International Journal of Research in Engineering and Management Sciences (IJREMS)
E-ISSN: 3107-7439
Research Article
VOL.: 1, Issue: 7, December 2025

Next-Generation Foundation AI Models for Precision Radiomics: Unlocking High-Dimensional Imaging Biomarkers for Precision Oncology

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ABSTRACT:
Next-generation foundation artificial intelligence (AI) models are redefining precision radiomics by enabling comprehensive extraction, integration, and interpretation of high-dimensional imaging biomarkers for personalized cancer diagnosis, prognostic prediction, therapeutic optimization, and longitudinal disease monitoring. Conventional radiomics has demonstrated considerable potential for quantitative characterization of tumor heterogeneity; however, handcrafted imaging features, limited generalizability, fragmented multimodal integration, and inadequate biological interpretability have constrained widespread clinical implementation. Recent advances in foundation AI models, multimodal transformer architectures, graph neural networks, self-supervised learning, reinforcement learning, and generative artificial intelligence have enabled automated learning of generalized imaging representations from computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), ultrasound, mammography, digital pathology, genomics, transcriptomics, proteomics, metabolomics, epigenomics, spatial biology, laboratory biomarkers, circulating tumor DNA, electronic health records, biomedical literature, and longitudinal clinical outcomes. These intelligent systems support radiogenomic biomarker discovery, molecular characterization, prognostic prediction, treatment response assessment, immunotherapy selection, digital twin simulation, adaptive disease monitoring, and evidence-based clinical decision support. Emerging technologies including multimodal large language models, agentic AI, federated learning, explainable artificial intelligence, retrieval-augmented generation, cancer knowledge graphs, cloud-native healthcare platforms, and digital health ecosystems further strengthen precision radiomics by enabling collaborative, privacy-preserving, transparent, and continuously adaptive biomedical intelligence. Despite remarkable technological advances, important scientific, technical, ethical, and regulatory challenges remain regarding imaging standardization, multimodal harmonization, computational scalability, interoperability, cybersecurity, clinical validation, and equitable implementation. This review provides a comprehensive overview of next-generation foundation AI models for precision radiomics, emphasizing their role in unlocking high-dimensional imaging biomarkers for precision oncology.[1]

Keyword: Precision radiomics, Foundation models, Artificial intelligence, Radiogenomics, Imaging biomarkers, Precision oncology, Digital pathology, Computational oncology, Personalized medicine, Multimodal learning.

Received Date: 5 December 2025; **Accepted Date:** 15 December 2025; **Published Date:** 20 December 2025.

1.Introduction

Medical imaging has become one of the cornerstones of modern oncology by enabling non-invasive characterization of tumor morphology, anatomical distribution, vascularity, metabolism, cellular heterogeneity, treatment response, recurrence, and metastatic progression. Cancer is a biologically dynamic disease characterized by continuous genomic evolution, epigenetic remodeling, immune adaptation, metabolic reprogramming, stromal interactions, angiogenesis, and therapeutic resistance. These biological processes frequently manifest as subtle imaging phenotypes that remain difficult to recognize through conventional visual interpretation alone.[2]

Modern oncology generates enormous quantities of biomedical information through computed tomography, magnetic resonance imaging, positron emission tomography, ultrasound, mammography, digital pathology, genomic sequencing, transcriptomics, proteomics, metabolomics, epigenomics, spatial biology, laboratory investigations, circulating tumor DNA, electronic health records, biomedical literature, and longitudinal clinical outcomes. Although imaging contributes valuable information regarding tumor phenotype, isolated interpretation frequently limits comprehensive understanding of the biological mechanisms underlying disease progression and therapeutic response.[3]

Foundation AI models provide a transformative computational framework capable of integrating high-dimensional imaging biomarkers with molecular biology and clinical intelligence, thereby enabling predictive, adaptive, and personalized precision oncology.

2.Evolution of Precision Radiomics

Radiomics has evolved from handcrafted quantitative feature extraction toward intelligent multimodal computational ecosystems capable of automatically learning biologically meaningful imaging representations. Early radiomics studies relied primarily on manually engineered features describing tumor shape, intensity, texture, wavelet characteristics, and spatial heterogeneity. Although these quantitative biomarkers demonstrated important prognostic potential, limited reproducibility and inadequate biological interpretation constrained widespread clinical translation.[4]

Deep learning substantially expanded computational capabilities by enabling automated representation learning directly from medical images without handcrafted feature engineering. Transformer architectures subsequently revolutionized biomedical artificial intelligence through contextual learning across heterogeneous imaging modalities.

Foundation AI models now acquire transferable imaging knowledge through multimodal self-supervised learning, enabling generalized computational reasoning supporting diagnosis, biomarker discovery, therapeutic optimization, disease monitoring, and translational precision oncology.[5]

3.Principles of Foundation Models for Precision Radiomics

Foundation AI models differ fundamentally from conventional predictive algorithms because they acquire generalized biomedical representations from massive multimodal datasets before specialization for individual oncology applications. Rather than learning isolated prediction tasks, these models develop transferable computational knowledge applicable across diagnosis, prognosis, biomarker discovery, therapeutic optimization, disease monitoring, translational research, and clinical decision support.[6]

Self-supervised learning enables discovery of latent imaging relationships without requiring extensive manual annotation, while multimodal transformer architectures align computed tomography, magnetic resonance imaging, positron emission tomography, ultrasound, digital pathology, genomics, transcriptomics, proteomics, metabolomics, epigenomics, laboratory biomarkers, physician documentation, patient-reported outcomes, biomedical literature, and longitudinal clinical trajectories within unified computational embedding spaces.

Graph neural networks further characterize interactions among imaging phenotypes, tissue architecture, genes, proteins, signaling pathways, metabolites, immune populations, therapeutic targets, physiological variables, environmental exposures, and clinical outcomes, enabling systems-level computational reasoning throughout precision radiomics.[7]

4.Computational Architecture

Modern precision radiomics platforms consist of interconnected computational layers responsible for imaging acquisition, preprocessing, multimodal representation learning, graph reasoning, adaptive inference, predictive analytics, digital twin simulation, knowledge integration, and intelligent clinical decision support.[8]

The acquisition layer continuously integrates CT, MRI, PET, ultrasound, mammography, digital pathology, genomic sequencing, transcriptomics, proteomics, metabolomics, epigenomics, laboratory investigations, circulating tumor DNA, physician documentation, biomedical literature, pharmacological databases, clinical guidelines, and electronic health records. Advanced preprocessing pipelines normalize imaging protocols, harmonize molecular datasets, encode biomedical narratives using natural language processing, synchronize temporal patient information, and continuously incorporate emerging scientific evidence.

Foundation AI models subsequently generate generalized multimodal embeddings representing imaging phenotypes, tissue architecture, molecular biology, physiological function, environmental exposures, and longitudinal clinical trajectories while enabling downstream computational reasoning supporting precision oncology.[9]

5.High-Dimensional Imaging Biomarker Discovery

One of the most important applications of foundation AI models is the discovery of high-dimensional imaging biomarkers associated with tumor biology, therapeutic response, recurrence, and survival. Foundation AI models automatically learn complex imaging representations from CT, MRI, PET, ultrasound, and hybrid imaging modalities without relying exclusively on handcrafted radiomic features.[10]

Multimodal transformer architectures integrate imaging-derived biomarkers with molecular biology, histopathology, laboratory biomarkers, and longitudinal clinical outcomes to generate comprehensive representations of tumor behavior. Self-supervised learning further enables discovery of previously unrecognized imaging biomarkers while improving robustness across imaging platforms and institutions.

These computational advances substantially improve early diagnosis, prognostic prediction, treatment planning, response assessment, and personalized oncology.[11]

6.Radiogenomic Integration

Radiogenomics represents one of the most significant advances in precision radiomics by establishing biological relationships between imaging phenotypes and molecular alterations. Foundation AI models integrate radiological imaging with genomics, transcriptomics, proteomics, metabolomics, epigenomics, immunomics, microbiomics, spatial biology, laboratory biomarkers, and histopathology using multimodal transformers and graph neural networks capable of generating generalized biological representations of evolving tumor ecosystems.[12]

Artificial intelligence identifies latent associations among imaging characteristics, genomic alterations, signaling pathways, immune responses, metabolic regulation, histopathological architecture, and therapeutic targets while continuously incorporating emerging biomedical evidence.

These integrated molecular-imaging representations substantially improve biomarker discovery, molecular classification, therapeutic selection, precision immunotherapy, adaptive therapeutics, and translational cancer research.[13]

7.Precision Radiopathomics

Integration of radiological imaging with digital pathology has established the rapidly expanding field of radiopathomics. Foundation AI models harmonize imaging phenotypes, microscopic tissue architecture, stromal composition, immune microenvironment, vascular organization, and cellular heterogeneity into unified computational representations capable of characterizing tumor biology across multiple spatial scales.[14]

Graph neural networks characterize spatial interactions among imaging regions, histological structures, malignant cells, immune populations, fibroblasts, endothelial cells, extracellular matrix, and signaling pathways while multimodal transformers align radiological and pathological information into generalized biological embeddings.

These integrated radiopathomic representations substantially improve diagnostic precision, biomarker discovery, prognostic modeling, therapeutic optimization, and translational oncology.[15]

8.Longitudinal Imaging Intelligence

Longitudinal imaging provides unique opportunities to characterize temporal evolution of tumor biology throughout diagnosis, treatment, recurrence, metastasis, and survivorship. Foundation AI models continuously integrate serial CT, MRI, PET, ultrasound, laboratory biomarkers, circulating tumor DNA, treatment history, and longitudinal clinical outcomes into adaptive computational representations of evolving disease.[16]

Temporal transformer architectures effectively model sequential imaging changes while graph neural networks characterize evolving biological interactions among imaging phenotypes, molecular biomarkers, therapeutic interventions, and disease progression. Continuous imaging intelligence substantially improves prediction of therapeutic response, recurrence, treatment resistance, progression-free survival, and overall survival.

Longitudinal radiomics therefore establishes a critical computational foundation for predictive precision oncology.[17]

9.Intelligent Multimodal Radiomic Ecosystems

One of the greatest strengths of foundation AI models is their ability to unify radiology, digital pathology, multi-omics, laboratory biomarkers, biomedical literature, pharmacological knowledge, electronic health records, patient-reported outcomes, and longitudinal clinical trajectories into comprehensive patient-specific computational representations. Rather than analyzing individual biomedical modalities independently, these models generate adaptive representations of evolving cancer biology capable of supporting diagnosis, biomarker discovery, molecular characterization, therapeutic optimization, disease monitoring, recurrence prediction, survival estimation, multidisciplinary communication, and precision clinical decision-making. These generalized computational representations establish the foundation for intelligent radiomics, radiogenomics, radiopathomics, digital twins, adaptive therapeutics, and continuously personalized precision oncology throughout the cancer care continuum.[18][19][20]

10.Digital Twins and High-Dimensional Radiomic Intelligence

Digital twin technology represents one of the most transformative applications of next-generation foundation AI models in precision radiomics by creating continuously evolving virtual representations of individual cancer patients synchronized with their biological counterparts. Foundation AI models integrate serial computed tomography, magnetic resonance imaging, positron emission tomography, ultrasound, digital pathology, genomics, transcriptomics, proteomics, metabolomics, epigenomics, spatial biology, 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 radiomic models based on isolated imaging studies, digital twins continuously update their computational representations as new multimodal biomedical information becomes available. Integration of imaging phenotypes, radiogenomic biomarkers, histopathological architecture, physiological monitoring, and predictive simulation enables virtual patients to evaluate alternative therapeutic strategies, optimize treatment sequencing, anticipate mechanisms of therapeutic resistance, personalize supportive care, and estimate long-term clinical outcomes according to evolving tumor biology.

By integrating high-dimensional imaging biomarkers with predictive simulation, digital

DOI: https://doi.org/10.65477/ijrems.v1.i7.11

twins bridge radiomics and individualized precision oncology.

11.Intelligent Clinical Decision Support

Foundation AI 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 independently interpreting radiological imaging, digital pathology, molecular diagnostics, laboratory investigations, physician documentation, patient-reported outcomes, biomedical literature, pharmacological knowledge, and evidence-based clinical guidelines, these systems synthesize diverse biomedical information into unified computational representations supporting multidisciplinary oncology practice.[22]

Interactive clinical dashboards generate individualized diagnostic summaries, high-dimensional radiomic analyses, radiogenomic correlations, radiopathomic interpretations, molecular biomarker profiles, digital twin simulations, therapeutic recommendations, toxicity estimates, recurrence probabilities, disease progression forecasts, survival predictions, and longitudinal treatment response assessments while facilitating collaboration among oncologists, radiologists, pathologists, surgeons, radiation oncologists, molecular biologists, pharmacists, nurses, genetic counselors, biomedical engineers, computational scientists, and translational researchers.

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

12.Continuous Learning and Adaptive Radiomic Intelligence

A defining characteristic of next-generation foundation AI models is the 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, biomedical literature, pharmacological evidence, clinical guidelines, and real-world treatment outcomes 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, while reinforcement learning optimizes imaging interpretation, biomarker prioritization, radiogenomic analysis, disease monitoring, toxicity prediction, and supportive care through iterative evaluation of longitudinal patient outcomes. Foundation AI models further integrate clinician feedback and multidisciplinary tumor board recommendations into continuous model refinement.

This adaptive computational paradigm transforms precision radiomics into a continuously learning scientific ecosystem capable of rapidly translating imaging discoveries into individualized clinical practice.

13.Federated Radiomic Intelligence Networks

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

Participating healthcare institutions independently train local multimodal models using CT, MRI, PET, ultrasound, digital pathology, genomics, transcriptomics, proteomics, metabolomics, laboratory investigations, liquid biopsy, electronic health records, biomedical literature, 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, transparency, and generalizability across diverse healthcare environments.

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

14.Explainability, Validation, and Ethical Governance

Successful implementation of precision radiomics 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 multimodal computational reasoning through radiomic attention visualization, imaging saliency maps, SHAP (Shapley Additive Explanations), integrated gradients, feature attribution analysis, uncertainty estimation, confidence calibration, multimodal attention mapping, and counterfactual explanations identifying the imaging, molecular, pathological, physiological, pharmacological, and clinical variables responsible for predictive outputs.[25]

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

Responsible implementation further depends upon patient privacy, informed consent, transparency, accountability, fairness, equitable access, responsible data governance, continuous post-deployment surveillance, clinician education, and multidisciplinary oversight to ensure trustworthy integration of intelligent radiomics into routine oncology practice.

15.Future Perspectives

Future precision radiomics 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, single-cell sequencing, liquid biopsy, quantum computing, cloud-native healthcare infrastructure, biomedical knowledge graphs, retrieval-augmented generation, explainable reasoning systems, and autonomous clinical intelligence 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, pharmacological databases, global clinical guidelines, and real-world clinical outcomes while autonomously coordinating imaging interpretation, biomarker discovery, adaptive therapeutics, personalized treatment planning, survivorship management, multidisciplinary communication, and continuous evidence synthesis.

Such intelligent radiomic ecosystems are expected to transform oncology from qualitative image interpretation toward predictive, adaptive, continuously learning, and precision-guided cancer medicine.

16.Discussion

Next-generation foundation AI models represent one of the most significant paradigm shifts in precision radiomics by integrating radiology, radiogenomics, radiopathomics, multi-omics, laboratory biomarkers, biomedical literature, pharmacological knowledge, digital biomarkers, digital twins, and longitudinal clinical intelligence into unified computational ecosystems capable of supporting comprehensive personalized cancer care. Unlike conventional radiomics approaches that rely on handcrafted imaging features, intelligent foundation models continuously synthesize heterogeneous imaging, molecular, pathological, physiological, pharmacological, and clinical information into adaptive biological representations supporting systems-level reasoning and precision medicine.[27]

Applications spanning computational radiology, radiogenomics, biomarker discovery, digital twins, precision immunotherapy, adaptive therapeutics, remote patient monitoring, federated collaboration, digital health, survivorship management, intelligent clinical decision support, and translational research demonstrate the extraordinary potential of foundation AI models to redefine precision radiomics. Nevertheless, successful implementation requires continued advances in imaging harmonization, explainable artificial intelligence, interoperability, computational infrastructure, cybersecurity, regulatory science, ethical governance, clinician education, and sustained multidisciplinary collaboration.

As biomedical knowledge and healthcare data continue to expand exponentially, next-generation radiomic intelligence is expected to become one of the foundational computational infrastructures supporting precision oncology worldwide.

17.Conclusion

Next-generation foundation AI models are transforming precision radiomics by integrating high-dimensional imaging biomarkers with radiogenomics, radiopathomics, multi-omics, laboratory biomarkers, biomedical literature, electronic health records, digital twins, and longitudinal clinical intelligence into unified computational ecosystems capable of supporting biomarker discovery, molecular characterization, prognostic prediction, therapeutic optimization, adaptive disease monitoring, and precision clinical decision-making throughout the cancer care continuum.[28]

Advances in multimodal transformer architectures, graph neural networks, self-supervised learning, federated learning, reinforcement learning, multimodal large language models, explainable artificial intelligence, digital twins, agentic AI, retrieval-augmented generation, and generative artificial intelligence are expected to further strengthen precision radiomics, enabling increasingly accurate imaging biomarker discovery, predictive clinical reasoning, adaptive therapeutics, continuous disease surveillance, and personalized precision oncology.[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, patients, and regulatory agencies will accelerate the responsible implementation of next-generation foundation AI models. These innovations have the potential to improve patient outcomes, enhance healthcare efficiency, reduce disparities in cancer care, accelerate translational research, facilitate precision therapeutics, and establish a new era of intelligent, adaptive, and continuously learning precision oncology worldwide.[30]

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