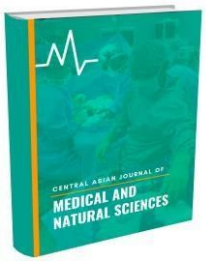

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Article

Multimodal AI Systems for Early Cancer Detection Through Integrated Imaging, Genomic Profiles, and Clinical Risk Indicators

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Abstract: Early cancer detection remains challenging due to disease heterogeneity and limitations of single-modality approaches. Multimodal artificial intelligence (AI) integrates imaging, genomic profiles, and clinical indicators to provide comprehensive insights for improved cancer prediction and personalized oncology. This review evaluates multimodal AI frameworks and their applications in integrating heterogeneous data sources for early cancer detection and precision medicine. A comprehensive review was conducted on recent advances in multimodal AI-based cancer detection systems, focusing on medical imaging, genomic and molecular data, and clinical risk indicators. Relevant literature was analyzed to summarize AI architectures, including machine learning, deep learning, radiomics, transformer-based models, and multi-omics integration strategies. The review also examined current applications, challenges, validation approaches, and future directions for clinical translation of multimodal AI technologies. Multimodal AI approaches demonstrate potential for improving cancer detection by combining complementary information from imaging, genomic, and clinical domains. Imaging-based AI models, including convolutional neural networks and radiomics approaches, effectively extract tumor-related features, while genomic AI models identify molecular signatures associated with cancer progression. Integration of multi-omics and electronic health record data enables more comprehensive patient characterization and risk prediction. However, current evidence highlights challenges related to data heterogeneity, missing information, model interpretability, privacy, bias, and limited external validation. Further development of robust and explainable AI systems is required for reliable clinical implementation. Multimodal AI represents a promising research direction for cancer detection, but standardized validation and responsible implementation are essential before routine clinical adoption.

Keywords: Multimodal Artificial Intelligence; Early Cancer Detection; Medical Imaging Analysis; Genomic Data Integration

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1. Introduction

Cancer remains one of the leading causes of morbidity and mortality globally and a major challenge for global health care systems. Early detection is crucial for better treatment outcomes, disease course modification, and patient survivability [1], [2]. Conventional cancer diagnosis relies on clinical evaluation, medical imaging interpretation, pathological examination, and molecular testing. Although these strategies have driven major advances in cancer treatment, they can still face challenges with diagnostic consistency, limited information, and diagnosing complex biological patterns at early disease stages. As a result, advanced computational models that integrate

information from multiple sources in biomedical contexts have emerged as an important area of oncology research [3].

By enabling automatic analysis of large amounts of biomedical data, artificial intelligence has become a powerful tool in cancer diagnosis and prediction. Machine learning (ML) and deep learning (DL) algorithms have proven effective in medical image analysis, genome interpretation, and clinical risk prediction. Many medical applications have already been identified for convolutional neural networks (CNNs), for instance, detecting and categorizing tumors in computed tomography (CT), magnetic resonance imaging (MRI), or positron emission tomography (PET), as well as in histopathological images. Likewise, AI-based models have been designed to analyze genomic alterations, gene expression patterns, and molecular biomarkers in cancer development and progression [4], [5].

Cancer, however, is a complicated and heterogeneous disease modulated by a variety of biological, genetic, environmental, and clinical factors. Single-modality AI models tend to provide less information because they capture only some aspects of disease characteristics. For instance, imaging-based models can help detect tumor morphology and spatial distribution, but they may overlook the molecular processes driving tumor behavior. On the other hand, genomic models can identify genetic changes but may miss crucial anatomical and clinical background information. This constraint has spurred the evolution of multimodal AI systems that incorporate complementary data from various sources, such as medical imaging, genomic profiles, and clinical risk indicators [6], [7].

Multimodal AI is an emerging technique that integrates multiple data modalities to generate more comprehensive representations of disease characteristics. These systems can be used in cancer research to incorporate imaging characteristics, molecular markers, and individualized clinical data for early detection, cancer risk categorization, and individualized treatment planning. Typically, multimodal AI systems consist of modality-specific feature extractors and data fusion modules, followed by a prediction module. Advanced fusion techniques such as feature-level fusion, decision-level fusion, and attention enable AI models to learn across data types and improve prediction accuracy [7], [8].

AI is increasingly used in oncology, especially in medical imaging. Radiomics techniques analyze medical images quantitatively, identifying features such as shape, intensity patterns, or texture that can serve as imaging markers for cancer diagnosis and prognosis. By automatically learning complex representations from raw image data, deep-learning models further improve image analysis. Imaging-based AI systems could offer a more detailed understanding of tumor biology and the specific characteristics of disease in a given patient, along with genomic data [9], [10].

Genomic and molecular information add further layers to multimodal cancer prediction. The advent of large-scale sequencing technologies has enabled the acquisition of molecular datasets such as transcriptomes, DNA mutations, methylation, and multi-omics data. AI techniques can analyze these complex, multidimensional datasets to detect molecular signatures, classify tumor type, and predict how the tumor will respond to treatment. Combining genomic, imaging, and clinical information can help better understand cancer heterogeneity and support more personalized approaches to diagnosis [11], [12], [13].

Clinical risk factors, such as electronic health records (EHRs), demographic data, family history, laboratory data, and lifestyle characteristics, provide important background for cancer prediction. By using clinical data and AI models, researchers can identify risk patterns that support personalized screening and decision-making. Multimodal AI systems leverage clinical, imaging, and genomic features together, potentially improving the accuracy and reliability of cancer prediction models [14], [15].

Although multimodal AI has great potential for clinical utility, several challenges remain for early clinical adoption. These include privacy concerns, model interpretability,

limited availability of high-quality labelled datasets, data heterogeneity, and missing information in many datasets. Many high-end AI systems are complex, black-box systems, which makes it hard for clinicians to understand the basis of the system's predictions [16]. Explainable AI, standardized data integration methods, and robust clinical evaluations address these challenges and are imperative for responsible implementation.

This review discusses integrating imaging, genomic profiles, and clinical risk indicators into multimodal AI systems for early cancer detection. The paper summarizes the state of the art in AI, data modalities, fusion methods, applications across cancer subtypes, challenges, and prospects. Understanding these advances can reveal opportunities and obstacles for multimodal AI implementation to improve cancer diagnosis and individualized oncology.

2. Materials and Methods

2.1 Fundamentals of Multimodal AI in Cancer Detection

Multimodal Artificial Intelligence (AI) is a computational approach that combines and processes multiple heterogeneous data types to enhance pattern recognition and predictive performance. For cancer diagnosis and detection, multimodal AI integrates complementary data modalities, such as medical imaging, genetic signatures, and clinical risk factors, to better represent cancer characteristics. Single-modality AI systems focus on specific information, while multimodal systems aim to capture relationships among multiple biological and clinical components that may contribute to cancer growth and development [17], [18].

Typically, a multimodal AI system's architecture consists of modality-specific feature extraction, data fusion, and prediction. Deep learning models can process imaging data from computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), or histopathological images to detect spatial or structural patterns, while genomic and molecular data may reveal genetic changes and biological mechanisms. Clinical data, such as Electronic Health Records (EHRs) and demographic details, provide additional patient context. Researchers can fuse these data at an early, intermediate, or later stage to develop predictive models for cancer classification, risk assessment, and prognosis [19], [20].

Artificial intelligence technologies like deep learning and transformer-based architectures, along with advances in multimodal representation learning, have strengthened AI systems' ability to handle complex biomedical data. However, data heterogeneity, interpretation, privacy, and clinical validation remain major concerns for real-world implementation. Hence, multimodal AI is a promising research path in cancer detection that needs further assessment to develop solutions that are reliable and applicable in clinical practice [21].

2.1.1 Concept and Architecture of Multimodal AI Systems

Multimodal artificial intelligence (AI) includes several data modalities to build models that access complementary information from various data sources. Multimodal AI systems are applied to cancer detection by integrating medical imaging with genomic data and clinical risk factors to reveal connections among anatomical features, molecular patterns, and patient-specific data. These systems can outperform single-modality systems in analyzing complex cancer-related patterns from heterogeneous biomedical information [22], [23].

Typically, a multimodal AI system comprises three main parts: Modality-specific Feature Extraction, Multimodal Fusion, and Prediction. Deep learning models like convolutional neural networks (CNNs) or vision transformers are applied to imaging data such as CT, MRI, PET, or histopathology images to identify imaging features. Machine learning models, deep neural networks, or graph-based AI models can analyze genomic and molecular data to identify molecular signatures, while clinical data capture patient-specific risk factors. The representations are then extracted and merged using fusion strategies (early fusion, feature-level fusion, decision-level fusion, or attention-based

fusion) to produce predictive outcomes for cancer diagnosis, risk stratification, and prognosis [24], [25].

Advances in multimodal learning and transformer-based algorithms have improved the analysis of complex biomedical data. However, data heterogeneity, missing data, interpretability, and clinical validation are still significant issues. In light of this, the potential applications of multimodal AI for cancer research are exciting, though more research is needed to ensure the technology is reliable and clinically effective [26].

2.1.2 Data Modalities used in Cancer Diagnostics

In multimodal AI-based cancer diagnosis, multiple types of imagery and data provide complementary information on cancer characteristics and patient-specific conditions. Major data sources include medical imaging, genomic and molecular profiles, and clinical risk indicators. Each modality provides unique biological and clinical context, such as the anatomic and structural tissue characteristics revealed by imaging data, the genomic alterations revealed by genomic data, and the patient-specific risk factors and medical history provided by clinical data. These multimodal datasets can create more complete descriptions of cancer patterns than single-modality approaches [27], [28].

AI technology has enabled the extraction of features from images in various medical imaging modalities such as computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and histopathological images, which are used for the detection and characterization of tumors.AI feature extraction has been applied to a wide range of medical imaging modalities including computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and histopathological images, for the detection and characterization of tumors. Genomic and molecular information, including gene expression profiles, DNA mutations, methylation patterns, and copy number variations, enables understanding of cancer biology and molecular subtyping. Furthermore, electronic health record (EHR) data provide valuable background information for risk measurement and prediction, in addition to clinical data. Beyond clinical data, data in electronic health records (EHRs), laboratory testing results, demographic data, and lifestyle factors can provide important contextual information for risk measurement and prediction. Including these modalities in a multimodal AI framework can enhance cancer classification, detection, and personalized risk prediction, but it also raises data quality, standardization, and integration challenges [29], [30], [31].

2.1.3 ML and DL Approaches

Machine learning (ML) and deep learning (DL) are essential pillars of multimodal AI systems in cancer diagnosis, enabling automated feature extraction, pattern recognition, and predictive modelling from complex biomedical information. Well-established machine learning techniques such as logistic regression, random forests, and support vector machines (SVMs) have been widely used for structured clinical information, radiomic features, and genomic data. These techniques are useful when training data is limited, when risk prediction is needed, and when model interpretability is required, particularly for classification and biomarker identification.

Deep learning techniques have advanced AI-powered cancer analysis and can map a hierarchy directly from massive amounts of biomedical data. CNNs have been widely used in medical image analysis because they can learn spatial features from medical images such as CT, MRI, PET, and histopathological images. Other powerful models such as recurrent neural networks (RNNs), graph neural networks (GNNs), and transformer models can handle sequential clinical notes, molecular structures, and multimodal information. These models can support multimodal cancer detection, where imaging, genomic, and clinical data may be fused in various ways to improve predictive power and enable personalized risk assessment. However, implementation challenges remain, including data availability, interpretability, and clinical validation [32], [33].

2.2 Introduction to Multimodal AI in Cancer Detection

2.2.1 Concept and Architecture of Multimodal AI Systems

Multimodal artificial intelligence (AI) is a class of computational techniques that fuse and process multiple distinct data modalities to achieve more complete and accurate predictions. Multimodal AI systems integrate medical imaging, genomic information, and

clinical risk factors in cancer detection, combining complementary information about tumor properties and patient-specific factors (Figure 1). These systems can outperform single-modality counterparts by learning relationships across data sources, improving diagnostic accuracy, forecasting risk, and supporting personalized treatment choices in oncology [23], [25], [34].

Typically, multimodal AI systems comprise feature extraction networks, multimodal AI networks, and prediction layers. Deep learning algorithms, including convolutional neural networks (CNNs) and transformer models, are usually applied to image data such as computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and pathological images. Machine learning or deep neural network models handle genomic and clinical data. The models then fuse extracted features from various modalities and generate outputs such as early cancer detection, risk stratification, and clinical prediction through feature-level, decision-level, and attention-based fusion. The synergy of medical imaging with electronic health records (EHRs) and other biological data shows strong potential for creating powerful AI-based cancer diagnostic systems [35], [36], [37].

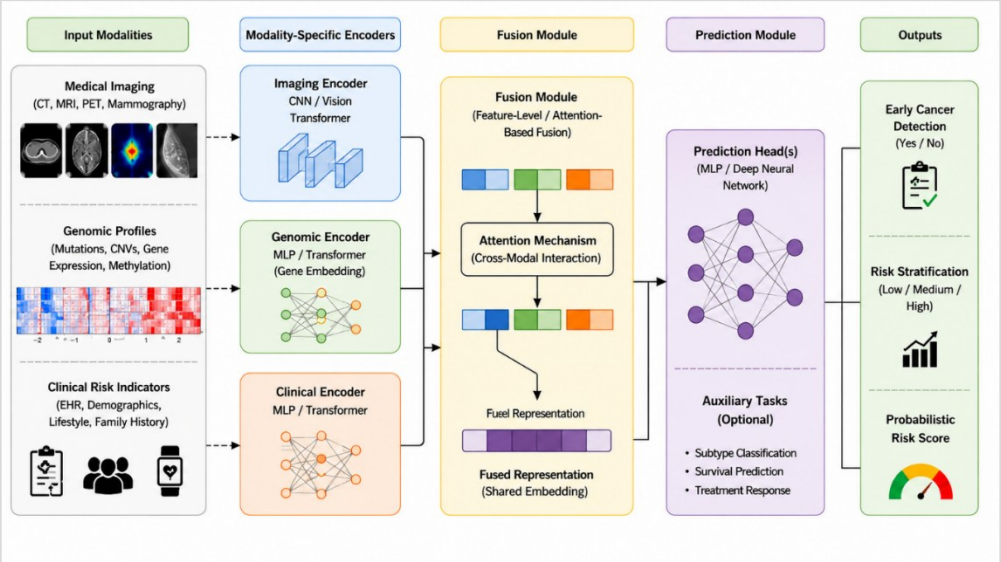

Figure 1. Conceptual architecture of a multimodal AI system for early cancer detection. The framework integrates heterogeneous data modalities, including medical imaging, genomic profiles, and clinical risk indicators, through modality-specific feature extraction models, multimodal fusion strategies, and prediction networks to generate outputs such as early cancer detection, risk assessment, and personalized clinical insights.

2.2.2 Data Modalities Used in Cancer Diagnosis

Multimodal AI systems for cancer detection combine multiple data modalities to create a holistic picture of the tumor and patient-specific factors involved in cancer detection. Key data sources include medical imaging, genomic profiles, and clinical risk indicators. Medical imaging techniques such as computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and mammography provide information on tumor morphology, spatial patterns, location, and size (Table 1). Convolutional neural networks (CNNs) and vision transformers are popular deep learning models for extracting imaging features for cancer classification, late-stage cancer diagnosis, or cancer detection [38], [39].

Genomic profiles identify biological mechanisms and molecular subtypes, providing molecular-level information on gene expression patterns, DNA mutations, DNA methylation, and other cancer-associated alterations. Other clinical factors, such as age, gender, family history, lifestyle habits, laboratory data, and e-health records (EHRs), add patient-specific details for risk assessment and prognosis prediction. Combining imaging,

genomic, and clinical data in multimodal AI frameworks can increase the accuracy of early cancer detection, improve risk prediction tools, and support precision oncology decisions [40], [41], [42].

Table 1. Major Data Modalities Integrated in Multimodal AI Systems for Early Cancer Detection.

Data Modality	Examples	Extracted Information	AI Methods	Contribution to Early Cancer Detection
Medical Imaging	CT, MRI, PET, Mammography, Histopathological images	Tumor morphology, size, location, texture, spatial features	CNN, Vision Transformer, Radiomics-based models	Lesion detection, tumor classification, early diagnosis
Genomic Profiles	Gene expression, DNA mutations, methylation patterns, copy number variations	Molecular alterations, genetic signatures, cancer-related pathways	Deep neural networks, Graph neural networks, Transformer models	Molecular subtype identification, cancer risk prediction, precision oncology
Clinical Risk Indicators	Age, gender, family history, lifestyle factors, laboratory results, EHR data	Patient-specific risk factors and clinical characteristics	Machine learning, Deep learning, Clinical prediction models	Risk assessment, early screening, prognosis prediction
Integrated Multi-Modal Data	Imaging + Genomics + Clinical information	Combined biological and clinical representation	Multimodal fusion networks, Attention-based models, Transformers	Improved cancer detection accuracy and personalized prediction

2.2.2.1 Medical Imaging Data

Medical imaging is one of the most crucial multimodality AI-based cancer detection data modalities, offering non-invasive data on tumor morphology, anatomical structure, and functional characteristics. Various imaging modalities provide complementary information, such as computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), mammography, and histopathological imaging; these can be analyzed with advanced AI models (Table 2). Recent years have seen strong performance by deep learning techniques, especially convolutional neural networks (CNNs), three-dimensional CNNs (3DCNNs), and vision transformers (VTs), in cancer detection and classification, particularly for extracting complex features from imaging information, including size, shape, texture, and spatial structures.

Multimodal AI frameworks embed imaging-derived features alongside genomic data and clinical risk markers, improving diagnostic accuracy and supporting personalized cancer evaluation. CT and PET imaging add value through localization, metabolic activity analysis, and metastasis detection, whereas MRI and histopathological imaging provide detailed structural and cellular information. Multimodal AI systems can integrate

imaging, molecular, and clinical data, improving precision oncology decisions, cancer risk stratification, and early cancer detection [43], [44], [45], [46].

Table 2. Medical Imaging Modalities and Their Role in Multimodal AI-Based Early Cancer Detection.

Imaging Modality	Examples	Key Information Extracted	AI Approaches	Contribution to Multimodal Cancer Detection
CT	Chest CT, Low-dose CT	Tumor size, shape, density, anatomical features	CNN, 3D CNN, Vision Transformer	Imaging biomarkers for early tumor detection and integration with clinical/genomic data
MRI	Brain MRI, Breast MRI	Tissue characteristics, structural and functional patterns	CNN, Transformer models	Tumor characterization and complementary information for precision diagnosis
PET	FDG-PET	Metabolic activity and functional abnormalities	Deep learning, Radiomics	Detection of tumor activity and metastatic risk assessment
Mammography	Digital mammograms	Lesion patterns and microcalcifications	CNN-based classifiers	Early breast cancer screening and risk prediction
Histopathology	Whole-slide images, biopsy images	Cellular morphology and tissue architecture	CNN, Vision Transformer	Cancer subtype classification and molecular correlation

2.2.2.2 Genomic and Molecular Data

Comparing the baseline genetic makeup of a patient's tumor cells with the genomes of normal cells can provide insight into how cancer develops at the genomic and molecular level and identify genes that are unusual during the onset, growth, and treatment of the cancer. Major genomic variants convey molecular information such as gene expression profiles, DNA mutations, DNA methylation patterns, and copy number variations (CNVs), which can be used to classify cancer, identify new cancer markers, and predict cancer risk (Table 3). High-throughput techniques such as RNA sequencing (RNA-seq), microarray analysis, and next-generation sequencing (NGS) generate large volumes of molecular data that can be analyzed using AI approaches to identify complex, cancer-relevant patterns [47], [48].

Integrating genomic and molecular data with medical imaging and clinical risk factors in multimodal AI systems enhances early cancer diagnosis and risk prediction. Analyzing high-dimensional genomic features using deep learning and graph neural networks, as well as inferring relationships via transformer models, helps uncover links between molecular alterations and clinical outcomes. Multi-omics integration approaches

combine multiple biological layers (genomics, transcriptomics, and proteomics) to build an all-encompassing picture of tumor biology. Using genomic data in multimodal AI systems can enable more precise molecular characterization, supporting diagnostics and precision oncology applications [5], [33], [36].

Table 3. Genomic and Molecular Data Modalities Integrated into Multimodal AI Systems for Early Cancer Detection.

Genomic Data Type	Examples	Typical Data Characteristics	Extracted Information	Common AI Approaches	Role in Multimodal Cancer Detection
Gene Expression Data	RNA sequencing (RNA-seq), Microarray	Thousands of gene expression features (~10^3–10^4 genes per sample)	Gene activity patterns, expression signatures, cancer-related pathways	Deep neural networks, Machine learning models, Transformer-based models	Identification of molecular biomarkers, cancer subtype classification, and integration with imaging features for improved prediction
DNA Mutation Data	Somatic mutations, Single nucleotide variants (SNVs), Driver mutations	Hundreds to thousands of genomic alteration features depending on cancer type	Genetic alterations, driver genes, mutation signatures	Deep learning, Graph neural networks, Ensemble learning models	Detection of cancer-associated mutations, molecular risk prediction, and targeted therapy guidance
DNA Methylation Data	CpG methylation profiles, Epigenetic markers	Genome-wide methylation patterns involving thousands of methylation sites	Epigenetic regulation patterns and gene expression control mechanisms	Machine learning, Neural networks, Deep learning models	Early cancer detection, molecular classification, and identification of epigenetic biomarkers
Copy Number Variation (CNV)	Gene amplification, Gene deletion events	Genome-wide chromosomal alteration profiles	Genomic instability, tumor evolution, and chromosomal abnormalities	Deep learning, multi-omics integration models	Tumor characterization, progression prediction, and prognosis assessment
Multi-Omics Data	Genomics, transcriptomics,	Multiple high-dimensional	Comprehensive molecular	Multimodal fusion networks,	Integration with imaging and clinical

Genomic Data Type	Examples	Typical Data Characteristics	Extracted Information	Common AI Approaches	Role in Multimodal Cancer Detection
	proteomics, metabolomics integration	biological feature spaces	signatures and biological interactions	Transformer-based models, Attention mechanisms	data for precision oncology, personalized risk prediction, and improved early cancer detection

2.3 Machine Learning and Deep Learning Approaches

Machine learning (ML) and deep learning (DL) are crucial to designing multimodal AI systems for cancer detection, involving automated feature extraction, pattern recognition, and predictive modeling. Structured clinical data, radiomics, and genomics have been extensively used with traditional machine learning algorithms, specifically Support Vector Machines (SVM), Random Forest, and Logistic Regression. These techniques are especially advantageous for predictive tasks and risk classification when limited data are available and decision interpretation is needed.

In this fast-changing, computationally intensive world of large biomedical datasets, deep learning techniques play an increasingly crucial role in cancer research. CNNs are widely used to analyze medical images, and recurrent neural networks (RNNs), graph neural networks (GNNs), and transformer-based models can process sequential, relational, and high-dimensional (e.g., genomic) biological information (Figure 2). These methods are then combined with imaging, genomic data, and clinical information in multimodal AI approaches that provide a holistic view. The complexity of these approaches allows integrated models to capture complex interactions among biological and clinical factors, improving early cancer detection, risk prediction, and personalized oncology [19], [39].

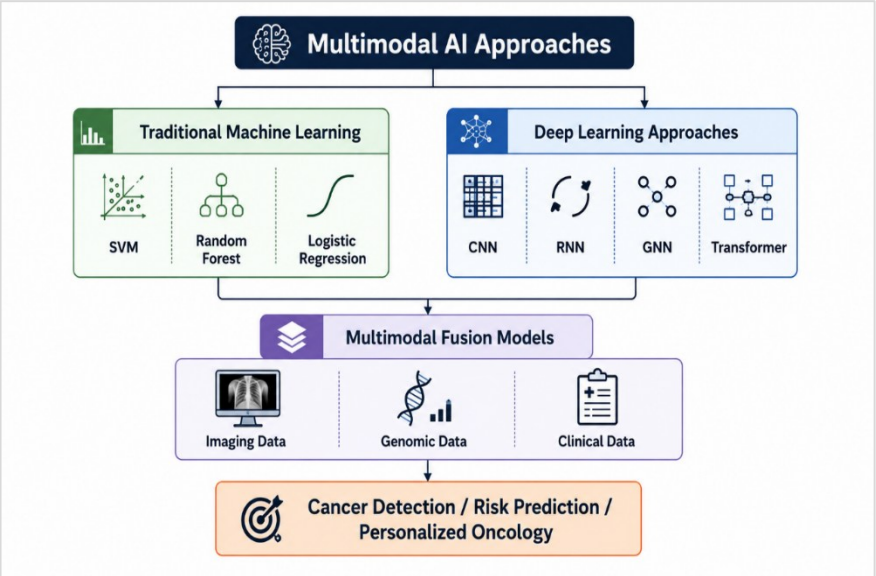

Figure 2. Overview of machine learning and deep learning approaches used in multimodal AI systems for early cancer detection. The framework illustrates traditional machine learning and deep learning models, followed by multimodal fusion of imaging, genomic, and clinical data for cancer detection, risk prediction, and personalized oncology applications.

2.4. Medical Imaging-Based AI for Early Cancer Detection

2.4.1 Radiomics and Imaging Feature Extraction

Radiomics is a quantitative approach to imaging analysis that extracts high-dimensional features from medical images to provide clues beyond visual analysis and may represent tumor features. The radiomics workflow consists of four steps: image preprocessing, identification of the tumor area of interest (ROI), feature extraction, and AI modeling (Figure 3). The main features extracted are shape features, first-order intensity features, texture features, and wavelet features, which contain information regarding tumor morphology, tumor intensity distribution, and intratumoral heterogeneity [49], [50], [51].

Radiomic features, such as texture, shape, and density measurements derived from medical imaging techniques, are used in AI cancer detection to guide cancer-type classification and early detection and prediction of cancer risk, using learning-based methods including CNN and transformer-based approaches. Incorporating imaging-derived features with clinical risk factors and genomic profiles enables multimodal AI systems that provide a more complete cancer representation and enhanced patient-based cancer applications [39], [52].

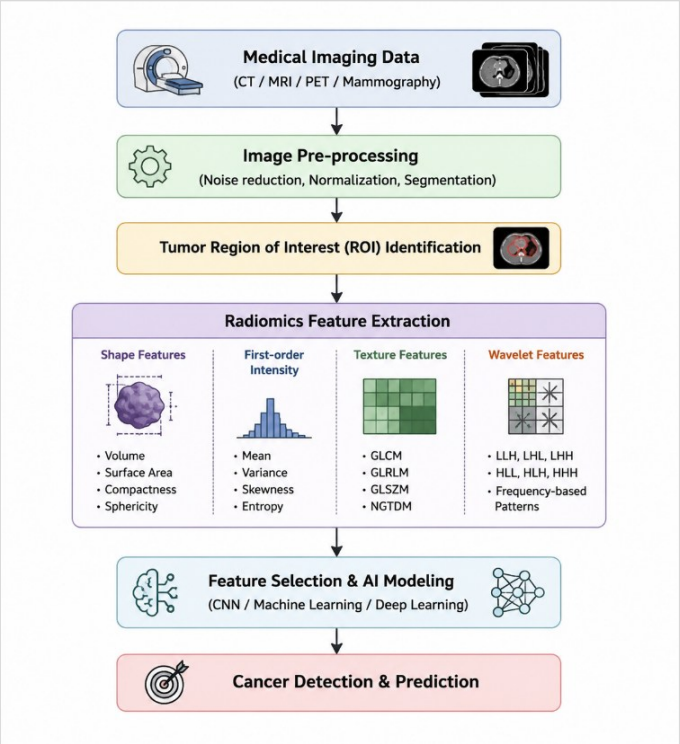

Figure 3. Radiomics workflow for AI-based cancer detection, showing image preprocessing, ROI identification, feature extraction, AI modeling, and cancer prediction.

2.4.2 Deep Learning Models for Cancer Imaging Analysis

Deep learning (DL) models have made remarkable progress in medical image analysis, enabling automatic extraction of relevant data features and precise pattern recognition from complex medical images. Deep learning techniques can learn hierarchical representations directly from raw medical images, without the manual feature engineering used in traditional image analysis methods (Table 4). Tumor detection, segmentation, and classification are popular CNN applications for CT/MR and PET images, and researchers have recently explored 2D and 3D CNNs for tumor segmentation and classification in histopathological images.

Transformer-based models, such as Vision Transformers (ViT), can capture long-range relationships through attention mechanisms, which are powerful for medical image

analysis. Feature representation learning (FL), image reconstruction, and data augmentation are other approaches supported by autoencoders and generative adversarial networks (GANs). In multimodal cancer detection, hybrid models with CNNs and transformers, or models that combine imaging data with genetic and clinical data, show improved effectiveness. By learning highly complex patterns from cancer imaging, these methodologies could help to better detect, characterize, and personalize cancer therapy [28], [32], [33], [35].

Table 4. Deep Learning Models Applied for Medical Imaging-Based Cancer Detection.

Deep Learning Model	Examples	Input Data	Key Features	Applications in Cancer Imaging
Convolutional Neural Networks (CNNs)	2D CNN, 3D CNN, ResNet, EfficientNet	CT, MRI, PET, Histopathology images	Automated spatial feature extraction and hierarchical representation learning	Tumor detection, segmentation, classification, and staging
Vision Transformers (ViT)	Transformer-based vision models, Swin Transformer	CT, MRI, Histopathology images	Attention-based learning of long-range spatial relationships	Tumor characterization and high-performance image classification
Autoencoders	Variational Autoencoder (VAE), Denoising Autoencoder	Medical imaging data	Unsupervised feature representation and dimensionality reduction	Feature extraction, anomaly detection, and image reconstruction
Generative Adversarial Networks (GANs)	DCGAN, CycleGAN	Medical imaging datasets	Synthetic image generation and image enhancement	Data augmentation, image quality improvement, and limited-data learning
Hybrid Deep Learning Models	CNN + Transformer, CNN + RNN	Imaging with clinical/molecular features	Combines multiple learning strategies and cross-modal feature integration	Multimodal cancer diagnosis and personalized prediction

2.4.3 Applications in Different Cancer Types

Earlier research has shown promising results using AI across cancer types, with potential for improved detection, diagnostic accuracy, and clinical advice. Combined decision support using deep learning models such as CNNs, 3D CNNs, and radiomics-based models has been extensively used in lung cancer for pulmonary nodule detection, pulmonary tumor classification (malignant vs benign), staging, and risk prediction.

Likewise, AI-assisted mammography, MRI, and ultrasound imaging have helped to enhance breast cancer detection and the categorization of malignancy.

Deep learning-based imaging techniques also show promise for brain, colorectal, prostate, and skin cancer (Table 5). Patents have explored MRI-derived AI models for brain tumor segmentation, grading, and treatment evaluation, as well as histopathology and colonoscopy image processing for colorectal cancer detection and tissue classification. For prostate and skin cancers, radiomics, CNNs, and transformers help detect tumor properties and segment lesions. Imaging-based AI applications offer valuable features that can be integrated with genomic and clinical data in multimodal AI systems to support early cancer detection and personalized oncology further [44], [53].

Table 5. Applications of AI-Based Medical Imaging Analysis for Early Detection Across Different Cancer Types.

Cancer Type	Common Imaging Modalities	AI Approaches	Role in Early Cancer Detection and Clinical Decision Support
Lung Cancer	CT, PET-CT	CNN, 3D CNN, Radiomics, Transformer models	Pulmonary nodule detection, early tumor identification, staging, and risk prediction
Breast Cancer	Mammography, MRI, Ultrasound	CNN, Deep learning classifiers, Vision Transformers	Early screening, lesion detection, malignancy classification, and risk assessment
Brain Cancer	MRI, PET	CNN, U-Net, Transformer models	Tumor segmentation, grading, and treatment response prediction
Colorectal Cancer	Colonoscopy images, Histopathology	CNN, Deep learning models	Polyp detection, tissue classification, and early cancer diagnosis
Prostate Cancer	Multiparametric MRI (mpMRI), Histopathology	CNN, Radiomics, Hybrid models	Tumor localization, grading, and clinical risk assessment
Skin Cancer	Dermoscopy images	CNN, Vision Transformers	Lesion classification and melanoma detection

2.5. Multi-Omics Data Integration Profiles in AI-Based Cancer Prediction

Multi-omics data integration combines genomics, transcriptomics, proteomics, and other biological data to provide a broader view of cancer biology. These layers capture tumor properties, including genetic changes, gene expression patterns, and surface protein changes. By combining these heterogeneous datasets, multi-omics approaches may reveal complex molecular relationships that single omics analyses alone may miss (Figure 4).

AI-based approaches to multi-omics integration are typically defined by early fusion, intermediate fusion, and late fusion models. Early fusion combines raw features from multiple omics data sources before model training, while intermediate fusion combines learned features across modalities. Late fusion merges predictions from each model to produce final predictions. Deep learning techniques such as transformers, graph neural networks (GNNs), and multimodal neural networks have advanced multi-omics analysis by improving feature representation and detecting biological patterns. These integrative frameworks enable molecular tumor profiling, biomarker identification, cancer risk

estimation, treatment response assessment, and personalized oncology use cases [26], [30], [31].

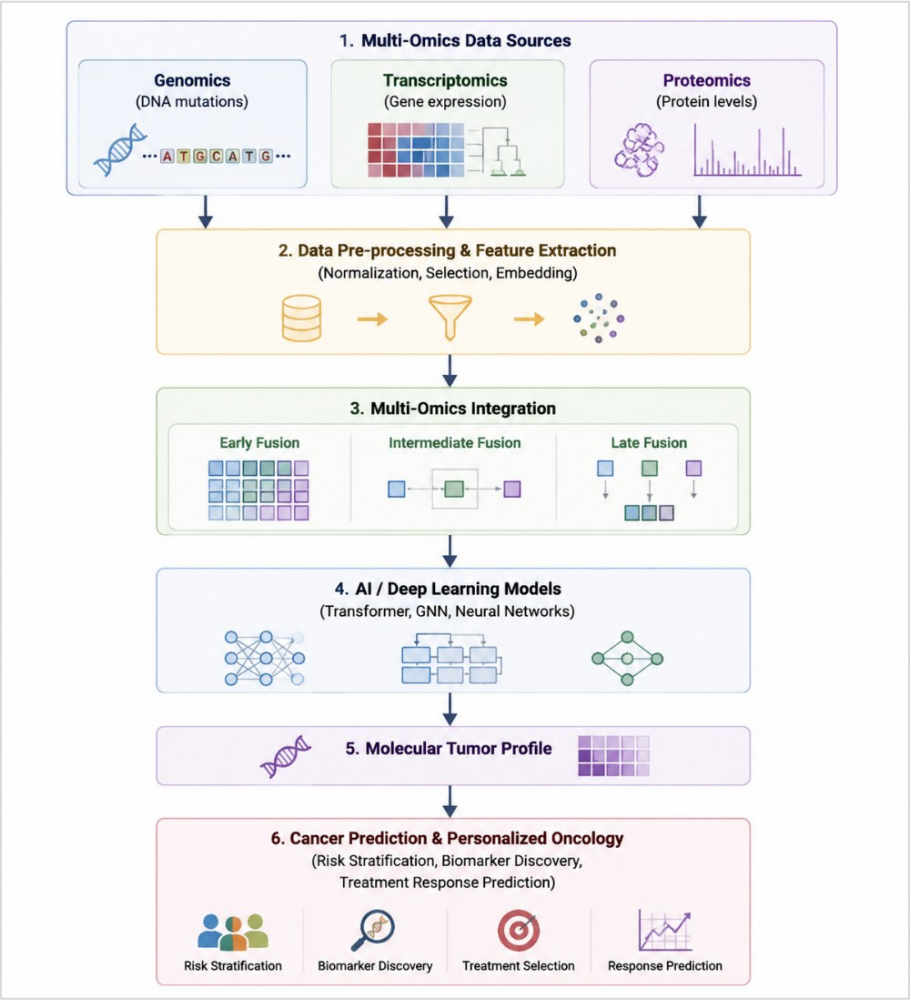

Figure 4. Multi-omics data integration framework using AI approaches for cancer prediction and personalized oncology. The framework combines genomic, transcriptomic, and proteomic information through feature extraction, fusion strategies, and AI-based analysis to generate molecular tumor profiles and clinical predictions.

3. Results

The narrative synthesis of the reviewed literature identified a consistent pattern: multimodal AI is most useful when the combined modalities capture complementary levels of cancer biology rather than duplicating the same information. Imaging contributes spatial and morphological phenotypes, genomic and molecular profiles describe biological mechanisms and tumor heterogeneity, and clinical variables provide patient-specific context. Studies that integrated these domains reported improved risk stratification or prediction compared with individual data streams in ovarian cancer, non-small cell lung cancer, and broader precision-oncology settings [6], [7], [12], [21].

Imaging was the most mature modality across the reviewed applications. CNNs, radiomics, and transformer-based models supported lesion detection, segmentation, tumor characterization, and risk assessment across breast, lung, prostate, brain, colorectal, and skin cancer applications. Radiomics provided structured quantitative descriptors of morphology and heterogeneity, whereas deep networks learned hierarchical representations directly from images. The evidence also indicates that imaging becomes more clinically informative when its features are linked to molecular or clinical variables rather than interpreted in isolation [36], [40], [41], [42], [45], [46], [47].

Genomic and multi-omics studies demonstrated a complementary role by identifying gene-expression signatures, mutations, methylation patterns, copy-number alterations,

and pathway-level relationships associated with cancer subtype, prognosis, and therapeutic response. Deep neural networks, graph neural networks, and transformer-based models were repeatedly used to organize high-dimensional molecular features, while multimodal fusion connected these representations with imaging or clinical data [23], [25], [33], [34], [39], [43], [44], [48].

Clinical information, including EHR-derived variables, demographics, family history, and laboratory measures, provided essential contextual information for patient-level risk estimation. Across the reviewed frameworks, clinical variables were not simply auxiliary inputs; they helped anchor imaging and molecular features to real-world risk and outcome interpretation. This supports the use of multimodal systems for risk-adapted screening and personalized decision support, while also emphasizing the need for complete and standardized clinical data [13], [14], [16].

At the same time, the synthesis revealed recurring barriers to clinical translation. Data heterogeneity, missing modalities, limited sample size, weak external validation, interpretability constraints, and potential bias were repeatedly identified as threats to generalizability. Consequently, the current literature supports multimodal AI as a promising approach rather than a uniformly validated clinical solution, and its performance should be interpreted in the context of dataset quality, fusion design, and validation setting [6], [15], [16], [22], [47].

4. Discussion

These results reinforce the rationale for multimodal AI in early cancer detection: cancer is biologically heterogeneous, and no single modality can adequately represent anatomy, molecular mechanism, and patient context at the same time. The main advantage of multimodal learning therefore lies in complementary information. Imaging may identify a suspicious phenotype, genomic data may explain molecular aggressiveness, and clinical variables may modify prior risk; integrating these layers can produce a more clinically meaningful representation than any one source alone [6], [7], [12], [21].

The findings also indicate that fusion strategy is as important as model choice. Early fusion is straightforward but can be sensitive to differences in scale, dimensionality, and missing values. Intermediate fusion can learn cross-modal representations, while late or decision-level fusion can preserve modality-specific models and may be more practical when data availability varies among patients. Attention-based and transformer architectures provide an additional mechanism for weighting cross-modal relationships, but increased architectural complexity does not automatically guarantee clinical benefit [6], [21], [22], [23], [25].

From a clinical perspective, diagnostic performance alone is insufficient for adoption. Multimodal systems should be evaluated for calibration, reproducibility, robustness across institutions, and external validity, especially because imaging protocols, sequencing platforms, EHR structures, and population characteristics differ between centers. Radiomics research has already shown how acquisition and preprocessing choices can affect feature stability, and similar standardization issues apply to multimodal pipelines [16], [47]. Explainability is equally important because clinicians need to understand which modality and which features contribute to a prediction, particularly in screening and high-stakes treatment decisions [15].

The review further suggests that multimodal AI should be developed as a clinical decision-support layer rather than as an isolated replacement for established diagnostic pathways. The strongest opportunities are likely to arise in risk-adapted screening, ambiguous lesion characterization, molecular subtyping, and identification of patients who may benefit from targeted or immune-based therapies. Evidence from multimodal ovarian and lung cancer studies illustrates the value of combining phenotype and molecular information, but broader prospective multicenter validation is still required before these approaches can be generalized to routine early-detection programs [12], [21].

Future research should therefore prioritize harmonized multimodal datasets, prospective validation, transparent reporting, handling of missing modalities, and

privacy-preserving collaborative learning. Models should also be evaluated for fairness across demographic and clinical subgroups and compared against strong unimodal and conventional clinical baselines. These steps would move the field from proof-of-concept accuracy toward reliable, explainable, and clinically actionable multimodal AI for early cancer detection [13], [16], [22].

5. Conclusion

While multimodal AI systems have great potential for early cancer detection, clinical implementation presents several challenges. Data heterogeneity and scarcity are among the main challenges. Multimodal AI models must combine datasets such as medical imaging, genomic data, and clinical records, which often differ in purpose, format, quality, and acquisition methods. Performance may vary because of differences in imaging devices, clinical practice, and patient populations. Missing clinical information and non-uniform electronic health records (EHRs) can reduce prediction accuracy and undermine AI-driven decision-making.

Another major drawback is model interpretability and explainability. Many sophisticated deep learning and multi-modal models are proposed as 'black box' systems, making it hard for clinicians to understand how they generate predictions. Limited transparency may affect healthcare uptake and clinical trust. Studies on Explainable AI (XAI) that improve model interpretability and provide actionable clinical insights are gaining attention.

Another concern is data privacy and security, as information related to genomes and clinical cases is highly sensitive. Ethical, regulatory, and legal considerations can limit the exchange and sharing of large-scale healthcare information between health institutions. Federated learning and privacy-preserving AI methods offer opportunities by enabling model training without sharing patient data. Still, security, communication efficiency, and trust in the model remain issues to address.

Additionally, AI systems can introduce bias and lack generalizability in real-world clinical practice. Small or non-diverse datasets might not perform well when tested on other ethnic groups, healthcare systems, and disease populations. Dataset imbalance may introduce prediction bias and limit clinical applicability, especially without external validation. Thus, developing accurate, reliable, transparent, and clinically applicable multimodal AI systems for cancer detection requires large-scale, multicenter studies, standardized data collection, and ongoing model evaluation.

The future of multimodal AI systems promises to greatly impact early cancer detection and precision oncology, delivering increasingly precise, personalized, and clinically relevant solutions. New foundation models and transformer networks that can process large-scale multimodal data could enable AI systems to handle multiple data sources like medical images, genomic data, clinical records, and molecular data. These models could uncover relationships among biological and clinical disease characteristics that traditional methods cannot easily detect.

Thus, developing strong, interpretable, and clinically validated AI systems will require future multi-center studies with large patient cohorts and standardized datasets. Adopting explainable AI (XAI) techniques will be crucial to improve transparency and increase confidence in clinician use of AI-assisted decision-making. Additionally, federated learning could help enable collaboration between health care institutions while preserving patient information security.

By combining multimodal AI with real-time clinical workflows, wearable health technologies and personalized medicine platforms could enable earlier cancer detection and ongoing patient monitoring. In addition, using AI prediction alongside molecular profiling may support personalized treatment selection and improve therapeutic response. While the journey from multimodal AI research to clinical applications in healthcare is poised for success, it requires addressing data quality, bias, regulatory concerns, and clinical adoption challenges. In conclusion, multimodal AI has the potential to revolutionize oncology care by enabling earlier detection, advancing precision medicine, and improving patient outcomes.

By combining complementary sources of information, multimodal AI systems have shown promise in integrating imaging data, the genetic makeup of breast cancer, and clinical risk factors. These systems have shown potential to enhance cancer detection and prediction by combining complementary information. They could yield more detailed information than single-modality models; however, their clinical utility will depend on several factors, including data quality, model reliability, interpretability, and external validation. Current research shows strong potential, and continued progress in data integration, explainability, and real-world testing will be essential to make multimodal AI a reliable tool for broader routine clinical use.

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