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MULTIMODAL ARTIFICIAL INTELLIGENCE INTEGRATION OF RADIOLOGY AND PATHOLOGY IN PRECISION ONCOLOGY: A COMPREHENSIVE NARRATIVE REVIEW OF ADVANCES, CHALLENGES, AND FUTURE DIRECTIONS

Prateek Yalawar[1], Manisha Kumari[2]
[1]Assistant Professor, Department of Medical Radiology and Imaging Technology, Srinivas University Institute of Allied Health Sciences, Mukka, Mangaluru, Karnataka,India.
[2]Assistant Professor, Department of Medical Laboratory Sciences, Srinivas University Institute of Allied Health Sciences, Mukka, Mangaluru, Karnataka,India.

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ABSTRACT
Precision oncology has emerged as a transformative paradigm aimed at tailoring cancer diagnosis and treatment based on individual patient characteristics. Traditional diagnostic workflows rely heavily on radiology and pathology as complementary yet often siloed disciplines. Radiology provides macroscopic insights into tumor morphology and spatial heterogeneity, whereas pathology offers microscopic and molecular-level characterization. The advent of artificial intelligence (AI), particularly deep learning, has enabled the integration of these heterogeneous data sources, giving rise to multimodal AI frameworks.

This narrative review explores the current landscape of multimodal AI integration of radiology and pathology in precision oncology. We discuss key technological advances, including radiomics, pathomics, and multimodal fusion strategies such as early, intermediate, and late fusion models. Clinical applications across major cancer types – including lung, breast, brain, and gastrointestinal malignancies – are examined, highlighting improvements in diagnostic accuracy, prognostic modeling, and treatment response prediction.

Despite promising developments, significant challenges remain, including data heterogeneity, limited annotated datasets, model interpretability, and regulatory concerns. Emerging directions such as explainable AI, foundation models, and large-scale multicenter validation studies are also discussed. Multimodal AI holds substantial potential to revolutionize cancer care by enabling more precise, data-driven decision-making, but its successful clinical translation requires overcoming technical, ethical, and infrastructural barriers.

KEYWORDS: *Multimodal AI; Radiology; Pathology; Precision Oncology; Radiomics; Pathomics; Deep Learning; Data Integration*

1. INTRODUCTION
Cancer is a complex and heterogeneous disease characterized by variations at molecular, cellular, and tissue levels. Traditional diagnostic approaches often rely on isolated data modalities, which may fail to capture the full spectrum of tumor biology. Precision oncology seeks to overcome these limitations by integrating diverse sources of patient data to enable individualized treatment strategies.

Radiology and pathology serve as the cornerstone of cancer diagnosis. Radiology provides non-invasive imaging that reflects tumor morphology, spatial distribution, and temporal evolution, while pathology offers detailed insights into cellular architecture and molecular alterations. However, these disciplines have historically operated independently, leading to fragmented clinical decision-making.

Recent advances in artificial intelligence (AI), particularly deep learning, have enabled the integration of multimodal biomedical data, including imaging, histopathology, genomics, and clinical records. Multimodal AI systems are capable of capturing complementary information across different biological scales, thereby improving diagnostic accuracy and prognostic prediction.

The integration of radiology and pathology through AI represents a paradigm shift in oncology. By bridging macroscopic and microscopic perspectives, multimodal AI can provide a more comprehensive understanding of tumor behavior and enhance precision medicine.

This narrative review aims to provide a comprehensive overview of multimodal AI integration of radiology and pathology in precision oncology, focusing on recent advances, clinical applications, challenges, and future directions.

2. METHODOLOGY
This study is a narrative review synthesizing current evidence on multimodal artificial intelligence in oncology. A literature search was conducted in March 2026 using PubMed, Scopus, Web of Science, and Google Scholar. Search terms included "multimodal artificial intelligence," "radiology–pathology

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integration," "radiomics," "pathomics," "precision oncology," and "deep learning in cancer," combined using Boolean operators.

Studies published between 2020 and 2026 were prioritized. Relevant articles were identified through title/abstract screening and full-text review, with additional studies obtained via citation tracking.

Given the narrative design, no strict inclusion or exclusion criteria were applied; however, studies were selected based on relevance, methodological quality, and clinical significance. Data were synthesized using a qualitative, thematic approach focusing on key applications and emerging trends in multimodal AI.

3. CONCEPTUAL FRAMEWORK OF MULTIMODAL AI IN ONCOLOGY

3.1 Radiomics

Radiomics refers to the extraction of high-dimensional quantitative features from medical imaging modalities such as CT, MRI, and PET, capturing tumor characteristics including shape, texture, and spatial heterogeneity. These features enable non-invasive assessment of tumor phenotype and have demonstrated utility in tumor characterization, risk stratification, and treatment response prediction (Lambin et al., 2017; Zhang et al., 2024). Radiomics serves as a foundational component of multimodal AI by transforming imaging data into analyzable quantitative biomarkers.

3.2 Pathomics

Pathomics involves computational analysis of digitized histopathological images, particularly whole-slide images (WSIs), to extract features related to cellular morphology and tissue architecture. Deep learning models, especially convolutional neural networks (CNNs), have achieved high performance in tumor detection, grading, and classification tasks, in some cases exceeding expert-level accuracy (Campanella et al., 2019; Chang et al., 2025).

3.3 Multimodal Data Integration

Multimodal AI integrates radiomics and pathomics features, often alongside genomic and clinical data, to generate comprehensive predictive models. This integration enables the capture of tumor heterogeneity across multiple biological scales and improves predictive performance compared to single-modality models (Marouf et al., 2025; Mtoor et al., 2026).

3.4 Fusion Strategies

Multimodal integration is typically achieved through early, intermediate, and late fusion approaches. Early fusion combines raw data, intermediate fusion integrates extracted features, and late fusion aggregates predictions from modality-specific models. Recent advances incorporate transformer-based architectures and attention mechanisms to enhance cross-modal feature alignment and model performance (Yang et al., 2025; Vavekanand, 2026).

4. ADVANCES IN MULTIMODAL ARTIFICIAL INTELLIGENCE INTEGRATION

Recent years have witnessed rapid progress in multimodal artificial intelligence (AI) for precision oncology, driven by advances in deep learning architectures and the increasing availability of heterogeneous biomedical data. Multimodal approaches integrate complementary information from radiology, pathology, genomics, and clinical data, enabling more robust and clinically meaningful predictive models compared to single-modality systems (Yang et al., 2025; Muneer et al., 2026).

4.1 Deep Learning Architectures for Multimodal Integration

Deep learning has emerged as the dominant paradigm for multimodal data fusion due to its ability to learn hierarchical feature representations across diverse data types. Convolutional neural networks (CNNs) remain central for imaging-based feature extraction, particularly in radiomics and pathomics pipelines, while more recent architectures such as transformers and attention-based models facilitate cross-modal interactions and long-range dependency modeling (Yang et al., 2025; Vavekanand, 2026).

Transformer-based multimodal frameworks, in particular, have demonstrated superior performance by dynamically weighting features from different modalities through self-attention mechanisms. These architectures enable effective alignment between radiological imaging features and histopathological patterns, thereby improving model interpretability and predictive accuracy (Marouf et al., 2025). In parallel, the emergence of foundation models trained on large-scale biomedical datasets is expected to further enhance generalizability and transfer learning capabilities in multimodal oncology applications (Muneer et al., 2026).

4.2 Improvements in Diagnostic Accuracy

Multimodal AI systems consistently outperform unimodal models in diagnostic tasks across multiple cancer types. By integrating radiomics and pathomics features, these systems capture both macroscopic tumor heterogeneity and microscopic cellular architecture, leading to improved classification performance. For example, multimodal deep learning models combining MRI radiomics with histopathological features have demonstrated higher accuracy in distinguishing malignant from benign lesions and in tumor grading tasks (Zhang et al., 2024; Krasniqi et al., 2025).

Furthermore, studies have shown that multimodal fusion strategies—particularly intermediate and late fusion—provide enhanced robustness by leveraging complementary feature spaces while mitigating modality-specific noise (Marouf et al., 2025). These findings underscore the clinical value of multimodal AI in improving diagnostic precision.

4.3 Prognostic Modeling and Risk Stratification

Accurate prognostic assessment remains a critical challenge in oncology. Multimodal AI models integrating imaging, pathology, and clinical variables have demonstrated significant improvements in predicting overall survival, disease-free survival, and recurrence risk. By capturing tumor heterogeneity across multiple biological scales, these models offer a more comprehensive representation of disease progression (Chang et al., 2025; Manzoor et al., 2025).

In particular, radiogenomic approaches that link imaging phenotypes with molecular characteristics have shown promise in identifying prognostic biomarkers and guiding personalized treatment strategies. The integration of multi-omics data further enhances predictive performance by incorporating genetic and transcriptomic information into multimodal frameworks (Mtoor et al., 2026).

4.4 Prediction of Treatment Response

Predicting treatment response is a key application of multimodal AI in precision oncology. Recent studies have demonstrated that models combining radiological imaging with histopathological and molecular data can more accurately predict response to chemotherapy, immunotherapy, and targeted therapies compared to single-modality approaches (Wang et al., 2025; Krasniqi et al., 2025).

For instance, multimodal deep learning models integrating MRI and pathology data have shown improved performance in predicting neoadjuvant treatment outcomes in breast cancer, highlighting the potential of these approaches in guiding therapeutic decision-making (Krasniqi et al., 2025). Similarly, radiomics–pathomics integration has been applied to assess treatment efficacy in various tumor types, demonstrating enhanced predictive capabilities (Wang et al., 2025).

4.5 Integration with Multi-Omics and Emerging Paradigms

The integration of multimodal imaging data with genomic, transcriptomic, and proteomic information represents a major advancement in AI-driven oncology. This multi-omics approach enables a deeper understanding of tumor biology by linking phenotypic characteristics with underlying molecular mechanisms (Mtoor et al., 2026; Chang et al., 2025).

Emerging paradigms such as multimodal large language models and foundation AI systems are further expanding the scope of data integration, enabling unified analysis across structured and unstructured biomedical data sources. These developments are expected to play a pivotal role in advancing precision oncology by facilitating scalable, generalizable, and interpretable AI systems (Vavekanand, 2026).

5. CLINICAL APPLICATIONS

5.1 Lung Cancer

In lung cancer, multimodal AI has been applied to pulmonary nodule classification, prediction of EGFR mutation status, and treatment response assessment. Integration of radiology and pathology improves diagnostic accuracy and supports targeted therapy decisions (Aerts et al., 2014; Wang et al., 2025).

5.2 Breast Cancer

Applications include tumor subtype classification, hormone receptor prediction, and response to neoadjuvant chemotherapy. Multimodal models combining imaging and histopathology data have demonstrated improved predictive performance and clinical utility (Krasniqi et al., 2025; Chang et al., 2025).

5.3 Brain Tumors

In neuro-oncology, multimodal AI supports glioma grading, molecular marker prediction (e.g., IDH mutation), and treatment planning. These models enhance diagnostic confidence and enable more personalized therapeutic strategies (Marouf et al., 2025; Mtoor et al., 2026).

5.4 Gastrointestinal and Prostate Cancers

Multimodal AI is increasingly used for risk stratification, prediction of tumor aggressiveness, and treatment planning across gastrointestinal and prostate cancers (Manzoor et al., 2025; Wang et al., 2025).

6. CHALLENGES IN MULTIMODAL AI INTEGRATION

6.1 Data Heterogeneity

Differences in imaging protocols, staining techniques, and data formats pose significant challenges to model generalizability.

6.2 Limited Annotated Datasets

High-quality, labeled datasets that combine radiology and pathology data are scarce, limiting model development and validation.

6.3 Model Interpretability

Many AI models function as “black boxes,” making it difficult for clinicians to understand their decision-making processes. This limits clinical adoption.

6.4 Technical and Computational Challenges

- Data alignment across modalities
- High computational requirements
- Complex model architectures

6.5 Ethical and Regulatory Concerns

- Patient data privacy
- Algorithmic bias
- Lack of standardized regulatory frameworks

7. Future Directions

7.1 Explainable AI (XAI)

Improving transparency and interpretability is essential for clinical adoption.

7.2 Foundation Models

Large-scale pretrained models are expected to play a major role in multimodal integration, enabling more generalizable and scalable AI systems.

7.3 Standardization and Data Sharing

Developing standardized protocols and large multicenter datasets will enhance model robustness.

7.4 Clinical Integration

Future AI systems should be seamlessly integrated into clinical workflows, providing real-time decision support.

7.5 Personalized Oncology

Multimodal AI will enable truly personalized cancer care by integrating data across multiple biological scales.

8. CONCLUSION

Multimodal AI integration of radiology and pathology represents a transformative advancement in precision oncology. By combining complementary data from different modalities, these systems provide a comprehensive understanding of tumor biology, leading to improved diagnosis, prognosis, and treatment planning.

Despite significant challenges, ongoing advancements in AI technologies, data integration strategies, and interdisciplinary collaboration are expected to accelerate clinical translation. Future efforts should focus on improving interpretability, standardization, and large-scale validation to fully realize the potential of multimodal AI in oncology.

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