A Comprehensive Review on Handling Multimodal Data Using Machine Learning Techniques in Healthcare Systems

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***Abstract*—The integration of multimodal data in healthcare systems constitutes one of the most consequential frontiers in contemporary medical informatics. This paper presents a systematic review of frameworks and methodologies developed for handling multimodal healthcare data using Machine Learning (ML) and Deep Learning (DL) techniques, spanning literature from 2020 to 2024. With the proliferation of advanced data acquisition technologies, healthcare environments now generate diverse modalities—Electronic Health Records (EHRs), medical imaging (CT, MRI, PET), genomic sequences, wearable sensor streams, and patient-generated health data—whose convergence holds transformative potential for diagnostic accuracy and personalized treatment. In this work, numerous related frameworks are studied across five thematic clusters: multimodal fusion architectures, federated learning, vision-language foundation models, cancer prognosis with multi-omics, and EHR-driven representation learning. Empirical results consistently demonstrate that multimodal approaches outperform unimodal baselines. It also enumerates open challenges in data fusion, privacy-preserving integration, missing-modality robustness, and interpretability, and propose concrete future research directions toward clinically deployable multimodal AI systems.**

***Index Terms*—Multimodal data, healthcare systems, data fusion, federated learning, vision-language models, EHR, genomics, deep learning, convolutional neural network, transformer, patient outcomes.**

I. INTRODUCTION

The exponential growth in healthcare data volume, variety, and velocity has catalyzed a paradigm shift in clinical informatics. Modern healthcare systems generate structured and unstructured information across an array of modalities—electronic health records (EHRs), medical imaging (X-ray, CT, MRI, PET, ultrasound), genomic and multi-omics profiles, physiological waveforms from wearables, and patient-reported outcomes. The holistic integration of these heterogeneous sources—broadly termed multimodal data fusion—enables richer, contextually complete representations of patient health states that single-modality approaches cannot provide independently [1].

Multimodal machine learning (MML) constitutes the algorithmic and theoretical framework for learning from such heterogeneous inputs. Unlike unimodal methods, MML exploits cross-modal correlations and complementary information to improve generalization, robustness, and interpretability. Machine learning methods in healthcare have traditionally focused on a single modality, limiting their ability to replicate the clinical practice of integrating multiple information sources [5]. Clinicians routinely combine demographic records, laboratory results, vital signs, and diverse imaging modalities to make informed, contextualized decisions—an integrative process that MML seeks to emulate computationally.

The rapid growth of MML publications across healthcare subdomains—oncology, neurology, cardiology, and infectious disease—reflects the field's recognition that multimodal models consistently outperform unimodal baselines when appropriately designed and trained [6], [8]. Nevertheless, systematic integration of multimodal healthcare data remains constrained by challenges including heterogeneous data protocols, missing modalities at inference time, privacy and regulatory constraints (HIPAA, GDPR), and the absence of standardized fusion benchmarks.

This review aims to: (i) categorize principal modalities encountered in clinical practice; (ii) survey state-of-the-art ML and DL architectures for multimodal fusion; (iii) critically evaluate representative frameworks with reported empirical results; and (iv) delineate open challenges and future research directions. The reviewed literature spans 2020–2024 and covers federated learning, vision-language models, transformer-based cross-modal attention, EHR-driven learning, and multi-omics fusion.

Paper Organization

Section II characterizes multimodal healthcare data types. Section III reviews ML and DL methodologies. Section IV presents the extended literature review across thematic clusters. Section V discusses challenges and limitations. Section VI concludes with future directions.

II. MULTIMODAL DATA IN HEALTHCARE

Multimodal healthcare data encompasses any combination of heterogeneous data sources that, when integrated, yield a more comprehensive representation of patient clinical state. Table I summarizes the primary modalities, their characteristics, and associated ML processing techniques.

Modality	Data Type	ML Approach
Clinical / EHR	Structured + free text	NLP, BERT, GBM
Medical Imaging	CT, MRI, PET, X-ray	CNN, ViT, ResNet
Genomics	DNA, RNA, CNVs	AE, GNN, Transformer
Wearables	HRV, SpO2, activity	LSTM, TCN, Bi-LSTM
PGHD	Symptoms, PROs	NLP, RF, Logistic Reg.

Table I. Summary of Healthcare Data Modalities

A. Clinical and EHR Data

Clinical data—encompassing EHRs, laboratory results, physician notes, medication histories, and discharge summaries—forms the foundational layer of patient information. EHRs encode longitudinal patient trajectories, combining structured fields (ICD codes, vital signs) with free-text clinical narratives that require natural language processing (NLP) for full exploitation [7]. AI-driven analytics transform EHRs into precision medicine tools by identifying disease patterns, optimizing treatment plans, and predicting patient outcomes [10].

B. Medical Imaging Data

Medical imaging modalities—including X-ray, CT, MRI, PET, and ultrasonography—constitute the most data-intensive clinical modality. Each encodes distinct physiological information: CT offers high-contrast bone visualization; MRI provides superior soft-tissue differentiation; PET captures metabolic activity. Fusion of complementary imaging modalities can resolve diagnostic ambiguities unresolvable by individual scans, particularly in oncology and neurology applications [2], [9].

C. Genomic and Multi-Omics Data

Genomic and multi-omics data—comprising single-nucleotide polymorphisms (SNPs), copy number variations (CNVs), gene expression (transcriptomics), protein profiles (proteomics), and DNA methylation (epigenomics)—enables personalized medicine by linking molecular markers to disease susceptibility and therapeutic response. Multi-omics integration with imaging data has demonstrated particularly strong performance in cancer prognosis, as molecular and tissue-architecture information encode complementary disease signals [17].

D. Wearable Sensor Data

Wearable devices generate longitudinal physiological streams—heart rate variability (HRV), electrodermal activity (EDA), activity levels, sleep architecture, and SpO2—enabling continuous, out-of-clinic monitoring that complements episodic clinical measurements. When fused with EHR and imaging data, wearable

streams improve chronic disease management models for conditions including atrial fibrillation, diabetes, and depression [14].

E. Patient-Generated Health Data (PGHD)

PGHD encompasses self-reported symptom journals, dietary logs, mental health assessments, and home-monitoring outcomes. It enriches the subjective experiential dimension often absent from clinician-curated records, supporting patient-centered model development and enabling more responsive clinical decision support [14].

III. MACHINE LEARNING METHODOLOGIES

ML architectures for multimodal healthcare data are taxonomized by fusion stage (early, intermediate, late) and learning paradigm (supervised, self-supervised, federated, contrastive). Table II summarizes the primary architectural families.

Architecture	Fusion Stage	Strength
CNN + Bi-LSTM	Intermediate	Image + sequence fusion
Cross-modal Transformer	Intermediate	Long-range dependencies
Federated Learning	Any	Privacy-preserving
Vision-Language (VLM)	Early/Intermediate	Image + text alignment
Graph Neural Network	Intermediate	Relational reasoning
Variational AE / GAN	Latent	Generative synthesis
Contrastive Learning	Latent	Self-supervised alignment

Table II. Multimodal ML Architecture Taxonomy

A. Fusion Strategies

1) Early (Feature-Level) Fusion:

Early fusion concatenates feature representations from individual modalities prior to joint model training. Computationally straightforward, it is sensitive to modality imbalance and requires complete multi-modal observations at training time. Common operators include concatenation, bilinear pooling, and Hadamard product. A scoping review of EHR-imaging fusion studies found early fusion was the most widely adopted technique, appearing in 22 of 34 reviewed studies [7].

2) Late (Decision-Level) Fusion:

Late fusion trains independent unimodal models and combines their predictions via ensemble strategies—majority voting, learned weighted averaging, or Bayesian combination. It is naturally modality-agnostic and handles missing modalities at inference time but sacrifices cross-modal feature interactions [12].

3) Intermediate (Hybrid) Fusion:

Intermediate fusion integrates modality-specific representations at internal network layers, enabling learned cross-modal interactions while preserving modality-specific processing. Transformer-based cross-attention mechanisms exemplify this approach and are increasingly dominant in state-of-the-art systems [5], [18].

B. Deep Learning Architectures

1) Convolutional Neural Networks (CNNs):

CNNs remain the dominant architecture for medical image feature extraction, with DenseNet, ResNet, EfficientNet, and ResNeXt variants providing improved gradient flow and feature reuse critical for limited-label medical settings [2], [9]. CNNs serve as the imaging encoder backbone in the majority of multimodal healthcare pipelines.

2) Recurrent Networks and Bi-LSTM:

LSTM and Bi-LSTM architectures are well-suited for sequential and temporal modalities including clinical time series and clinical narrative text. Bi-LSTM with attention mechanisms has achieved state-of-the-art performance in clinical report processing, achieving accuracy up to 96.42% when paired with CNN-based image encoders [5].

3) Transformer and Vision-Language Models:

Transformers have been extended from NLP to vision (ViT, Swin) and cross-modal tasks. Domain-adapted models such as MedCLIP, BioViL, and BioViL-T use contrastive learning on paired medical image-text data to achieve powerful zero-shot and few-shot clinical capabilities [18], [20]. The self-attention mechanism enables modeling of long-range intra- and inter-modal

dependencies that are critical for radiology report generation and visual question answering.

4) Graph Neural Networks (GNNs):

GNNs model relational structure among clinical entities—patients, diseases, genes, drugs—and are especially valuable when heterogeneous data naturally forms graph-structured representations such as patient similarity networks and knowledge graphs. Recent multimodal GNN frameworks unify EHR, imaging, genomic, and sensor data within attention-based architectures to support clinical prediction and treatment planning [16].

C. Federated and Privacy-Preserving Learning

Federated learning (FL) enables distributed model training across decentralized clinical sites without raw data sharing, directly addressing HIPAA and GDPR constraints. FL frameworks for multimodal settings have introduced modality-specific normalization layers and personalized aggregation strategies to handle heterogeneous imaging protocols across sites [3], [4].

D. Contrastive and Self-Supervised Learning

Contrastive learning methods such as CLIP-style pre-training on image-text pairs have produced powerful cross-modal representations without requiring dense annotations. Medical adaptations (MedCLIP, BioMedCLIP) leverage large-scale image-report corpora from sources such as MIMIC-CXR and PubMed to learn aligned visual and linguistic representations, enabling zero-shot disease classification and report generation [18], [20].

E. Generative Models

VAEs, GANs, and diffusion models are employed for cross-modal synthesis (CT-to-MRI translation), training data augmentation, and missing modality imputation. GAN-based imputation has shown particular utility for reconstructing incomplete EHR datasets with high fidelity [10]. Diffusion models represent the current frontier for text-conditioned medical image synthesis [12].

IV. REVIEW OF LITERATURE

This section reviews twenty representative frameworks organized across five thematic clusters: (A) core multimodal fusion architectures; (B) federated learning; (C) vision-language foundation models; (D) multi-omics and cancer prognosis; and (E) EHR-driven representation learning.

A. Core Multimodal Fusion Architectures

A1. CNN-ELM Hybrid (CELM) [2]:

Kong et al. proposed CELM, integrating an Extreme Learning Machine within a CNN framework for lesion detection across six heterogeneous modality pairs including MR-T2/MR-T1 and CT/MR-T2. The ELM's single-hidden-layer design reduced training complexity while maintaining competitive detection accuracy across all modality combinations, demonstrating the viability of hybrid shallow-deep fusion in clinical image analysis.

A2. Multimodal Deep Fusion of Images and Clinical Reports [5]:

Yao et al. developed a deep fusion model combining CNN-extracted spatial image features with Bi-LSTM-encoded clinical report text via a dedicated cross-modal interaction layer. Evaluated on a target classification benchmark, the model achieved 96.42% accuracy, 98.48% recall, F1-score of 0.97, and IoU of 0.89—demonstrating the substantial benefit of image-text interaction over unimodal processing.

A3. HAIM Framework [6]:

Soenksen et al. proposed HAIM (Holistic AI in Medicine), a general-purpose framework for evaluating multimodal AI on the MIMIC-IV dataset using XGBoost with embedding extraction from arbitrary modality combinations. Systematic ablation studies revealed that: (i) multimodal ensembles consistently outperformed unimodal baselines; and (ii) the relative predictive contribution of each modality varied substantially by clinical outcome—underscoring the necessity of adaptive modality selection strategies.

A4. Dense-ResNet for Multimodal Image Fusion [9]:

Ghosh and Jayanthi introduced an efficient Dense-ResNet architecture specifically designed for fusing multi-modal medical images. By combining the feature-reuse advantages of DenseNet with residual learning from ResNet, the model achieved improved fusion quality for MRI-CT and PET-MRI combinations while maintaining computational

efficiency suitable for clinical deployment on standard GPU hardware [9].

A5. Krones et al. — Multimodal ML Review [5]:
Krones et al. conducted a comprehensive review of multimodal machine learning approaches in healthcare, evaluating data fusion techniques, existing multimodal datasets, and common training strategies with particular emphasis on imaging data. Their analysis revealed that the effectiveness of any fusion method is inherently task-dependent, and that benchmark datasets remain a critical bottleneck: most existing multimodal clinical datasets are small, privately held, and disease-specific, severely limiting generalizability assessments.
A6. Multi-Modal Transformer for Report Generation [20]:
Raminedi et al. proposed a multi-modal transformer architecture pairing a Vision Transformer (ViT) encoder with a GPT-based decoder augmented by retrieval-augmented generation (RAG) for automated radiology report generation from chest X-rays. Published in Scientific Reports (2024), the system achieved state-of-the-art BLEU and ROUGE scores on the MIMIC-CXR benchmark, demonstrating the power of combining visual transformers with language generation for clinical workflow automation [20].

B. Federated Learning for Multimodal Healthcare
B1. FedNorm — Modality-Based Normalization [3]:
Bernecker et al. addressed multi-site, multi-modal liver segmentation under federated constraints, proposing FedNorm algorithms exploiting Modality-based Normalization (MN). FedNorm separates CT and MRI normalization parameters while sharing non-normalization weights across 428 patients, achieving a Dice Similarity Coefficient (DSC) of 96.1% and demonstrating robustness to out-of-distribution acquisition protocols. FedNorm established a new benchmark for privacy-preserving multi-modal organ segmentation.
B2. FedMEMA — Personalized Brain Tumor Segmentation [4]:
Dai et al. introduced FedMEMA, addressing inter-client heterogeneity from missing MRI modalities across clinical sites through site-specific encoders and multimodal anchor embeddings for cross-site distributional alignment. FedMEMA achieved mean DSC of approximately 64% under missing-modal conditions and 84% with full modalities on the server—establishing the importance of anchor-based alignment for personalized federated multimodal learning.
B3. Yan et al. — Multimodal ML in Medical Diagnostics [19]:
Yan et al. conducted a focused review of multimodal machine learning for disease detection published in Mathematical Biosciences and Engineering (2023), analyzing how ECG, imaging, and clinical data are jointly processed for cardiac, neurological, and oncological diagnostics. Their work highlighted that while multimodal models reduce physician workload, the lack of annotated multi-modal clinical datasets—particularly for rare diseases—constrains model generalization and remains a critical barrier to clinical translation [19].

C. Vision-Language Foundation Models
C1. BioViL-T — Temporal Chest X-Ray Analysis [18]:
BioViL-T (Biomedical Vision-Language model with Temporal modeling), accepted at CVPR 2023, is a domain-specific model for joint chest X-ray and radiology report analysis. It employs a hybrid encoder combining a Vision Transformer with a ResNet-50 backbone to extract spatiotemporal image features, jointly trained with a clinical text encoder via multi-modal contrastive learning. BioViL-T demonstrated superior performance on phrase grounding and disease progression tracking tasks on the MS-CXR benchmark, showing that temporal modeling is critical for radiology report interpretation [18].
C2. MedCLIP and BioMedCLIP [18]:
MedCLIP applies contrastive language-image pre-training to medical image-text pairs from MIMIC-CXR using BioClinicalBERT for text encoding and ViT for imaging. BioMedCLIP extends this paradigm with PubMedBERT and a larger training corpus of biomedical image-text pairs from PMC. Both models achieve strong zero-shot disease classification and support downstream tasks including visual question answering (VQA) and report grounding without task-specific fine-tuning [18].
C3. Multimodal LLMs in Medical Imaging [21]:
A comprehensive PMC review of multimodal large language models (MLLMs) in medical imaging surveyed architectures including LLaVA-Med, BiomedGPT, and CheXagent. The review identified

that domain adaptation through medical image-text pre-training is critical for clinical applicability, and that frozen encoder approaches with lightweight adapters (Q-Former, LLaMA-Adapter) offer parameter-efficient routes to multimodal clinical capability. Key unresolved challenges include hallucination in generated reports and the gap between benchmark performance and real-world clinical reliability [21].

D. Multi-Omics and Cancer Prognosis

D1. MultiSurv — Pan-Cancer Survival Prediction [17]:

Vale-Silva and Rohr proposed MultiSurv, a multimodal deep learning method for long-term pan-cancer survival prediction using six data modalities: clinical, imaging (histopathology), and four omics streams (copy number variation, gene expression, miRNA, DNA methylation). Each modality is handled by a dedicated submodel (ResNeXt-50 for imaging; fully-connected networks for omics) outputting 512-dimensional feature vectors, which are fused via attention-weighted aggregation. MultiSurv was evaluated on The Cancer Genome Atlas (TCGA) and demonstrated that multi-omics models substantially outperformed clinical-only baselines, and that tissue imaging encodes complementary information not captured by bulk omics data [17].

D2. Steyaert et al. — Cancer Biomarker Discovery [14]:

Steyaert et al. proposed a multimodal data fusion framework for cancer biomarker discovery published in Nature Machine Intelligence (2023), integrating histopathology whole-slide images (WSI) with multi-omics profiles. Their framework demonstrated that fusion of morphological and molecular modalities improves cancer subtype classification and biomarker identification, and applied ablation analyses to quantify individual modality contributions—providing a systematic methodology for assessing multimodal benefit in high-stakes oncological settings [14].

D3. Stahlschmidt et al. — Multimodal Deep Learning for Biomedical Data Fusion [14]:

Stahlschmidt, Ulfenborg, and Synnergren published a structured review in Briefings in Bioinformatics (2022) of deep learning methods for biomedical data fusion, covering imaging, omics, clinical time series, and text. Their taxonomy distinguishes early, late, and mixed fusion approaches and evaluates their applicability across disease domains. They identify co-training and multi-task learning as underexplored paradigms that may substantially improve cross-modal generalization in data-scarce biomedical settings [14].

E. EHR-Driven Multimodal Representation Learning

E1. Mohsen et al. — AI Methods for EHR-Imaging Fusion [7]:

Mohsen et al. conducted a scoping review of AI-based methods for fusing EHRs with imaging data (arXiv:2210.13462, 2022), analyzing 34 studies. Key findings: multimodal fusion models consistently outperformed single-modality models; early fusion was most common (22/34 studies); neurological disorders dominated (16 studies); and conventional ML models were more prevalent than DL despite DL's growing performance advantage. The majority of included studies relied on private datasets, limiting reproducibility and external validation [7].

E2. Multimodal GNN in Healthcare — Frontiers Review [16]:

A 2025 Frontiers in Artificial Intelligence review surveyed multimodal GNN frameworks across healthcare domains, documenting how GNNs unify EHR, imaging, genomics, and wearable sensor data within graph-structured learning. The review found that knowledge-graph-augmented GNNs—integrating structured EHR (diagnoses, procedures, medications, vitals) with clinical notes (BioBERT-encoded) and imaging (CNN-encoded)—achieved the strongest performance for clinical prediction and treatment optimization tasks, particularly in ICU outcome forecasting and ER triage [16].

E3. Barua et al. — Systematic Review on MML [14]:

Barua, Ahmed, and Begum published a systematic literature review on multimodal machine learning in IEEE Access (2023), covering applications, challenges, gaps, and future directions across 200+ publications. The review identified that the fusion of translation, alignment, and co-learning techniques—rather than fusion alone—represents the most promising future direction, and that co-learning (handling noisy or missing modalities through cross-modal regularization) remains a substantially underdeveloped area particularly relevant to clinical settings where sensor dropout and incomplete records are endemic [14].

E4. Ahmed et al. — Big Data Analytics for Healthcare [8]:
Ahmed et al. surveyed frameworks, implications, applications, and impacts of big data analytics in healthcare in IEEE Access (2023), providing a comprehensive landscape of infrastructure approaches for multimodal data at scale. The survey highlighted that efficient data management strategies—including federated data lakes, edge computing for wearables, and privacy-preserving aggregation pipelines—are essential prerequisites for operational deployment of multimodal ML systems in resource-constrained healthcare environments [8].

V. CHALLENGES AND LIMITATIONS

Despite significant progress documented across the reviewed literature, several fundamental challenges constrain the clinical deployment of multimodal ML systems. Table III summarizes key challenges and potential mitigation strategies identified across the reviewed works.

Challenge	Impact	Mitigation
Data Heterogeneity	Reduced fusion quality	Modality-specific encoders
Missing Modalities	Inference failure	Generative imputation
Privacy / HIPAA	Data sharing limits	Federated learning
Label Scarcity	Limited supervision	Self-supervised pre-training
Interpretability	Low clinical trust	Attention viz., SHAP
Compute Cost	Deployment barrier	Quantization, pruning

Table III. Challenges and Mitigation Strategies

A. Data Heterogeneity and Missing Modalities

Real-world clinical datasets exhibit substantial heterogeneity in acquisition protocols, sensor types, and temporal resolution. Complete multimodal observations are rarely available at inference time—patients may lack genomic data or specific imaging sequences. Models must be designed to gracefully degrade under missing modalities [4], [11]. The scoping review by Mohsen et al. found that the majority of existing studies do not report missing-modality robustness metrics, representing a critical gap in the literature [7].

B. Data Privacy and Regulatory Compliance

Aggregation of imaging, genomic, and behavioral data amplifies re-identification risks beyond conventional anonymization. Federated learning and differential privacy offer partial mitigations, but tension between privacy guarantees and model utility remains active [3]. Most multimodal datasets reviewed by Mohsen et al. were from private repositories, highlighting the urgent need for standardized, privacy-preserving public benchmarks [7].

C. Label Scarcity and Annotation Cost

Supervised training of deep multimodal models requires large annotated datasets, but clinical annotation is expensive, time-consuming, and requires specialist expertise. Self-supervised contrastive learning approaches (MedCLIP, BioViL-T) partially address this by learning from unannotated image-text pairs, but their performance on rare disease classes with limited positive examples remains limited [18].

D. Computational and Storage Scalability

Processing high-resolution volumetric images alongside genomic and longitudinal sensor data demands substantial GPU memory and I/O bandwidth. Ahmed et al. emphasize that efficient data management strategies—including federated data lakes and edge computing—are essential prerequisites for operational clinical deployment [8]. Model compression techniques (pruning, quantization, knowledge distillation) offer complementary pathways to deployment on resource-constrained infrastructure.

E. Interpretability and Clinical Trust

Deep multimodal models are inherently opaque. Post-hoc explainability methods (Grad-CAM, SHAP, attention visualization) provide partial insights but do not fully address the need for causally interpretable, auditable clinical decision support. MLLM reviews note that hallucination in generated clinical reports—where models produce plausible but factually incorrect statements—poses a patient safety risk that

current evaluation benchmarks inadequately capture [21].

F. Fusion Architecture Design Space

The multimodal fusion design space—choice of fusion stage, interaction mechanism, loss function, and modality weighting—is vast and poorly characterized. Barua et al. identify co-learning (cross-modal regularization with noisy or missing modalities) as a substantially underexplored direction that may yield robust fusion in clinical settings where sensor dropout and incomplete records are endemic [14].

VI. CONCLUSION AND FUTURE DIRECTIONS

This paper has presented an extended review of multimodal data integration in healthcare systems, spanning data modality taxonomy, ML/DL fusion methodologies, and twenty representative frameworks across five thematic clusters: core fusion architectures, federated learning, vision-language foundation models, multi-omics cancer prognosis, and EHR-driven representation learning. The reviewed literature collectively demonstrates that multimodal approaches consistently and substantially outperform unimodal counterparts across diagnostic, segmentation, and prognostic tasks.

Key observations from the review are as follows. First, federated learning with modality-specific normalization (FedNorm, FedMEMA) enables privacy-preserving multi-site training with competitive Dice scores exceeding 84–96% on segmentation benchmarks. Second, vision-language foundation models (BioViL-T, MedCLIP, BioMedCLIP) enable powerful zero-shot clinical capabilities through contrastive pre-training on image-report pairs. Third, multi-omics fusion with imaging (MultiSurv, Steyaert et al.) demonstrates that molecular and morphological modalities encode complementary signals critical for cancer prognosis. Fourth, existing work remains predominantly focused on imaging-clinical combinations, with genomic, wearable, and PGHD modalities underrepresented—particularly in fusion with imaging data.

Future research directions should prioritize: (i) development of clinical multimodal foundation models analogous to GPT-4V, trained on large-scale heterogeneous clinical corpora with medical supervision; (ii) robust missing-modality handling through generative imputation and modality-dropout training; (iii) underlying multimodal inference frameworks that untie confounding from genuine cross-modal relationships; (iv) standardized multimodal benchmarks beyond TCGA and MIMIC-IV encompassing genomics, wearables, and PGHD; and (v) prospective clinical validation studies assessing real-world impact on diagnostic accuracy, treatment adherence, and patient outcomes. Co-learning—leveraging noisy and incomplete modalities through cross-modal regularization—remains a substantially underexplored avenue that could substantially improve robustness in real-world clinical environments [14].

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