



Review Article

Multimodal Deep Learning for Integrating Radiology and Genomic Data in Precision Oncology

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Precision oncology seeks to tailor cancer diagnosis, prognosis, and treatment according to the molecular and phenotypic characteristics of individual tumors. Recent advances in high-throughput sequencing and medical imaging have generated unprecedented volumes of heterogeneous data, creating opportunities for comprehensive characterization of cancer biology. Radiological imaging provides non-invasive information regarding tumor morphology, spatial heterogeneity, and treatment response, whereas genomic profiling reveals molecular alterations that drive tumor initiation, progression, and therapeutic resistance. However, conventional analytical approaches often fail to capture the complex relationships between these complementary data modalities. Multimodal deep learning has emerged as a powerful computational paradigm capable of integrating radiological and genomic information to enhance clinical decision-making in precision oncology. By leveraging sophisticated neural network architectures, including convolutional neural networks, transformers, graph neural networks, and multimodal fusion frameworks, these approaches can uncover latent associations between imaging phenotypes and genomic signatures. Recent studies have demonstrated improved performance in cancer diagnosis, molecular subtyping, prognosis prediction, treatment response assessment, and biomarker discovery through multimodal integration compared with unimodal models. Despite these promising advances, significant challenges remain, including limited availability of multimodal datasets, data heterogeneity, model interpretability, privacy concerns, and barriers to clinical implementation. Furthermore, the emergence of foundation models and self-supervised learning approaches is transforming the landscape of multimodal oncology by enabling scalable learning from large-scale unlabeled datasets. This review examines the current state of multimodal deep learning for integrating radiology and genomic data in precision oncology, highlighting methodological advances, clinical applications, challenges, and future directions. Particular emphasis is placed on radiogenomics, multimodal fusion strategies, and emerging foundation models that may facilitate the translation of artificial intelligence-driven precision medicine into routine clinical practice.

Keywords: Precision oncology; Multimodal deep learning; Radiogenomics; Artificial intelligence; Medical imaging; Genomics; Data fusion; Foundation models.

INTRODUCTION

Cancer remains one of the leading causes of morbidity and mortality worldwide despite substantial advances in diagnosis and treatment. The increasing recognition of interpatient and intratumoral heterogeneity has accelerated the transition from traditional one-size-fits-all treatment paradigms toward precision

oncology, which aims to customize therapeutic strategies according to the unique biological characteristics of individual tumors [1,2]. Central to this transformation is the integration of diverse sources of clinical and biological information that collectively capture the complexity of cancer.

Medical imaging has become an indispensable component of modern oncology. Imaging modalities such as computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and ultrasound provide non-invasive visualization of tumor anatomy, physiology, metabolism, and response to therapy. Radiological assessments guide diagnosis, staging, treatment planning, and longitudinal monitoring of disease progression [3]. Simultaneously, advances in next-generation sequencing technologies have enabled comprehensive genomic profiling of tumors, revealing actionable mutations, gene expression patterns, epigenetic modifications, and molecular pathways associated with disease behavior and therapeutic response [4]. Although radiological and genomic data independently contribute valuable clinical insights, each modality captures distinct aspects of tumor biology. Imaging reflects macroscopic phenotypic manifestations of underlying molecular processes, whereas genomic analyses characterize the genetic and epigenetic mechanisms driving tumor development. Integrating these complementary information sources can provide a more comprehensive understanding of cancer biology than either modality alone [5]. The field of radiogenomics has emerged to bridge this gap by investigating relationships between imaging phenotypes and genomic characteristics. Early radiogenomic studies demonstrated associations between imaging features and molecular alterations in glioblastoma, breast cancer, lung cancer, and other malignancies [6]. However, traditional statistical and machine learning methods often struggle to model the high-dimensional, nonlinear relationships inherent in multimodal oncology data. Recent breakthroughs in artificial intelligence, particularly deep learning, have transformed biomedical data analysis. Deep learning models possess the capacity to automatically learn hierarchical representations from large-scale heterogeneous datasets, enabling effective integration of imaging, genomic, pathological, and clinical information. Multimodal deep learning extends these capabilities by simultaneously processing multiple data modalities and learning shared representations that capture complex biological interactions [7,8]. The growing availability of multimodal cancer datasets, coupled with advances in computational infrastructure and neural network architectures, has

accelerated research in multimodal precision oncology. Applications now span cancer detection, molecular classification, survival prediction, treatment selection, immunotherapy response assessment, and biomarker discovery. Moreover, emerging foundation models and self-supervised learning approaches promise to further enhance multimodal integration by leveraging vast quantities of unlabeled biomedical data [9]. This review provides a comprehensive overview of multimodal deep learning approaches for integrating radiology and genomic data in precision oncology. We discuss foundational concepts, methodological frameworks, and current developments in multimodal learning, while critically examining their clinical applications, limitations, and future potential. The review aims to provide researchers and clinicians with a detailed understanding of how multimodal artificial intelligence can advance personalized cancer care.

2. Fundamentals of Multimodal Deep Learning in Oncology

Multimodal deep learning refers to artificial intelligence approaches that simultaneously process and integrate information from multiple heterogeneous data sources. In oncology, these modalities commonly include radiological imaging, genomic data, digital pathology, clinical records, laboratory measurements, and molecular biomarkers. The objective is to exploit complementary information across modalities to improve predictive performance and generate more comprehensive biological insights than can be achieved using individual data sources alone [7,10]. Radiological imaging constitutes one of the most important modalities in cancer management. Computed tomography remains the primary imaging technique for detecting, staging, and monitoring many solid tumors because of its widespread availability and high spatial resolution. Magnetic resonance imaging offers superior soft-tissue contrast and functional imaging capabilities, making it particularly valuable in brain, prostate, liver, and breast cancers. Positron emission tomography provides metabolic and molecular information that complements anatomical imaging, while ultrasound serves as a cost-effective modality for diagnosis and treatment guidance in numerous clinical settings. Additionally, digital pathology has

emerged as a high-resolution imaging modality that captures microscopic tumor architecture and cellular morphology [11]. Genomic modalities provide molecular-level characterization of cancer. Whole-genome sequencing enables comprehensive detection of genomic alterations across coding and non-coding regions. Whole-exome sequencing focuses on protein-coding regions and has become a standard tool for identifying clinically actionable mutations. Transcriptomic analyses, including RNA sequencing, reveal gene expression patterns associated with tumor biology and therapeutic response. Epigenomic profiling characterizes DNA methylation and chromatin modifications, while multi-omics approaches integrate genomic, transcriptomic, proteomic, and metabolomic information to provide a systems-level understanding of cancer [12].

Deep learning serves as the computational foundation for multimodal integration. Convolutional neural networks (CNNs) remain the dominant architecture for analyzing medical images due to their ability to automatically learn spatial features from pixel-level data. CNNs have demonstrated remarkable performance in tumor detection, segmentation, and classification tasks across diverse imaging modalities [13].

Recurrent neural networks (RNNs), particularly long short-term memory networks, are designed to model sequential data and have been applied to longitudinal clinical records and temporal imaging studies. However, transformer architectures have increasingly supplanted RNNs because of their superior ability to capture long-range dependencies and process large-scale datasets efficiently [14].

Vision Transformers (ViTs) have emerged as powerful alternatives to CNNs for medical image analysis. By leveraging self-attention mechanisms, ViTs can capture global contextual information and have achieved state-of-the-art performance in numerous imaging tasks. Similarly, graph neural networks (GNNs) are gaining prominence for modeling complex biological relationships among genes, proteins, pathways, and patient cohorts [15]. The integration of these architectures within multimodal frameworks enables the extraction of modality-specific features and their fusion into shared

representations. Such representations can capture intricate interactions between imaging phenotypes and molecular characteristics, thereby supporting more accurate predictions and biologically meaningful interpretations. As oncology datasets continue to expand in scale and complexity, multimodal deep learning is becoming an essential tool for translating heterogeneous biomedical data into actionable clinical knowledge

3. Radiogenomics: Connecting Imaging Phenotypes with Genomic Signatures

Radiogenomics is an interdisciplinary field that aims to establish associations between quantitative imaging characteristics and underlying genomic, transcriptomic, and molecular alterations within tumors [16]. The fundamental premise of radiogenomics is that medical images represent macroscopic manifestations of microscopic biological processes. Consequently, imaging phenotypes may serve as non-invasive surrogates for molecular characteristics, enabling repeated assessment of tumor biology without the need for invasive tissue sampling [17]. The biological rationale for radiogenomics arises from the inherent heterogeneity of cancer. Tumors consist of multiple cellular populations exhibiting distinct genetic, epigenetic, and metabolic characteristics. Traditional biopsy-based molecular profiling often captures only a limited portion of this heterogeneity, whereas radiological imaging provides comprehensive spatial characterization of the entire tumor and its surrounding microenvironment [18]. Deep learning methods have enhanced radiogenomic analyses by automatically extracting high-dimensional imaging features and identifying complex nonlinear relationships with molecular biomarkers. Glioblastoma has become one of the most extensively studied cancers in radiogenomics. Several investigations have demonstrated associations between MRI-derived imaging features and key molecular alterations such as isocitrate dehydrogenase (IDH) mutations, epidermal growth factor receptor (EGFR) amplification, O6-methylguanine-DNA methyltransferase (MGMT) promoter methylation, and telomerase reverse transcriptase (TERT) mutations [19,20]. Deep learning-based radiogenomic models have achieved

high predictive accuracy for identifying these biomarkers, potentially reducing reliance on invasive neurosurgical procedures and facilitating personalized treatment planning [21].

Breast cancer represents another major application area. MRI-based radiogenomic studies have linked imaging features with intrinsic molecular subtypes, including luminal A, luminal B, HER2-enriched, and triple-negative breast cancer [22]. Recent multimodal deep learning frameworks integrating dynamic contrast-enhanced MRI with transcriptomic data have demonstrated improved prediction of treatment response and disease recurrence compared with single-modality approaches [23]. Such findings highlight the potential of radiogenomics for risk stratification and individualized therapeutic decision-making.

In lung cancer, radiogenomic analyses have focused primarily on non-small cell lung cancer (NSCLC). Researchers have identified imaging signatures associated with actionable genomic alterations, including EGFR mutations, ALK rearrangements, KRAS mutations, and PD-L1 expression [24]. The ability to predict these molecular biomarkers from routine CT scans could substantially improve patient selection for targeted therapies and immunotherapy while reducing diagnostic delays [25].

Prostate cancer has also benefited from advances in radiogenomics. Multiparametric MRI combined with genomic profiling has enabled improved characterization of tumor aggressiveness and prediction of clinically significant disease [26]. Deep learning models integrating imaging and molecular data have demonstrated enhanced performance in identifying high-risk tumors and guiding treatment selection [27].

Similarly, colorectal cancer radiogenomics has explored relationships between imaging features and microsatellite instability (MSI), KRAS mutations, and consensus molecular subtypes [28]. Several studies have reported that multimodal integration improves predictive accuracy for molecular classification and prognosis assessment compared with conventional radiomics alone [29].

Despite these achievements, radiogenomics faces several challenges. Many studies rely on relatively small cohorts, limiting model generalizability. Furthermore, differences in imaging protocols, sequencing platforms, and patient populations introduce variability that complicates external validation. Nevertheless, the convergence of advanced imaging technologies, genomic profiling, and multimodal deep learning continues to strengthen the role of radiogenomics as a cornerstone of precision oncology [30].

4. Multimodal Data Fusion Strategies

The effectiveness of multimodal deep learning largely depends on how information from different data sources is integrated. Data fusion strategies determine the extent to which complementary information can be exploited and significantly influence predictive performance. Contemporary multimodal oncology systems generally employ early fusion, intermediate fusion, late fusion, or hybrid fusion architectures [31]. Early fusion, also known as feature-level fusion, combines data from different modalities before model training. In this approach, imaging features, genomic profiles, and clinical variables are concatenated into a single feature representation that serves as input to a neural network [32]. Early fusion enables direct modeling of cross-modal interactions and may capture synergistic relationships between radiological and molecular characteristics. However, the approach is sensitive to differences in feature dimensionality and data quality. High-dimensional genomic datasets can dominate learning processes, potentially reducing the contribution of imaging features [33]. Intermediate fusion, often referred to as representation-level fusion, has become increasingly popular in multimodal oncology. Separate neural networks first extract modality-specific representations from imaging and genomic data. These learned embeddings are subsequently integrated through shared layers that model cross-modal interactions [34]. This strategy preserves modality-specific information while enabling the discovery of biologically meaningful relationships. Transformer-based multimodal architectures frequently employ intermediate fusion because self-attention mechanisms effectively capture complex dependencies among heterogeneous data types [35].

Late fusion, or decision-level fusion, integrates predictions generated independently by separate modality-specific models. The outputs are combined using methods such as weighted averaging, voting schemes, or meta-learning algorithms [36]. Late fusion offers greater flexibility because individual models can be developed and optimized independently. It also provides robustness against missing data, as predictions can still be generated when one modality is unavailable. However, late fusion may fail to capture deeper biological interactions between imaging and genomic information [37]. Hybrid fusion approaches combine multiple fusion strategies to leverage their respective advantages. For example, imaging and genomic representations may first undergo intermediate fusion, followed by late-stage integration with clinical variables. Such architectures have demonstrated superior performance in several cancer prediction tasks because they preserve both modality-specific and shared information [38]. Deep learning architectures play a central role in multimodal fusion. Convolutional neural networks remain the primary choice for extracting imaging features, whereas fully connected networks, autoencoders, and transformer encoders are commonly used for genomic data [39]. Recently, graph neural networks have gained attention because biological systems naturally exhibit graph structures involving genes, proteins, pathways, and cellular interactions [40]. By incorporating biological network information into multimodal frameworks, GNNs can improve interpretability and predictive performance. Transformer-based architectures have emerged as particularly promising for multimodal oncology. Their self-attention mechanisms enable flexible integration of heterogeneous modalities while capturing long-range relationships within and across data types [41]. Several studies have reported that transformer-based multimodal models outperform traditional CNN-based fusion methods in cancer prognosis prediction and molecular subtype classification [42]. Despite significant advances, selecting an optimal fusion strategy remains challenging. The best approach often depends on dataset characteristics, modality availability, and clinical objectives. Future research will likely focus on adaptive fusion mechanisms capable of dynamically weighting modalities

according to their relevance for specific prediction tasks [43].

5. Clinical Applications in Precision Oncology

The integration of radiological and genomic information through multimodal deep learning has produced transformative advances across multiple areas of precision oncology. These applications extend from early cancer detection to treatment optimization and long-term disease management [44]. Cancer diagnosis represents one of the most mature applications of multimodal artificial intelligence. Deep learning models that combine imaging and molecular information consistently outperform unimodal systems in distinguishing benign from malignant lesions and identifying early-stage cancers [45]. In breast cancer, multimodal approaches integrating MRI features with gene expression profiles have demonstrated improved diagnostic sensitivity and specificity compared with imaging-based assessments alone [46]. Tumor classification and molecular subtyping constitute another major area of clinical impact. Accurate classification is essential because therapeutic strategies increasingly depend on molecular characteristics rather than solely histopathological findings. Multimodal models have shown remarkable success in classifying gliomas according to IDH mutation status, breast cancers according to intrinsic molecular subtype, and lung cancers according to actionable genomic alterations [47,48]. By incorporating both phenotypic and molecular information, these systems provide more comprehensive characterization of tumor biology. Prognosis prediction and survival analysis have emerged as particularly valuable applications. Traditional prognostic models often rely on clinical and pathological variables, which may not fully capture disease complexity. Multimodal deep learning frameworks integrating imaging biomarkers and genomic signatures have achieved superior performance in predicting overall survival, progression-free survival, and disease-specific outcomes across numerous cancer types [49]. Studies involving glioblastoma, hepatocellular carcinoma, and NSCLC have reported significant improvements in risk stratification compared with conventional approaches [50]. Treatment response prediction is increasingly important as oncology transitions toward

personalized therapeutic strategies. Multimodal models can identify patients likely to benefit from specific interventions by analyzing relationships between imaging phenotypes and molecular determinants of drug sensitivity [51]. In breast cancer, combined MRI-transcriptomic models have demonstrated enhanced prediction of neoadjuvant chemotherapy response. Similarly, multimodal approaches have improved prediction of radiotherapy outcomes and targeted therapy efficacy in lung and prostate cancers [52]. Immunotherapy response prediction has become a rapidly expanding research area. Immune checkpoint inhibitors have revolutionized cancer treatment, but only a subset of patients derive substantial benefit. Deep learning systems integrating radiological features with genomic biomarkers such as tumor mutational burden, PD-L1 expression, and immune-related gene signatures have shown promising performance in predicting immunotherapy response [53]. Such models may help optimize patient selection and reduce unnecessary exposure to potentially toxic treatments [54]. Recurrence prediction and disease monitoring represent additional applications where multimodal integration offers substantial advantages. Imaging captures dynamic changes in tumor morphology and treatment response, whereas genomic profiling provides insight into residual disease and emerging resistance mechanisms. Combining these data sources enables earlier detection of recurrence and more accurate assessment of disease progression [55]. Clinical decision support systems increasingly incorporate multimodal artificial intelligence to assist oncologists in complex treatment planning. These systems integrate radiological, genomic, pathological, and clinical data to generate personalized recommendations regarding diagnosis, prognosis, and therapeutic options [56]. Several studies have demonstrated that multimodal decision-support frameworks can improve diagnostic consistency and treatment selection while reducing clinician workload [57]. Despite encouraging results, widespread clinical adoption remains limited. Most studies remain retrospective and involve relatively small datasets. External validation across diverse populations is often lacking, and regulatory requirements for clinical implementation remain substantial [58]. Nevertheless, the growing body of evidence suggests that multimodal deep learning will

play an increasingly important role in precision oncology by enabling more accurate, individualized, and data-driven cancer care.

6. Foundation Models and Large Multimodal Models in Oncology

Recent advances in artificial intelligence have led to the emergence of foundation models, a new paradigm that is rapidly transforming precision oncology. Unlike traditional deep learning systems that are developed for specific tasks using limited labeled datasets, foundation models are trained on massive and diverse datasets using self-supervised learning and can subsequently be adapted to a wide range of downstream applications with minimal additional training [59]. These models have the potential to address several longstanding challenges in oncology, including data scarcity, limited generalizability, and fragmented multimodal information integration. Self-supervised learning has become a key enabling technology for foundation models. Instead of relying on manually annotated datasets, models learn meaningful representations from unlabeled data through pretext tasks. In medical imaging, self-supervised approaches allow neural networks to extract biologically relevant features from millions of radiological images, while in genomics, transformer-based architectures can learn patterns from large-scale sequencing data [60]. These representations often outperform conventional supervised models when transferred to cancer-specific tasks. Contrastive learning further enhances multimodal integration by encouraging representations from related modalities to occupy similar positions within a shared latent space. For example, imaging features extracted from MRI or CT scans can be aligned with corresponding genomic signatures, enabling models to identify biologically meaningful associations between phenotype and genotype [61]. Such approaches have demonstrated improved performance in tumor classification, survival prediction, and biomarker discovery. Transformer architectures have accelerated the development of large multimodal models capable of simultaneously processing images, genomic sequences, pathology slides, clinical notes, and electronic health records. These systems employ attention mechanisms to model relationships across heterogeneous data modalities, thereby generating

comprehensive patient-level representations [62]. In oncology, transformer-based multimodal models have shown considerable promise for integrating radiological and genomic information while maintaining scalability across diverse cancer types. Vision-language models represent another important development. Inspired by large multimodal systems such as CLIP and GPT-derived architectures, these models learn joint representations of images and textual information. In oncology, they can integrate radiology reports, pathology descriptions, molecular findings, and imaging data to support diagnosis and clinical decision-making [63]. Emerging evidence suggests that multimodal foundation models may facilitate automated report generation, treatment recommendation, and precision risk assessment. Transfer learning has become particularly valuable in radiogenomics because many cancer datasets remain relatively small. Foundation models pretrained on large biomedical datasets can be fine-tuned for specialized oncology applications, substantially reducing data requirements while improving predictive performance [64]. Recent studies indicate that foundation models can capture generalized biological knowledge that transfers effectively across tumor types and clinical settings. Despite their promise, foundation models remain at an early stage of clinical development. Questions regarding interpretability, fairness, computational requirements, and regulatory approval remain unresolved. Nevertheless, their ability to learn from heterogeneous multimodal datasets positions them as a central component of future precision oncology systems.

7. Challenges and Limitations

Although multimodal deep learning has demonstrated considerable promise, several challenges continue to impede its widespread clinical implementation. One of the most significant barriers is the limited availability of large-scale multimodal datasets. Successful deep learning models typically require thousands of patients with matched radiological, genomic, pathological, and clinical information. However, such comprehensive datasets remain scarce due to logistical, financial, and regulatory constraints [65]. Many published studies rely on relatively small cohorts collected from single institutions, increasing

the risk of overfitting and reducing external validity. Data harmonization represents another major challenge. Variability in imaging protocols, scanner manufacturers, sequencing technologies, and preprocessing pipelines can introduce substantial technical bias into multimodal datasets [66]. These inconsistencies often degrade model performance when systems are applied across institutions or populations. Standardized acquisition and preprocessing frameworks are therefore essential for achieving robust and reproducible results. Missing data are particularly problematic in precision oncology. Not all patients undergo comprehensive genomic profiling, and imaging examinations may vary according to clinical circumstances. Conventional deep learning models frequently struggle when one or more modalities are unavailable [67]. Developing flexible architectures capable of accommodating incomplete multimodal data remains an active area of research.

Batch effects pose additional challenges, especially in genomic and transcriptomic datasets. Technical variation arising from differences in laboratory procedures can obscure biologically meaningful signals and compromise predictive performance [68]. Advanced normalization strategies and domain adaptation techniques are increasingly being incorporated into multimodal frameworks to address this issue. Interpretability and explainability remain critical concerns for clinical adoption. Deep learning models often function as "black boxes," making it difficult for clinicians to understand the rationale behind specific predictions [69]. This lack of transparency can undermine trust and limit integration into clinical workflows. Explainable artificial intelligence (XAI) techniques, including attention visualization, saliency mapping, and graph-based explanations, are being developed to improve model interpretability. Generalizability represents another important limitation. Many multimodal models demonstrate excellent performance during internal validation but experience substantial performance degradation when evaluated in independent cohorts [70]. Differences in patient demographics, disease prevalence, healthcare systems, and data acquisition methods contribute to these challenges. Algorithmic bias is increasingly recognized as a significant concern. Underrepresentation of certain demographic

groups in training datasets may lead to disparities in model performance and potentially exacerbate healthcare inequities [71]. Ensuring fairness and inclusivity in model development is therefore essential. Privacy and data security also present substantial obstacles. Genomic information is inherently identifiable, and sharing multimodal datasets across institutions raises important ethical and legal concerns [72]. Regulatory frameworks such as GDPR and HIPAA impose strict requirements regarding patient data protection, which can complicate collaborative research initiatives. Finally, regulatory approval and clinical validation remain major hurdles. Most multimodal AI systems have not yet undergone prospective multicenter evaluation, and regulatory agencies continue to develop frameworks for assessing the safety and effectiveness of adaptive machine learning algorithms [73]. Addressing these challenges will be crucial for translating research advances into routine clinical practice.

FUTURE PERSPECTIVES

The future of multimodal deep learning in precision oncology will likely be shaped by several emerging technological and clinical developments. Federated learning is expected to play a transformative role by enabling institutions to collaboratively train AI models without directly sharing sensitive patient data [74]. This approach can increase dataset diversity while maintaining privacy and regulatory compliance. Early studies suggest that federated learning may improve model robustness and generalizability across geographically distributed healthcare systems. Explainable artificial intelligence will become increasingly important as multimodal models transition toward clinical deployment. Future systems are expected to provide transparent reasoning pathways that connect radiological findings, genomic alterations, and clinical outcomes. Such capabilities will improve clinician trust and facilitate regulatory approval [75]. Digital twins represent another promising direction. By integrating longitudinal imaging, genomic, clinical, and treatment data, digital twins may create dynamic computational representations of individual patients. These virtual models could enable simulation of disease progression and prediction of therapeutic responses

before treatment initiation [76]. Foundation models are likely to become the dominant computational paradigm in oncology. As larger multimodal datasets become available, these models will increasingly learn generalized representations that can be adapted to numerous downstream tasks. Integration of radiology, pathology, genomics, and electronic health records within unified foundation models may substantially enhance predictive accuracy and clinical utility. Multicenter prospective validation studies will be essential for establishing clinical credibility. Future investigations must demonstrate reproducibility across diverse populations and healthcare environments while evaluating real-world clinical impact [77]. Real-world evidence generated through routine clinical practice will also contribute to model refinement and validation. Continuous learning systems capable of incorporating new data may facilitate adaptive precision oncology strategies that evolve alongside emerging evidence [78]. Ultimately, successful integration of multimodal deep learning into clinical workflows will require close collaboration among oncologists, radiologists, bioinformaticians, data scientists, regulators, and healthcare administrators. Such interdisciplinary efforts are essential for ensuring that artificial intelligence technologies improve patient outcomes while maintaining safety, equity, and transparency.

CONCLUSION

Multimodal deep learning has emerged as a powerful framework for integrating radiological and genomic data in precision oncology. By combining complementary information from imaging and molecular profiling, these approaches provide a more comprehensive characterization of tumor biology than traditional unimodal methods. Advances in radiogenomics, multimodal fusion architectures, and transformer-based learning have significantly improved cancer diagnosis, molecular subtyping, prognosis prediction, treatment response assessment, and biomarker discovery. The recent emergence of foundation models and large multimodal systems represents a major step toward scalable and generalizable artificial intelligence in oncology. These technologies have the potential to overcome limitations associated with small datasets and fragmented information sources while enabling more

personalized and data-driven clinical decision-making. Despite encouraging progress, substantial challenges remain. Data scarcity, heterogeneity, missing modalities, limited interpretability, privacy concerns, algorithmic bias, and regulatory barriers continue to restrict widespread clinical implementation. Addressing these limitations will require standardized datasets, explainable AI methodologies, multicenter validation studies, and robust governance frameworks. As federated learning, foundation models, digital twins, and real-world evidence infrastructures continue to evolve, multimodal deep learning is expected to become an integral component of future precision oncology ecosystems. Continued interdisciplinary collaboration will be essential for translating these innovations into clinically actionable tools that improve cancer outcomes and advance personalized medicine.

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