Multimodal Cancer Foundation Models: Bridging Radiology, Pathology, Genomics, and Electronic Health Records

[1]Dr.Mehul Patel,[2]Dr.Sneha George,[3]Dr.Vivek Sharma,[4]Mrs.Komal Singh,[5]Dr. Nikhil Das,[6]Dr. Priya Iyer

[1]Professor,Department of Oncology, Dr. Vasantrao Pawar Medical College, Nashik, India.

Mehulpatel71@gmail.com

[2]Associate Professor,Department of Pathology, Dr. Vasantrao Pawar Medical College, Nashik, India.Snehageorge88@gmail.com

[3]Assistant Professor,Department of Pharmacology, Dr. Vasantrao Pawar Medical College, Nashik, India.Viveksharma29@gmail.com

[4]Assistant Professor,Department of Clinical Pharmacy, Dr. Vasantrao Pawar Medical College, Nashik, India.Komalsingh145@gmail.com

[5]Professor,Department of Radiodiagnosis, Dr. Vasantrao Pawar Medical College, Nashik, India.Nikhildas75@gmail.com

[6]Associate Professor,Department of Medical Genetics, Dr. Vasantrao Pawar Medical College, Nashik, India.Priyaiyer61@gmail.com

ABSTRACT:
Cancer remains one of the leading causes of morbidity and mortality worldwide despite remarkable advances in molecular diagnostics, targeted therapeutics, immunotherapy, and precision medicine. The rapid expansion of biomedical data generated through radiological imaging, digital pathology, genomic sequencing, transcriptomics, proteomics, metabolomics, laboratory investigations, wearable technologies, and electronic health records has created unprecedented opportunities for artificial intelligence (AI)-driven precision oncology while simultaneously introducing major computational challenges. Multimodal cancer foundation models have emerged as a transformative computational paradigm capable of learning generalized biomedical representations across heterogeneous data modalities using large-scale self-supervised learning. Unlike conventional machine learning systems designed for individual diagnostic tasks, these models integrate radiology, pathology, genomics, laboratory biomarkers, longitudinal clinical information, and electronic health records into unified patient-centered computational representations that support diagnosis, prognostic prediction, molecular characterization, therapeutic optimization, clinical decision support, and personalized medicine. Advances in transformer architectures, multimodal learning, graph neural networks, large language models, retrieval-augmented generation, foundation model pretraining, and generative AI have substantially accelerated development of multimodal oncology ecosystems capable of comprehensive biomedical reasoning across the entire clinical workflow. Despite remarkable progress, important challenges remain regarding multimodal data harmonization, computational scalability, explainability, interoperability, cybersecurity, regulatory validation, and equitable implementation. This review provides a comprehensive overview of multimodal cancer foundation models, highlighting computational principles, clinical applications, implementation challenges, and future perspectives for bridging radiology, pathology, genomics, and electronic health records in precision oncology.[1]

Keywords: Foundation models, Multimodal learning, Precision oncology, Artificial intelligence, Digital pathology, Radiology, Genomics, Electronic health records, Clinical decision support, Personalized medicine.

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1.Introduction

Cancer is a biologically heterogeneous disease characterized by genomic instability, epigenetic dysregulation, transcriptional diversity, metabolic reprogramming, immune heterogeneity, and continuous interactions within the tumor microenvironment. Although precision medicine has substantially improved patient outcomes through molecular diagnostics and targeted therapies, individuals with apparently similar pathological diagnoses frequently demonstrate markedly different therapeutic responses and long-term clinical outcomes because of complex biological variability extending across multiple biomedical domains.[2]

Modern oncology continuously generates enormous quantities of heterogeneous biomedical information through computed tomography, magnetic resonance imaging, positron emission tomography, mammography, digital pathology, genomic sequencing, transcriptomics, proteomics, metabolomics, laboratory investigations, wearable biosensors, and electronic health records. Traditionally, these diverse information sources have been analyzed independently despite describing complementary aspects of the same biological disease process.[3]

Artificial intelligence has emerged as one of the most transformative technologies in computational oncology by enabling automated analysis of complex biomedical information. More recently, multimodal foundation models have fundamentally changed computational medicine by learning generalized biomedical representations capable of integrating radiology, pathology, genomics, laboratory medicine, and longitudinal clinical information into unified patient-centered computational frameworks.[4]

These multimodal cancer foundation models are redefining precision oncology by enabling comprehensive clinical intelligence that bridges traditionally independent diagnostic disciplines throughout the entire cancer care continuum.[5]

2.Evolution of Multimodal Foundation Models

Artificial intelligence within oncology has progressed through several major developmental stages. Early computational systems relied primarily on rule-based algorithms and handcrafted features that demonstrated limited adaptability. Machine learning subsequently introduced statistical prediction models capable of identifying nonlinear relationships among clinical variables, molecular biomarkers, imaging characteristics, and patient outcomes.[6]

Deep learning revolutionized biomedical image analysis through automated extraction of hierarchical representations from radiological imaging and digital pathology. Transformer architectures further expanded computational capability by introducing self-attention mechanisms capable of modeling long-range contextual relationships across heterogeneous biomedical information.

Foundation models extended these advances through large-scale self-supervised learning on multimodal biomedical datasets, enabling generalized representation learning transferable across numerous downstream oncology applications. Recent multimodal cancer foundation models integrate imaging, pathology, genomics, electronic health records, laboratory investigations, and longitudinal clinical information into unified computational ecosystems supporting comprehensive precision medicine.[7]

3.Principles of Multimodal Foundation Models

Foundation models differ fundamentally from conventional machine learning systems because they are pretrained on extremely large biomedical datasets before adaptation to specialized clinical applications. Rather than learning isolated diagnostic tasks, these models acquire generalized biological, anatomical, molecular, and clinical representations applicable across diverse oncology domains.[8]

Self-supervised learning enables discovery of latent biomedical relationships without extensive manual annotation, while contrastive learning aligns heterogeneous biomedical modalities within shared computational embedding spaces. Transformer architectures provide cross-modal attention mechanisms that integrate imaging, pathology, genomics, laboratory investigations, and clinical narratives into unified patient-specific representations.

Graph neural networks further strengthen computational reasoning by modeling interactions among genes, proteins, signaling pathways, imaging biomarkers, histopathological characteristics, immune responses, therapeutic targets, and clinical outcomes. These computational principles substantially improve transfer learning, few-shot learning, and generalizability across multiple cancer types and healthcare systems.[9]

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4.Computational Architecture

Modern multimodal cancer foundation models consist of several interconnected computational layers responsible for multimodal biomedical data acquisition, preprocessing, representation learning, multimodal fusion, downstream adaptation, and clinical decision support.[10]

The acquisition layer collects radiological imaging, digital pathology, genomic sequencing, transcriptomics, proteomics, metabolomics, laboratory biomarkers, wearable sensor information, medication history, physician documentation, and electronic health records. Advanced preprocessing pipelines normalize imaging studies, harmonize molecular datasets, encode clinical narratives using natural language processing, and synchronize longitudinal patient information.

Large transformer-based neural networks convert heterogeneous biomedical information into generalized computational embeddings through self-supervised learning. Cross-modal fusion mechanisms subsequently generate unified patient-centered representations supporting diagnosis, prognostic prediction, molecular characterization, therapeutic optimization, toxicity estimation, and survival prediction.

Continuous integration of longitudinal clinical information enables adaptive computational intelligence throughout diagnosis, treatment, follow-up, and survivorship.[11]

5.Foundation Models in Radiology

Radiological imaging represents one of the largest biomedical domains supporting multimodal foundation model development. Computed tomography, magnetic resonance imaging, positron emission tomography, mammography, ultrasound, and hybrid imaging collectively generate enormous image repositories suitable for large-scale representation learning.[12]

Foundation models pretrained on millions of medical images automatically learn generalized anatomical and pathological features that can subsequently be adapted to tumor detection, lesion segmentation, disease classification, radiomics, treatment response assessment, recurrence prediction, and longitudinal disease monitoring.

Compared with conventional convolutional neural networks trained for isolated imaging tasks, foundation models demonstrate improved robustness, transfer learning, zero-shot learning, and few-shot learning capabilities across multiple malignancies while substantially reducing dependence on manually annotated imaging datasets.[13]

6.Foundation Models in Digital Pathology

Digital pathology has become one of the most important application areas for multimodal foundation models because whole-slide imaging generates extremely high-resolution tissue images ideally suited for self-supervised learning. Transformer-based pathology models automatically learn generalized histomorphological representations before adaptation to tumor classification, grading, biomarker prediction, recurrence estimation, lymph node metastasis detection, immune-cell quantification, and survival prediction.[14]

Artificial intelligence further predicts clinically important biomarkers including EGFR mutations, KRAS mutations, HER2 amplification, microsatellite instability, estrogen receptor status, progesterone receptor status, PD-L1 expression, and additional therapeutic biomarkers directly from routine histopathological images.

Integration of pathology representations with imaging, genomics, laboratory biomarkers, and longitudinal clinical information substantially strengthens computational pathology while improving diagnostic reproducibility and personalized medicine.[15]

7.Foundation Models in Genomics and Multi-Omics

Modern precision oncology increasingly depends upon comprehensive integration of genomics, transcriptomics, proteomics, metabolomics, epigenomics, immunomics, lipidomics, microbiomics, and single-cell sequencing into unified molecular representations. Foundation models enable generalized learning across these heterogeneous biological modalities through transformer architectures, graph neural networks, multimodal learning, and biological knowledge graphs.[16]

Artificial intelligence identifies interactions among genes, proteins, signaling pathways, immune responses, metabolites, and therapeutic targets while supporting molecular subtype classification, biomarker discovery, systems biology research, therapeutic prediction, and personalized medicine.

These generalized molecular representations substantially improve biological understanding while enabling transfer learning across multiple cancer types and healthcare environments.[17]

8.Electronic Health Records and Clinical Intelligence

Electronic health records represent one of the richest sources of longitudinal clinical information available for computational oncology. Structured clinical variables, physician documentation, pathology reports, radiology reports, medication histories, laboratory investigations, treatment timelines, wearable technologies, and patient-reported outcomes collectively describe the evolving clinical trajectory of individual patients.[18]

Large language models and multimodal foundation models integrate structured and unstructured electronic health record information with imaging, pathology, genomics, and laboratory biomarkers into continuously evolving patient-centered computational representations.

These clinical intelligence systems improve diagnostic reasoning, prognostic prediction, therapeutic planning, toxicity monitoring, recurrence estimation, and survivorship management while reducing fragmentation of information across diverse healthcare systems.[19]

9.Multimodal Clinical Decision Support

One of the greatest strengths of multimodal cancer foundation models is their ability to integrate radiology, pathology, genomics, laboratory biomarkers, and electronic health records into comprehensive clinical decision-support systems. Rather than analyzing individual biomedical modalities independently, these intelligent systems generate unified patient-specific representations that support diagnosis, prognostic prediction, therapeutic planning, and longitudinal disease monitoring throughout the oncology workflow.[20]

Artificial intelligence combines radiomic features, histopathological characteristics, molecular alterations, laboratory investigations, physician documentation, medication history, and longitudinal clinical trajectories to improve tumor classification, disease staging, recurrence prediction, treatment selection, and individualized risk stratification.

Interactive clinical dashboards present these multimodal insights through evidence-based recommendations that enhance multidisciplinary collaboration while preserving physician oversight and clinical accountability.

10.Personalized Therapeutics and Adaptive Treatment Planning

Personalized treatment planning has become one of the most important applications of multimodal foundation models in precision oncology. Artificial intelligence integrates imaging, pathology, genomics, transcriptomics, proteomics, laboratory investigations, electronic health records, and patient-specific clinical characteristics to generate individualized therapeutic recommendations.[21]

Machine learning algorithms estimate treatment response, recurrence probability, progression-free survival, overall survival, treatment-related toxicity, and mechanisms of acquired resistance across chemotherapy, targeted therapy, endocrine therapy, immunotherapy, radiation therapy, surgery, and multimodal treatment strategies.

Continuous incorporation of updated clinical information enables adaptive therapeutic planning that evolves throughout disease progression, allowing clinicians to optimize treatment according to changing tumor biology and patient health status.

11.Immunotherapy and Tumor Microenvironment Modeling

The tumor microenvironment exerts profound influence on cancer progression and responsiveness to immunotherapy. Multimodal cancer foundation models integrate radiological imaging, computational pathology, genomics, transcriptomics, immunomics, laboratory biomarkers, and longitudinal clinical outcomes into unified computational representations of tumor–immune interactions.[22]

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Artificial intelligence evaluates tumor-infiltrating lymphocytes, immune checkpoint expression, cytokine signaling pathways, stromal architecture, angiogenesis, immune-cell spatial organization, and molecular biomarkers to estimate responsiveness to immune checkpoint inhibitors, CAR-T cell therapies, cancer vaccines, bispecific antibodies, and adoptive cellular therapies.

By simultaneously integrating multiple biomedical modalities, these computational systems substantially improve immunotherapy prediction while supporting increasingly personalized therapeutic strategies.

12.Drug Discovery and Translational Oncology

Multimodal foundation models are accelerating oncology drug discovery by integrating molecular biology, structural biology, pharmacology, systems biology, clinical outcomes, and real-world healthcare data into generalized computational frameworks. Artificial intelligence identifies novel therapeutic targets, predicts drug-target interactions, estimates toxicity profiles, and models mechanisms of therapeutic resistance.[23]

Generative AI further enhances pharmaceutical research by designing candidate molecules, predicting protein structures, simulating biological interactions, and generating synthetic biomedical datasets that facilitate preclinical investigation and hypothesis generation.

These intelligent systems also improve translational oncology by supporting adaptive clinical trial design, molecular eligibility assessment, patient stratification, and identification of patients most likely to benefit from emerging therapeutic strategies.

13.Digital Twins and Intelligent Oncology Ecosystems

The convergence of multimodal cancer foundation models with digital twin technology is creating continuously evolving computational representations of individual cancer patients capable of integrating imaging, pathology, genomics, laboratory biomarkers, wearable technologies, medication history, and electronic health records into adaptive virtual patient models.[24]

Artificial intelligence continuously updates these digital twins as new biomedical information becomes available, allowing simulation of disease progression, therapeutic response, recurrence, treatment-related toxicity, and long-term clinical outcomes.

Within intelligent oncology ecosystems, digital twins function alongside clinical decision-support systems, enabling multidisciplinary teams to compare multiple therapeutic strategies, optimize treatment planning, and continuously monitor disease evolution throughout the cancer care continuum.

14.Explainability, Trustworthiness, and Clinical Translation

Although multimodal cancer foundation models demonstrate remarkable predictive performance, successful implementation requires transparency, interpretability, and clinician trust. Explainable artificial intelligence (XAI) enables healthcare professionals to understand computational reasoning through attention visualization, saliency maps, SHAP (Shapley Additive Explanations), feature attribution analysis, uncertainty estimation, and counterfactual explanations that identify variables contributing most strongly to model predictions.[25]

Several additional challenges remain. Integration of radiology, pathology, genomics, and electronic health records requires standardized biomedical ontologies, secure computational infrastructure, interoperability across healthcare systems, prospective multicenter validation, continuous monitoring for algorithmic bias, and robust cybersecurity.

Patient privacy, regulatory approval, equitable implementation, standardized reporting frameworks, and transparent governance will remain essential prerequisites for responsible clinical translation of multimodal foundation models.

15.Future Perspectives

Future precision oncology will increasingly depend upon multimodal cancer foundation models capable of continuously learning from radiological imaging, digital pathology, multi-omics, laboratory medicine, wearable technologies, electronic health

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records, and real-world clinical outcomes across diverse healthcare systems.[26]

Emerging technologies including multimodal large language models, agentic artificial intelligence, digital twins, federated learning, reinforcement learning, spatial multi-omics, liquid biopsy, quantum computing, cloud-native healthcare infrastructure, and Internet of Medical Things (IoMT) technologies are expected to substantially strengthen intelligent oncology ecosystems.

These next-generation computational platforms may ultimately function as comprehensive biomedical reasoning systems capable of adaptive clinical decision-making, autonomous workflow coordination, personalized patient communication, continuous evidence synthesis, and intelligent healthcare optimization.

16.Discussion

Multimodal cancer foundation models represent one of the most significant paradigm shifts in computational oncology by bridging radiology, pathology, genomics, and electronic health records within unified patient-centered computational representations. Unlike conventional artificial intelligence systems that independently analyze isolated biomedical datasets, these models provide holistic understanding of cancer biology across multiple diagnostic disciplines.[27]

Applications spanning cancer diagnosis, molecular characterization, therapeutic optimization, immunotherapy prediction, digital twins, drug discovery, computational pathology, radiogenomics, and intelligent clinical decision support demonstrate the extraordinary potential of these technologies for advancing precision medicine.

Nevertheless, successful implementation requires continued advances in explainable artificial intelligence, computational infrastructure, interoperability, regulatory science, cybersecurity, ethical governance, and multidisciplinary collaboration to ensure safe and equitable clinical deployment.

17.Conclusion

Multimodal cancer foundation models are redefining precision oncology by integrating radiology, digital pathology, genomics, electronic health records, laboratory biomarkers, wearable technologies, and longitudinal clinical information into unified computational frameworks capable of supporting every stage of the clinical workflow.[28]

Advances in transformer architectures, multimodal learning, graph neural networks, large language models, digital twins, federated learning, agentic AI, and generative artificial intelligence are expected to further strengthen these intelligent systems, enabling increasingly accurate diagnosis, adaptive therapeutics, continuous disease monitoring, automated clinical reasoning, and evidence-based decision-making.[29]

Although important scientific, technical, ethical, and regulatory challenges remain, continued interdisciplinary collaboration among oncologists, radiologists, pathologists, molecular biologists, biomedical engineers, computer scientists, healthcare organizations, and regulatory agencies will accelerate responsible implementation of multimodal cancer foundation models, ultimately improving patient outcomes and advancing the future of precision cancer medicine worldwide.[30]

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