responses and outcomes, providing valuable insights for personalized medicine [17], [18].

Benefits and Limitations of Deep Learning Techniques in Spinal Cord Cancer Detection

The incorporation of deep learning techniques in spinal cord cancer detection offers numerous benefits. One of the most important benefits is the potential for increased accuracy and consistency in diagnoses. Unlike traditional methods, which may rely heavily on subjective interpretation, deep learning algorithms can provide objective assessments based on extensive training data. This objectivity can reduce variability in diagnoses among different practitioners, leading to more standardized care [19]. Additionally, deep learning models can process images at an unprecedented speed, enabling rapid analysis and facilitating timely clinical decisions. This efficiency is particularly crucial in emergency scenarios where swift identification of malignancies can alter treatment trajectories and improve patient survival rates.

However, despite these advantages, there are notable limitations to consider. One key challenge is the requirement for large, superior annotated datasets to train CNNs effectively. In the medical field, acquiring such datasets can be time-consuming and expensive, often requiring extensive collaboration among institutions. Moreover, deep learning architectures possess the characteristic of functioning as "black boxes," thereby complicating the efforts of clinicians to elucidate their decision-making mechanisms. This deficiency of transparency can hinder trust and acceptance among healthcare professionals, who may be hesitant to rely on algorithms without a clear understanding of their reasoning [19].

Moreover, the generalizability of deep learning models can be a concern. Models trained on particular datasets might not perform better on images from different populations or imaging devices due to differences in imaging properties or patient demographics. Ensuring that these models are robust and adaptable across diverse clinical settings remains an ongoing area of research [20].

The deep learning, particularly through the use of CNNs, holds significant promise for enhancing spinal cord cancer detection, it is essential to address the associated challenges to fully realize its potential in clinical practice. Continued advancements in data collection, model interpretability, and cross-institutional collaboration will be crucial in overcoming these limitations and ensuring that deep learning becomes an integral part of the medical imaging landscape. This synergy between technology and clinical expertise has the potential to not only improve diagnostic accuracy but also facilitate earlier interventions, which are critical for better patient outcomes. The future of spinal cord cancer detection will likely depend on the integration of artificial intelligence with traditional diagnostic methods, ultimately leading to more tailored and effective treatment plans for patients.

Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs) constitutes a seminal progression in the domain of artificial intelligence, especially in the field of machine learning and computer vision. Ian Goodfellow and his colleagues introduced GAN in 2014. GANs contains of two neural networks, i.e. the generator and the discriminator, that are trained concurrently using a process known as adversarial training. The generator's objective is to create synthetic data that closely mimics real data, whereas the discriminator's function is to differentiate between the actual data and the data generated by the generator. This adversarial interaction fosters a competitive environment in which both networks improve their performance over time, leading to the generation of highly realistic data [21].

GANs architecture of is relatively straightforward yet powerful. The general architecture is shown Figure 2. The generator input is a random noise and transforms it into a sample data, such as an image. This generated sample is then fed into the discriminator alongside real data samples. The discriminator has to generate probability score which tells, whether the input is real or forged. The objective of the generator is to optimize the likelihood of the discriminator committing an error, whereas the discriminator seeks to reduce its rate of inaccuracies. This back-and-forth process carry on until the generator yields data that will not distinguishable from real data, attaining a state of equilibrium known as Nash equilibrium [22].

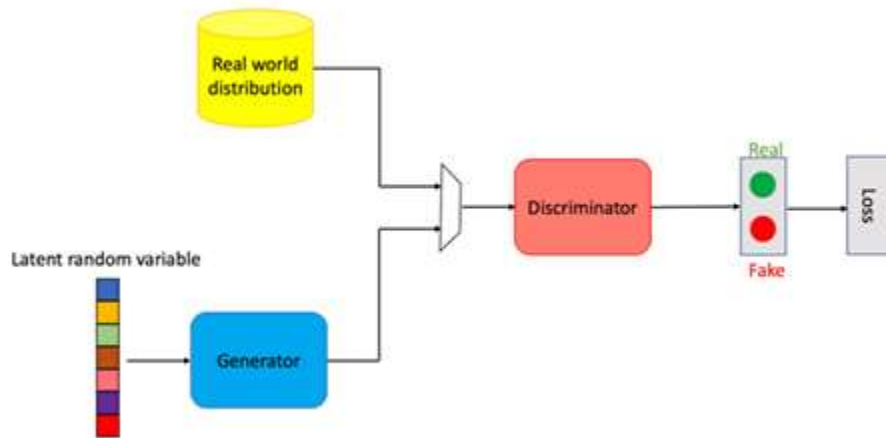


Figure 2: Basic architecture of GAN

In the medical imaging domain, GANs have garnered significant attention for their ability to enhance image quality and augment datasets, which are often limited due to the high costs and ethical concerns associated with acquiring medical images. One of the most compelling applications of GANs is in data augmentation, where they can generate additional training samples from existing datasets. This is especially valuable in situations where acquiring new data is challenging, in case of rare diseases or specific conditions, allowing for improved model training and performance. Additionally, GANs can synthesize high-resolution medical images from low-resolution inputs, enabling better visualization and analysis for diagnostic purposes [23]–[25].

In the perspective of spinal cord tumor detection, several studies have demonstrated the efficacy of GANs in improving diagnostic accuracy. For instance, researchers have employed GANs to generate synthetic MRI scans that mimic the characteristics of spinal cord tumors. By augmenting existing

datasets with these synthetic images, they have been able to train more robust machine learning models that enhance the detection rates of spinal cord cancers [26]. One notable study highlighted the use of GANs to create diverse tumor representations, which significantly improved the model's capability to generalize throughout different patient populations and imaging modalities. The findings indicated that models trained with GAN-augmented data achieved a higher sensitivity and specificity in identifying malignant lesions compared to those trained on limited real data alone [26]. Moreover, GANs have been instrumental in addressing the issue of class imbalance in medical datasets, where certain conditions may be underrepresented. By generating artificial examples of understated classes, GANs help ensure that machine learning models are well-equipped to recognize and classify various types of spinal cord tumors, ultimately leading to earlier detection and better patient outcomes.

Generative AI (GenAI) in Healthcare

GenAI refers to a subset of AI technologies that focus on generating content based on new data on existing datasets. With the help of machine learning techniques and use of complex algorithms, GenAI creates models that can mimic human-like creativity and reasoning. This technology encompasses several applications, including text generation and image, and has seen substantial advancements in latest years, specifically in the healthcare sector. The scope of generative AI in healthcare is vast, encompassing areas such as drug discovery, personalized medicine, and diagnostic imaging, where it can enhance clinical decision-making and patient outcomes [27].

One of the greatest promising roles of generative AI in healthcare is its capability to enhance diagnostic accuracy. By analyzing great volumes of medical data, including patient records, images such as X-rays, and genomic information, generative AI can detect patterns and anomalies that may be overlooked by human clinicians. This type of capability is crucial in the early identification of diseases, where timely intervention can significantly alter the prognosis. For instance, generative AI algorithms can help radiologists in inferring medical images, such as MRIs and CT scans, by providing real-time insights and highlighting areas of concern. This not only improves diagnostic precision but also decreases the likelihood of misdiagnosis, thereby ensuring that patients receive appropriate and timely treatment [28].

A further noteworthy case study underscores the incorporation of generative artificial intelligence in the examination of pathology slides. By training AI models on extensive datasets of histopathological images, researchers have demonstrated that generative AI can accurately identify malignant cells associated with spinal cord tumors. In one study, the AI system achieved a diagnostic accuracy rate exceeding that of experienced pathologists, showcasing its potential as a valuable tool in pathology labs [29], [30]. This technology not only assists in diagnosis but also aids in treatment planning by providing insights into tumor characteristics and behavior.

Integration of GANs, Deep Learning, and Generative AI

The convergence of GANs, deep learning frameworks, and generative artificial intelligence represents a transformative leap in the field of medical diagnostics and patient care. The synergistic effects of this

integration are profound, as it not only enhances the capabilities of traditional deep learning models but also introduces innovative methodologies that can redefine clinical workflows and improve patient outcomes.

The operational mechanics of Generative Adversarial Networks (GANs), which consist of a discriminator and a generator, facilitate the generation of high-fidelity synthetic data that can be employed to enhance current datasets, especially in contexts where the paucity of data poses a considerable challenge. When GANs are integrated with deep learning models, they can enhance the training process by providing additional, realistic samples that help mitigate issues related to overfitting and improve the generalization capabilities of these models.

For instance, in medical imaging, GANs can generate synthetic images of rare diseases, thereby enriching the training datasets for convolutional neural networks (CNNs). This augmentation not only bolsters the models' predictive accuracy but also enhances their robustness, allowing for more reliable diagnostic tools that can be deployed in clinical settings. Furthermore, the integration of GANs with other advanced deep learning methods, like transfer learning and reinforcement learning, can facilitate more sophisticated approaches to problem-solving in medical diagnostics, leading to more nuanced insights and better-informed clinical decisions.

The combination of GANs and deep learning into diagnostic workflows holds the potential revolution patient care. By leveraging the enhanced data generation capabilities of GANs, healthcare providers can develop more precise diagnostic algorithms that can identify diseases at earlier stages, potentially leading to more timely interventions and improved patient care. For example, GANs can assist in generating synthetic datasets that include variations in disease presentations, which can help train models to recognize less common manifestations of conditions, thereby reducing the likelihood of misdiagnosis. Moreover, the ability to simulate patient responses and disease progression through generative AI can facilitate personalized medicine approaches. Clinicians can utilize these models to predict how individual patients might respond to specific treatments, allowing for tailored therapeutic strategies that optimize efficacy while minimizing adverse effects. This integration ultimately fosters a more patient-centered approach to healthcare, where treatments can be customized based on predictive analytics derived from advanced AI methodologies.

Challenges and Considerations in Implementing These Technologies in Clinical Settings

Despite the promising advantages of integrating GANs, deep learning, and generative AI into clinical practice, several challenges and considerations must be addressed. One of the prime concerns is the ethical implications surrounding data privacy and security. The use of synthetic data, while beneficial, raises questions about the authenticity of the information and its implications for patient confidentiality. Confirming that these technologies conform to regulatory standards and ethical guidelines is paramount to gaining the trust of both patients and healthcare professionals.

Additionally, the complexity of these models can pose significant barriers to their adoption in clinical settings. Healthcare practitioners may require extensive training to effectively interpret the outputs of GAN-enhanced deep learning systems, and there may be resistance to adopting new technologies that challenge established practices. Furthermore, the incorporation of these advanced AI systems into present healthcare infrastructure necessitates substantial investment in technology and training, which can be a daunting prospect for many institutions.

In summary, while the integration of GANs, deep learning, and generative AI presents exciting opportunities for enhancing diagnostic workflows and improving patient outcomes, it is vital to navigate the related challenges thoughtfully. Ensuring proper training, addressing ethical considerations, and investing in the necessary infrastructure, healthcare providers can harness the full potential of these innovative technologies to transform patient care and clinical practice.

Current Trends and Future Directions

In recent years, the realm of spinal cord neoplasm identification has witnessed considerable advancements, especially through the integration of Generative Adversarial Networks (GANs) and deep learning technologies. Researchers have been exploring innovative methodologies that leverage the capabilities of these sophisticated algorithms to improve diagnostic accuracy and patient outcomes. One of the most notable trends is the increasing utilization of machine learning techniques to analyze complex medical imaging data, enabling more precise identification of malignant lesions within the spinal cord. Latest researches have demonstrated that deep learning methods can outperform traditional imaging analysis methods, providing clinicians with tools that not only enhance diagnostic speed but also reduce the likelihood of human error.

Looking towards the future, the potential applications of GANs and deep learning in spinal cord cancer detection are vast and promising. These technologies can be harnessed to produce artificial medical images that increase training datasets, particularly in scenarios where obtaining sufficient labeled data is challenging. Additionally, advancements in unsupervised and semi-supervised learning approaches could facilitate the development of robust models capable of detecting subtle anomalies that may escape conventional diagnostic techniques. As these technologies continue to evolve, there is a strong possibility that they will play a vital role in tailored medicine, allowing for personalized treatment plans based on the exact characteristics of a patient's tumor malignancy.

However, the rapid evolution of these technologies also brings forth critical ethical considerations and governing challenges that must be considered to address. The deployment of AI-driven diagnostic tools raises questions regarding data privacy, informed consent, and the possibility of algorithmic bias. Confirming that these systems are trained on diverse datasets is essential to avoid disparities in healthcare outcomes among different demographic groups. Moreover, regulatory bodies will need to establish comprehensive frameworks to evaluate the safety and efficacy of AI applications in clinical settings, balancing innovation with the imperative of patient protection. As the field progresses, ongoing dialogue among stakeholders—including researchers, clinicians, ethicists, and policymakers—will be

vital to navigate these complexities and harness the full potential of GANs and deep learning in spinal cord cancer detection.

Conclusion

In this comprehensive exploration of the intersection between advanced technologies and oncology, several key findings have emerged from the literature that highlight the transformative potential of these innovations in cancer detection and treatment. Firstly, the incorporation of advanced imaging techniques, such as positron emission tomography (PET) scans and MRI, has significantly enhanced the precision of tumor localization and characterization. This advancement permits for earlier finding of malignancies, which is critical in improving patient prognoses. Moreover, the advent of artificial intelligence and machine learning algorithms has revolutionized the diagnostic process by enabling faster and more accurate interpretations of imaging data. Studies have shown that AI can outperform human radiologists in certain diagnostic tasks, thereby reducing the likelihood of misdiagnosis and facilitating timely interventions.

Additionally, the development of targeted therapies and immunotherapies represents a paradigm shift in cancer treatment. These remedies are intended to precisely attack cancer cells while sparing healthy tissue, leading to less side effects and enhanced quality of life for patients. The literature highlights the success of personalized medicine, where treatments are adapted based on the genetic profile of both the patient and the tumor, leading to enhanced efficacy and better treatment outcomes. The implications for clinical practice are profound. Healthcare professionals must stay abreast of these technological advancements to incorporate them effectively into patient care protocols. This includes not only adopting new diagnostic tools but also considering the complexities of emerging therapies and their respective mechanisms of action. Continuous education and training will be essential to equip clinicians with the knowledge needed to navigate this rapidly evolving landscape.

Looking ahead, future research should emphasize on some key areas. There is a need for extensive clinical trials to confirm the efficacy and safety of new technologies and treatments in diverse patient populations. Additionally, exploring the integration of digital health solutions, such as telemedicine and remote monitoring, could further improve patient engagement and adherence to treatment plans. Investigating the socio-economic barriers to accessing these advanced technologies will also be critical to ensure equitable healthcare delivery.

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