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MULTIMODAL FOUNDATION MODELS FOR PREDICTIVE ONCOLOGY: UNIFYING RADIOMICS, PATHOMICS, GENOMICS, AND ELECTRONIC HEALTH RECORDS

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Abstract: Predictive oncology is undergoing a paradigm shift through the emergence of multimodal foundation models capable of integrating radiomics, pathomics, genomics, electronic health records (EHRs), and other heterogeneous biomedical data into unified computational frameworks for precision cancer care. Conventional artificial intelligence (AI) models have achieved remarkable success in individual diagnostic or prognostic tasks; however, their dependence on task-specific training and isolated data modalities limits their ability to fully characterize the biological complexity of cancer. Recent advances in foundation AI models, multimodal transformer architectures, graph neural networks, self-supervised learning, and generative artificial intelligence have enabled generalized representation learning across radiological imaging, digital pathology, genomics, transcriptomics, proteomics, metabolomics, epigenomics, spatial biology, laboratory biomarkers, liquid biopsy, wearable physiological monitoring, electronic health records, and longitudinal clinical outcomes. These intelligent computational systems support precision diagnosis, biomarker discovery, molecular characterization, prognostic prediction, therapeutic optimization, immunotherapy selection, adaptive disease monitoring, and personalized clinical decision support. Emerging technologies including multimodal large language models, federated learning, reinforcement learning, retrieval-augmented generation, explainable artificial intelligence, and agentic AI further strengthen predictive oncology by enabling collaborative, privacy-preserving, and continuously adaptive biomedical intelligence. Despite substantial technological progress, important scientific, technical, ethical, and regulatory challenges remain regarding multimodal data harmonization, computational scalability, interpretability, interoperability, cybersecurity, clinical validation, and equitable implementation. This review provides a comprehensive overview of multimodal foundation models for predictive oncology, emphasizing the integration of radiomics, pathomics, genomics, and electronic health records as a transformative framework for personalized cancer medicine.[1]

Keywords: *Foundation models, Predictive oncology, Artificial intelligence, Radiomics, Pathomics, Genomics, Electronic health records, Computational oncology, Precision medicine, Multimodal learning.*

1. Introduction

Cancer is a biologically heterogeneous disease characterized by continuous genomic evolution, epigenetic remodeling, immune adaptation, metabolic reprogramming, angiogenesis, tissue remodeling, and dynamic interactions among malignant cells, stromal components, immune populations, and host physiology. These interconnected biological processes evolve throughout diagnosis, treatment, recurrence, metastasis, and survivorship, making precision oncology increasingly dependent upon computational systems capable of integrating heterogeneous biomedical information across multiple biological scales.[2]

Modern oncology routinely generates enormous quantities of biomedical data through radiological imaging, digital pathology, genomic sequencing, transcriptomics, proteomics, metabolomics, epigenomics, spatial biology, laboratory investigations, liquid biopsy, wearable physiological monitoring, electronic health records, physician documentation, and patient-reported outcomes. Although each modality contributes unique biological insight, isolated interpretation frequently overlooks systems-level relationships governing tumor evolution, therapeutic response, resistance mechanisms, and long-term clinical outcomes.[3]

Artificial intelligence has emerged as a transformative computational technology capable of integrating these heterogeneous biomedical datasets into unified patient-centered representations. Foundation AI models extend these capabilities through generalized multimodal learning that enables transfer of computational knowledge across numerous oncology applications while continuously adapting to evolving biomedical evidence.

The convergence of multimodal foundation models with predictive oncology therefore establishes a transformative computational paradigm capable of supporting personalized cancer care throughout the entire disease continuum.[4]

2. Evolution of Multimodal Foundation Models

Computational oncology has evolved from isolated statistical analyses toward intelligent multimodal computational ecosystems. Early machine learning approaches primarily relied on handcrafted feature engineering and task-specific predictive models developed for individual diagnostic or prognostic applications. Although these systems demonstrated clinical value, they remained constrained by fragmented biomedical information, limited adaptability, and narrow generalizability.[5]

Deep learning substantially advanced computational oncology through automated representation learning from radiological imaging, digital pathology, genomic sequencing, and electronic health records. Transformer architectures further revolutionized biomedical artificial intelligence by enabling generalized contextual learning across heterogeneous biomedical datasets.

Foundation AI models have now transformed predictive oncology through large-scale self-supervised pretraining capable of generating transferable biomedical knowledge applicable across diagnosis, prognosis, biomarker discovery, therapeutic prediction, disease monitoring, radiomics, pathomics, genomics, and intelligent clinical decision support.[6]

3. Principles of Multimodal Foundation Models

Multimodal foundation models differ fundamentally from conventional artificial intelligence because they acquire generalized biomedical representations from massive heterogeneous datasets before specialization for individual clinical applications. Rather than learning isolated predictive tasks, these models develop transferable computational knowledge applicable across diagnosis, prognosis, molecular characterization, biomarker discovery, therapeutic optimization, disease monitoring, computational pathology, radiomics, and clinical decision support.[7]

Self-supervised learning enables discovery of latent biological relationships without requiring extensive manual annotation, while multimodal transformer architectures align radiological imaging, digital pathology, genomics, transcriptomics, proteomics, metabolomics, laboratory biomarkers, wearable physiological monitoring, physician documentation, electronic health records, and longitudinal clinical trajectories within unified computational embedding spaces.

Graph neural networks further characterize interactions among genes, proteins, signaling pathways, immune populations, imaging phenotypes, tissue architecture, therapeutic targets, physiological variables, and clinical outcomes, thereby enabling systems-level computational reasoning supporting predictive oncology.[8]

4. Computational Architecture

Modern multimodal foundation model platforms consist of interconnected computational layers responsible for biomedical data acquisition, preprocessing, representation learning, multimodal fusion, adaptive learning, predictive analytics, digital twin simulation, and intelligent clinical decision support.[9]

The acquisition layer continuously incorporates radiological imaging, digital pathology, genomic

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sequencing, transcriptomics, proteomics, metabolomics, epigenomics, spatial biology, laboratory investigations, circulating tumor DNA, wearable physiological monitoring, medication history, physician documentation, patient-reported outcomes, and electronic health records. Advanced preprocessing pipelines normalize imaging studies, harmonize molecular datasets, encode clinical narratives using natural language processing, and synchronize temporal patient information.

Foundation AI models subsequently generate generalized multimodal embeddings representing molecular biology, tissue architecture, imaging phenotypes, physiological function, and longitudinal clinical trajectories. These unified computational representations support downstream applications including diagnosis, biomarker discovery, prognostic prediction, therapeutic optimization, adaptive learning, and predictive oncology.[10]

5. Radiomics Intelligence

Radiomics transforms conventional medical imaging into high-dimensional quantitative biological information describing tumor morphology, texture, vascularity, metabolism, spatial heterogeneity, and temporal evolution. Foundation AI models automatically extract generalized imaging representations from computed tomography, magnetic resonance imaging, positron emission tomography, ultrasound, and hybrid imaging platforms without requiring handcrafted feature engineering.[11]

Artificial intelligence identifies latent imaging biomarkers associated with molecular alterations, immune infiltration, angiogenesis, fibrosis, hypoxia, therapeutic responsiveness, treatment resistance, and disease progression. Integration of radiomics with molecular biology and clinical information substantially improves diagnosis, prognostic prediction, biomarker discovery, therapeutic optimization, and longitudinal disease monitoring.

These imaging representations provide a non-invasive computational window into evolving tumor biology while strengthening predictive oncology throughout the patient journey.[12]

6. Pathomics Intelligence

Digital pathology has transformed oncological diagnosis by enabling computational analysis of whole-slide images containing billions of cellular structures. Foundation AI models extract generalized pathomic representations describing cellular morphology, tissue architecture, stromal remodeling, angiogenesis, necrosis, fibrosis, immune infiltration, and spatial cellular organization across diverse tumor types.[13]

Transformer architectures identify microscopic tissue patterns associated with molecular alterations, therapeutic responsiveness, disease progression, and clinical outcomes, while graph neural networks characterize interactions among malignant cells, stromal components, vascular structures, and immune populations.

Integration of pathomics with radiomics, genomics, and clinical intelligence substantially enhances systems-level understanding of tumor biology while supporting personalized precision oncology.[14]

7. Genomic Intelligence

Comprehensive molecular characterization represents one of the greatest strengths of multimodal foundation models in predictive oncology. Artificial intelligence integrates genomics, transcriptomics, proteomics, metabolomics, epigenomics, immunomics, microbiomics, spatial biology, and single-cell sequencing into generalized molecular representations capable of characterizing evolving tumor biology across multiple organizational scales.[15]

Transformer architectures identify latent biological relationships among genes, proteins, signaling pathways, metabolites, immune responses, and therapeutic targets, while graph neural networks model complex biological interaction networks supporting systems-level computational reasoning.

These generalized molecular representations enable discovery of molecular subtypes, therapeutic biomarkers, resistance mechanisms, prognostic signatures, and novel drug targets while substantially improving individualized precision medicine.[16]

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8. Electronic Health Records as Clinical Intelligence

Electronic health records represent one of the richest longitudinal sources of clinical information available in modern oncology. Structured laboratory investigations, medication history, procedural records, physician documentation, pathology reports, treatment timelines, hospitalizations, patient-reported outcomes, and survivorship information collectively provide comprehensive clinical context extending beyond molecular diagnostics.[17]

Foundation AI models employ natural language processing, temporal transformers, and multimodal reasoning architectures to integrate structured and unstructured EHR data with radiomics, pathomics, genomics, laboratory biomarkers, and physiological monitoring into unified patient-specific computational representations.

These comprehensive clinical embeddings substantially improve prognostic prediction, therapeutic optimization, recurrence surveillance, toxicity estimation, survivorship management, and evidence-based clinical decision-making.[18]

9. Unified Multimodal Predictive Oncology

The defining capability of multimodal foundation models is the unification of radiomics, pathomics, genomics, electronic health records, laboratory biomarkers, wearable physiological monitoring, physician documentation, and longitudinal clinical trajectories into comprehensive patient-specific computational representations. Artificial intelligence employs multimodal transformers, graph neural networks, biological knowledge graphs, and cross-modal attention mechanisms to identify latent biological relationships spanning molecular, cellular, tissue, organ, physiological, and clinical scales.[19]

These integrated multimodal representations substantially improve diagnostic classification, biomarker discovery, prognostic prediction, therapeutic optimization, digital twin simulation, adaptive disease monitoring, and personalized precision oncology while establishing a comprehensive computational framework for predictive cancer medicine.[20]

10. Digital Twins and Predictive Patient Modeling

Digital twin technology represents one of the most transformative applications of multimodal foundation models in predictive oncology by creating continuously evolving virtual representations of individual cancer patients synchronized with their biological counterparts. Foundation AI models integrate serial radiological imaging, digital pathology, genomics, transcriptomics, proteomics, metabolomics, laboratory biomarkers, circulating tumor DNA, wearable physiological monitoring, medication history, patient-reported outcomes, and longitudinal clinical information into adaptive computational patient models capable of simulating disease progression, therapeutic response, treatment-related toxicity, recurrence, metastatic dissemination, and survival.[21]

Unlike conventional predictive models, digital twins continuously update their computational representations as new biomedical information becomes available. These intelligent virtual patients enable clinicians to evaluate multiple therapeutic strategies before implementation, optimize treatment sequencing, anticipate mechanisms of therapeutic resistance, and personalize supportive care according to evolving patient biology.

By combining multimodal biomedical intelligence with predictive simulation, digital twins transform computational oncology from retrospective analysis toward proactive precision medicine supported by continuously adaptive virtual patient ecosystems.

11. Intelligent Clinical Decision Support

Multimodal foundation models provide the computational infrastructure for next-generation clinical decision-support systems capable of integrating heterogeneous biomedical information into comprehensive patient-centered recommendations. Rather than interpreting radiological imaging, digital pathology, genomic diagnostics, laboratory investigations, wearable physiological monitoring, medication history, physician documentation, patient-reported outcomes, and evidence-based clinical guidelines independently, these models synthesize diverse

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biomedical information into unified computational representations supporting multidisciplinary oncology practice.[22]

Interactive clinical dashboards generate individualized diagnostic summaries, multimodal biomarker analyses, digital twin simulations, therapeutic recommendations, toxicity estimates, recurrence probabilities, disease progression forecasts, and survival predictions while facilitating collaboration among oncologists, radiologists, pathologists, surgeons, radiation oncologists, molecular biologists, pharmacists, nurses, genetic counselors, and computational scientists.

These intelligent systems improve workflow efficiency, strengthen multidisciplinary communication, reduce information fragmentation, and promote evidence-based personalized cancer management throughout the cancer care continuum.

12. Continuous Learning and Adaptive Predictive Oncology

A defining characteristic of multimodal foundation models is their ability to continuously evolve as new biomedical information becomes available. Artificial intelligence incorporates serial imaging examinations, computational pathology, circulating tumor DNA, laboratory biomarkers, wearable physiological monitoring, medication adherence, patient-reported outcomes, and real-world clinical evidence into adaptive computational frameworks capable of continuously refining predictive accuracy throughout the patient's clinical journey.[23]

Continual learning algorithms enable incremental refinement of computational knowledge without catastrophic forgetting of previously acquired information, while reinforcement learning optimizes therapeutic recommendations through iterative evaluation of treatment outcomes. Consequently, predictive oncology platforms remain synchronized with evolving tumor biology, emerging scientific discoveries, changing clinical guidelines, and diverse patient trajectories. This adaptive computational paradigm transforms oncology into a continuously learning healthcare ecosystem capable of supporting real-time personalized precision medicine.

13. Federated Multimodal Foundation Model Networks

Development of highly generalizable multimodal foundation models requires access to diverse biomedical datasets representing multiple healthcare systems, imaging platforms, pathology laboratories, molecular technologies, treatment protocols, and patient populations. Federated learning enables collaborative development of foundation AI models while preserving patient privacy and institutional governance through decentralized computational training.[24]

Participating healthcare institutions independently train local models using radiological imaging, digital pathology, genomics, transcriptomics, laboratory investigations, wearable monitoring, electronic health records, liquid biopsy, and longitudinal clinical records while securely exchanging encrypted model parameters rather than identifiable patient information. This collaborative learning strategy substantially improves algorithm robustness, fairness, external validity, and generalizability across diverse healthcare environments.

Federated multimodal ecosystems therefore establish international computational oncology networks capable of accelerating scientific discovery, improving equitable access to precision medicine, and supporting global cancer research while maintaining responsible biomedical data stewardship.

14. Explainability, Validation, and Ethical Governance

Successful implementation of multimodal foundation models in predictive oncology requires transparent, interpretable, reproducible, and rigorously validated computational systems capable of supporting clinician confidence, patient trust, and regulatory approval. Explainable artificial intelligence (XAI) enables clinicians to understand computational reasoning through attention visualization, saliency maps, SHAP (Shapley Additive Explanations), feature attribution analysis, uncertainty estimation, and counterfactual explanations identifying the radiomic, pathomic, genomic, physiological, and clinical variables contributing to predictive outputs.[25]

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Clinical deployment additionally requires standardized multimodal datasets, interoperable computational infrastructure, prospective multicenter validation, external benchmarking, cybersecurity safeguards, continuous monitoring for algorithmic bias, and compliance with evolving international regulatory frameworks governing AI-enabled healthcare technologies.

Responsible implementation further depends upon protection of patient privacy, informed consent, transparency, accountability, equitable access, responsible data governance, and continuous post-deployment surveillance to ensure trustworthy integration of multimodal artificial intelligence into routine oncology practice.

15. Future Perspectives

Future predictive oncology ecosystems will increasingly integrate multimodal foundation models, multimodal large language models, agentic artificial intelligence, graph neural networks, reinforcement learning, federated learning, digital twins, spatial multi-omics, liquid biopsy, quantum computing, Internet of Medical Things (IoMT), robotics, cloud-native healthcare infrastructure, and autonomous clinical reasoning systems into unified precision oncology platforms.[26]

These next-generation computational ecosystems will continuously integrate molecular biology, radiological imaging, digital pathology, laboratory medicine, wearable physiological monitoring, environmental exposures, electronic health records, biomedical literature, and real-world clinical outcomes while autonomously coordinating diagnostic workflows, optimizing therapeutic strategies, supporting adaptive clinical trials, generating personalized patient communication, and continuously synthesizing biomedical evidence.

Such intelligent ecosystems are expected to transform oncology from fragmented and reactive disease management toward predictive, preventive, adaptive, continuously learning, and precision-guided healthcare across the global cancer community.

16. Discussion

Multimodal foundation models represent one of the most significant paradigm shifts in predictive oncology by unifying radiomics, pathomics, genomics, electronic health records, laboratory biomarkers, wearable technologies, and longitudinal clinical intelligence into comprehensive computational ecosystems capable of supporting personalized cancer care. Unlike conventional artificial intelligence systems developed for isolated predictive tasks, these intelligent frameworks simultaneously analyze molecular biology, tissue architecture, radiological imaging, clinical documentation, laboratory biomarkers, physiological monitoring, and longitudinal patient trajectories to generate holistic computational representations of evolving cancer biology.[27]

Applications spanning computational pathology, radiogenomics, biomarker discovery, digital twins, precision immunotherapy, adaptive therapeutics, disease surveillance, continuous learning, federated collaboration, digital health, survivorship management, and intelligent clinical decision support demonstrate the extraordinary potential of multimodal foundation models to redefine future oncology. Nevertheless, successful implementation requires continued advances in multimodal data harmonization, explainable artificial intelligence, interoperability, computational infrastructure, cybersecurity, regulatory science, ethical governance, and sustained multidisciplinary collaboration.

As biomedical knowledge and healthcare data continue to expand exponentially, multimodal foundation models are expected to become the central computational infrastructure supporting predictive oncology worldwide.

17. Conclusion

Multimodal foundation models are transforming predictive oncology by integrating radiomics, pathomics, genomics, electronic health records, laboratory biomarkers, wearable technologies, digital twins, and longitudinal clinical intelligence into unified computational ecosystems capable of supporting accurate diagnosis, biomarker discovery, prognostic prediction, therapeutic optimization, adaptive disease monitoring, and

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personalized cancer care throughout the disease continuum.[28]

Advances in transformer architectures, multimodal learning, graph neural networks, self-supervised learning, federated learning, reinforcement learning, digital twins, multimodal large language models, agentic AI, and generative artificial intelligence are expected to further strengthen these intelligent ecosystems, enabling increasingly accurate molecular characterization, predictive clinical decision-making, adaptive therapeutics, continuous disease surveillance, and continuously personalized oncology care.[29]

Although important scientific, technical, ethical, regulatory, and implementation challenges remain, sustained collaboration among oncologists, radiologists, pathologists, molecular biologists, biomedical engineers, computer scientists, healthcare organizations, policymakers, industry partners, and regulatory agencies will accelerate the responsible implementation of multimodal foundation models in predictive oncology. These innovations have the potential to improve patient outcomes, enhance healthcare efficiency, reduce disparities in cancer care, accelerate translational research, and establish a new era of intelligent, adaptive, and continuously learning precision oncology worldwide.[30]

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