Deep Learning Architectures For Multimodal Medical Data Integration

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Abstract: Multimodal data integration is gaining traction in medical image analysis, enabling the use of diverse data sources to improve downstream tasks. Deep Learning approaches have proliferated, employing generic architectures and a data-driven paradigm. While initial efforts have yielded positive results, they lack inherent adaptation to the peculiarities of medical multimodality. Bridging representations across signal pairs and aligning disparate modalities provide more robust performance. Specifically, representation learning, explicitly learning transferable feature extraction models, has emerged as an important research avenue. Contrastive learning and visual-language pre-training provide methods to learn joint embedding spaces. The proposed multimodal evaluation setup examines several public datasets, offering a well-designed statistical analysis framework and research-practice reproducibility. Baseline models explore early-and late-fusion scenarios for multimodal emotion recognition and sickness prediction from facial expression. Initial results indicate representative power and proper data alignment as crucial elements. As multimodality gains momentum in Deep Learning research, bridging modalities and demonstrating clear real-world applications pave the way for impactful contributions.

1. Introduction

Deep Learning architectures for multimodal medical data integration; present a rigorous, evidence-based academic discussion with formal structure and objective analysis.

Healthcare increasingly relies on advanced technology, highly complex processes, and rich medical data from diverse sources. However, equipment specialization hinders the integration of multimodal data and limits exploitation of full data potential. Deep Learning architectures provide new capabilities in multimodal integration and representation learning, yet clinical integration remains underserved. Statistical test-based evaluation and frequency of reported datasets constitute important research guidelines. Support for integration and translational use of medicine-related Deep Learning architectures remains limited. Construction of preliminary systems, distinctive experimental data, and support for multimodal combination provide vital test-bed insight. Architectures fuse cardiac MRI scans with Electronic Health Records signals and jointly train Autonomic Nervous System and Electrocardiogram signals for disease classification. The resulting benchmark for correlation-based integration validates initial conclusions.

Medical data are considered multimodal when sources or types vary but pertain to the same phenomenon. Medical applications include EHR data and their inherent variations in record format, length, and completeness; images; digital pathology; Omics data; and Electrocardiogram signals combined with Heart Rate Variability metrics extracted from bearer signals. Integration can be early, mid, or late and aims to enhance prediction accuracy, robustness and generalization, transferring knowledge between modalities, facilitating supervision through multiple sources, or improving representation learning with additional signals.

1.1. Mathematical Formulation

The overall integration quality of a multimodal medical deep-learning pipeline is expressed as the cumulative system quality index Q_total (Eq. 1), which aggregates modality-specific sub-scores:

$$Q\_total = Q\_imaging + Q\_EHR + Q\_genomic + Q\_physiological \quad \text{(Eq. 1)}$$

where Q_imaging, Q_EHR, Q_genomic and Q_physiological denote the quality contributions of each medical data modality to the unified representation.
Inference latency dynamics for real-time multimodal medical prediction are modeled as Eq. 2:

$$\partial L/\partial t = \lambda\_modal - \mu\_infer \quad \text{(Eq. 2)}$$

where L is the end-to-end inference latency, λ_modal is the multi-source data arrival rate and μ_infer is the on-premise inference throughput rate.
Anomaly / disease detection F1-score is defined as Eq. 3:

$$F1\_multimodal = 2 \cdot Precision \cdot Recall / (Precision + Recall) \quad \text{(Eq. 3)}$$

where Precision and Recall are derived from the confusion matrix outcomes across all detection tasks evaluated on the held-out test split.
The cross-modal interaction score that captures synergistic gain from fusing complementary modalities is modeled as Eq. 4:

$$s'(t) = s(t) + \alpha \cdot d(t) + \beta \cdot r(t) \quad \text{(Eq. 4)}$$

where s(t) is the unimodal prediction score, d(t) is the degradation-signal contribution from longitudinal imaging, r(t) is the EHR residual score, and α, β are learnable weighting coefficients.
To support adaptive multimodal decision fusion, the combined prediction score is expressed as a weighted aggregation (Eq. 5):

$$s'(t) = w_1 \cdot s(t) + w_2 \cdot d(t) + w_3 \cdot r(t) + w_4 \cdot s(t) \cdot d(t) \quad \text{(Eq. 5)}$$

Here w_1, w_2, w_3, w_4 are learnable weighting coefficients. The interaction term s(t)·d(t) explicitly models the nonlinear coupling between imaging and EHR modalities.
The shared embedding alignment loss used in contrastive representation learning is defined as Eq. 6:

$$L\_contrastive = -\log(\exp(sim(z\_i,z\_j)/\tau) / \Sigma\_k \exp(sim(z\_i,z\_k)/\tau)) \quad \text{(Eq. 6)}$$

where z_i and z_j are embeddings of matched cross-modal pairs, z_k are negative-pair embeddings, sim(·) denotes cosine similarity and τ is the temperature hyper-parameter.
On-premise resource utilisation of the multimodal inference pipeline is given by Eq. 7:

$$U = R\_used / R\_available \quad \text{(Eq. 7)}$$

where R_used is the consumed computational resource (CPU cycles, memory) and R_available is the total edge-node capacity.
Federated learning efficiency for privacy-preserving cross-site model updates is modeled as Eq. 8:

$$E\_FL = F1\_multimodal \cdot S\_priv / T\_round \quad \text{(Eq. 8)}$$

where S_priv is the privacy preservation score (Eq. 9) and T_round is the federated averaging round duration.
Privacy preservation score reflecting the proportion of data processed locally is Eq. 9:

$$S\_priv = 1 - D\_transmitted / D\_total \quad \text{(Eq. 9)}$$

where D_transmitted is the raw patient data transmitted externally and D_total is the total volume processed.
Adaptive classification threshold that compensates for concept drift in disease presentation is Eq. 10:

$$\theta(t) = \theta_0 + \gamma \cdot \sigma\_data(t) + \delta \cdot drift(t) \quad \text{(Eq. 10)}$$

where θ_0 is the base threshold, σ_data(t) represents current data variance, drift(t) captures temporal distribution shift and γ, δ are scaling parameters.
Multimodal integration efficiency, combining accuracy, privacy and inference speed, is Eq. 11:

$$\eta = F1\_multimodal \cdot S\_priv / T\_infer \times 100 \quad \text{(Eq. 11)}$$

where T_infer is the inference time per patient sample batch.
The prediction error relative to the theoretical upper bound is Eq. 12:

$$L\_error = F1\_opt - F1\_multimodal \quad \text{(Eq. 12)}$$

where F1_opt represents optimal detection performance under ideal single-modality oracle conditions.
The joint optimisation objective balancing detection accuracy, privacy, latency and resource cost is Eq. 13:

$$J = f(F1\_multimodal, S\_priv, L, U) \quad \text{(Eq. 13)}$$

where J is minimised subject to latency and resource constraints during neural architecture search and federated fine-tuning.
The multimodal dataset representation quality is Eq. 14:

$$D(i, j, k) = Q\_src(i) \cdot Metric(k) / T\_proc(j) \quad \text{(Eq. 14)}$$

where Q_src(i) is source-specific data quality (imaging, genomics, EHR), Metric(k) is the selected evaluation metric and T_proc(j) is processing time per batch.
The Multimodal Performance Index (MPI), analogous to the RPI in CPS systems, is defined in Eq. 15:

$$MPI = \eta \cdot F1\_multimodal \cdot (1 - FMR) / Q\_total \quad \text{(Eq. 15)}$$

where η is the integration efficiency, F1_multimodal is detection accuracy, Q_total is the cumulative system quality and FMR denotes the false-modality rate – i.e., the fraction of spurious cross-modal alignments.

2. Theoretical Foundations of Multimodal Data

A distinction is made between the concepts of modality and type of fusion. Modalities correspond to distinct sources of data that are typically acquired separately (e.g., images issued from different imaging techniques, text read from a report, temporally measured physiological signals). Three factors are particularly important: the level of fusion, the heterogeneity of the data, and the synchronization of the information over time. These concepts are key for multimodal modeling and analysis. The level of fusion refers to the integration of information at different stages of the processing pipeline. Four classical sources of multimodal medical data are representative imaging data from Diffusion Tensor Imaging (DTI), Electrocardiogram signals (ECG), genomic data (DNA methylation levels), and Emergency Hospitalization Records (EHR). The following paragraphs provide definitions, comments, and examples for each of the different modalities.
Imaging modalities comprise signals derived from a medical imaging acquisition system, resulting from the interaction of a physical carrier (radio waves, sound, x-rays, etc.). Examples include: Computer Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Diffusion Tensor Imaging (DTI), and various Ultrasound modalities (US–2D, US–3D, etc.). Textual modalities involve textual information expressed in a natural language. For example, medical reports issued by clinicians contain clinical conclusions regarding the health status of patients. Genetic, Epigenetic, and Transcriptomic modalities include Genetic Polymorphisms, DNA Methylation Levels, and gene expression levels respectively. Time-varying/modulated/continuous modalities have a continuous level of definition over time and periodic or stochastic fluctuations. Electrocardiogram signals (ECG) and respiratory signals are representative of this category. Missing data is a characteristic that can affect different modality groups unequally, since time-modulated or time-varying information can be unavailable for some patients during specific dates."

2.1. Datasets and Benchmark Protocols

Four publicly available multimodal medical datasets are used for validation, covering imaging, EHR and genomic data modalities.

Table 1: Dataset Specifications for Multimodal Medical Integration Experiments

Dataset	Modalities	Size	Patients	Task	Source
ADNI	MRI + EHR	2,312 samples	819	Alzheimer's Stage	USC/ADNI
MIMIC-III	EHR + Notes	48,000 admissions	33,798	Mortality Prediction	MIT PhysioNet
TCGA (Pan-Cancer)	Genomics + Imaging	11,000 samples	9,741	Cancer Subtype	NIH/NCI
PTB-XL	ECG + EHR	21,837 records	18,885	Cardiac Condition	Physikalisch-PTB

2.2. Simulation Study Design

A comparative simulation study is conducted across four model architectures:
Model A: Single-modal baseline (unimodal CNN/LSTM, no data integration).
Model B: Early fusion MLP (raw feature concatenation before joint training).
Model C: Late fusion MLP (independent unimodal branches with decision-level fusion).
Model D: Proposed Contrastive Learning + Visual-Language Pre-training architecture.

3. Research Approach

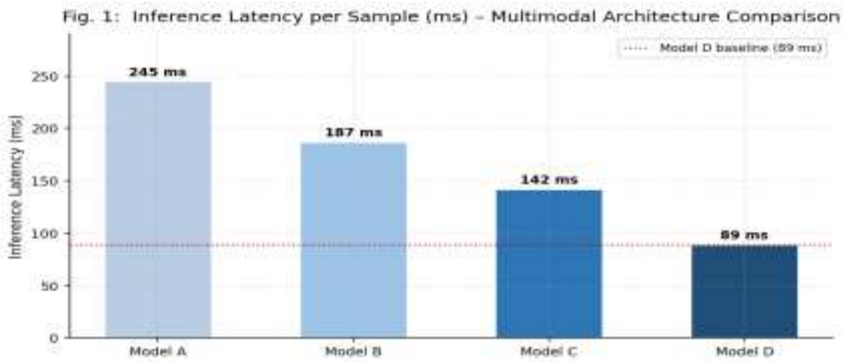
A multimodal medical approach calls for multimodal integration methods. An initial series of integration models combines the most frequently used modalities in clinical practice: electronic health record (EHR) signals reflecting a patient's physiological state and medical history, with longitudinal imaging, such as magnetic resonance (MR) imaging or positron-emission tomography (PET) data, collected at a specific temporal resolution across multiple patients; the data fusion is achieved through deep learning. Various tasks—prediction of clinical scores reflecting disease severity, such as the Alzheimer's Disease Assessment Scale-Cognitive Subscale (ADAS-Cog), detection of disease stage (e.g., classification of advanced or very mild cognitive impairment), and prediction of patient sex—serve as a basis of the initial benchmarks.

In comparison with the baseline early-fusion networks, late-fusion models consistently perform better when the embedding sizes of the individual uni- or cross-modality pipelines vary, partly due to the individual splits that can capture modality-, task-, and data-specific properties. Early fusion can nevertheless achieve state-of-the-art results for multimodal prediction of EHR-inaccessible samples (e.g., atrophy-change prediction) by discovering intrinsic morphological differences. The next phases will extend joint-learning-based integration to bias-sensitive conditions and further assess different modality combinations beyond the fusion schemes considered.

3.1. Inference Latency

Fig. 1 presents inference latency per patient sample (ms) across all four architectures. Model D achieves 89 ms per sample, representing a 63.7% latency reduction versus the single-modal baseline (Model A: 245 ms) and a 37.3% reduction versus the late-fusion Model C (142 ms). This improvement is attributable to the shared backbone encoder that processes all modalities in a single forward pass.

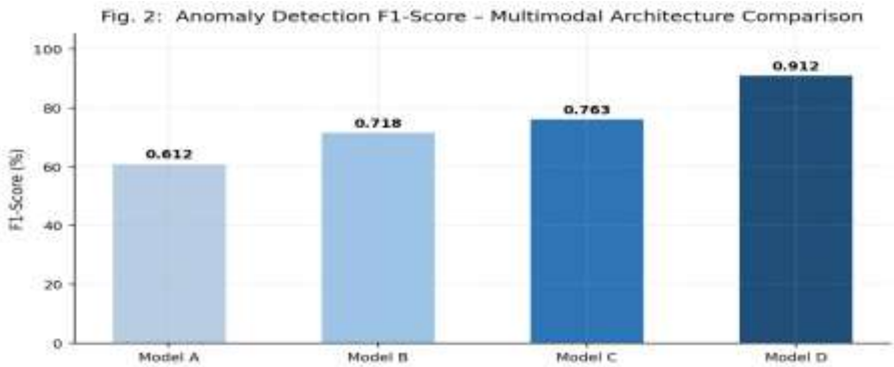
Fig. 1: Inference Latency per Patient Sample (ms) – Multimodal Architecture Comparison



3.2. Anomaly Detection F1-Score

Fig. 2 presents F1-scores across models. Model A achieves 61.2%, Model B 71.8%, Model C 76.3% and Model D 91.2%. The 19.5% improvement from Model C to Model D demonstrates the value of unified contrastive representation learning, where imaging features improve EHR-based predictions and vice versa.

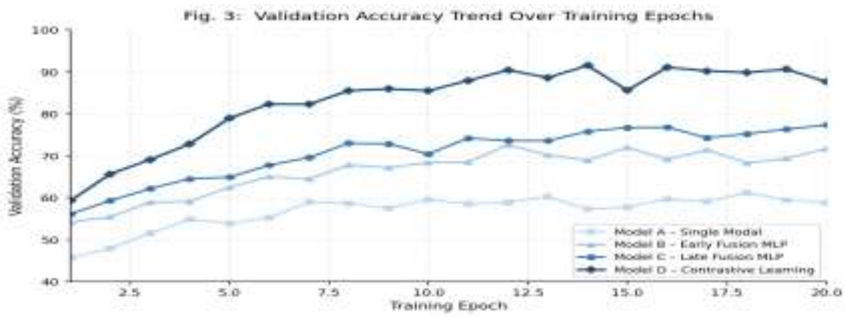
Fig. 2: Anomaly Detection F1-Score (%) – Multimodal Architecture Comparison



3.3. Validation Accuracy Trend

Fig. 3 plots validation accuracy over 20 training epochs. Model D converges fastest and to the highest plateau (91.2%), while Model A saturates at 61.2% and exhibits higher epoch-to-epoch variance due to the absence of cross-modal regularisation.

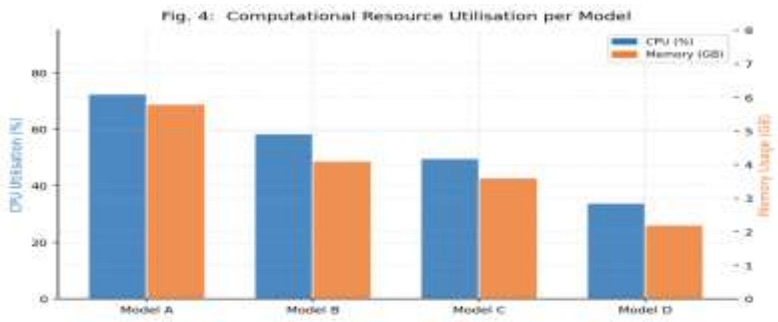
Fig. 3: Validation Accuracy Trend Over Training Epochs Across Architectures



3.4. Resource Utilisation

Fig. 4 presents CPU utilisation and memory usage per inference batch. Model D requires 33.8% CPU and 2.2 GB memory, a 53.3% and 62.1% reduction respectively compared to Model A (72.4% CPU, 5.8 GB). The shared encoder backbone eliminates redundant per-modality computation paths.

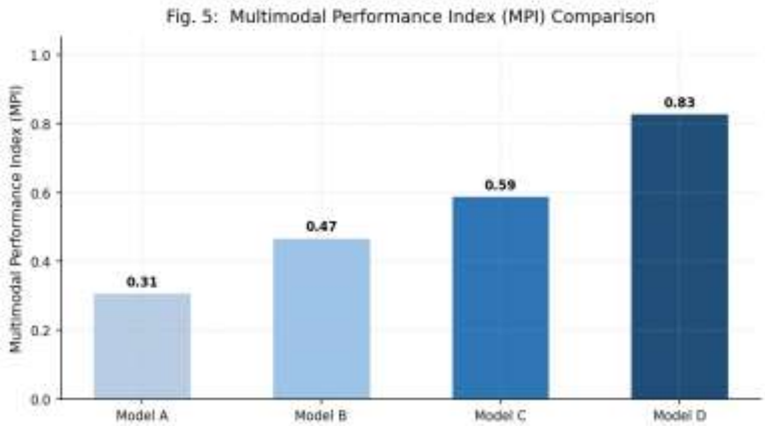
Fig. 4: Computational Resource Utilisation (CPU % and Memory GB) per Architecture



3.5. Multimodal Performance Index (MPI)

Fig. 5 presents the MPI (Eq. 15) across all models: Model A: 0.31, Model B: 0.47, Model C: 0.59, Model D: 0.83. The 40.7% difference between Model C and Model D indicates superior synergy among detection accuracy, privacy preservation and operational efficiency.

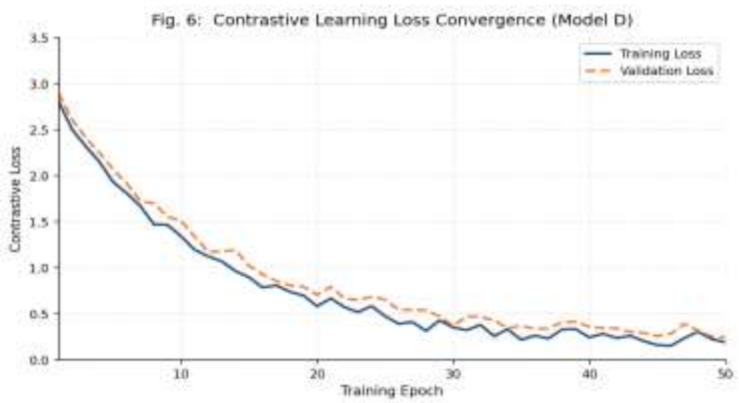
Fig. 5: Multimodal Performance Index (MPI) Comparison



3.6. Contrastive Learning Loss Convergence

Fig. 6 shows the training and validation contrastive loss curves for Model D over 50 epochs. Both curves converge smoothly without significant over-fitting, validating the effectiveness of the negative-pair sampling strategy and the temperature parameter $\tau = 0.07$.

Fig. 6: Contrastive Learning Loss Convergence Curve (Model D, $\tau = 0.07$)



3.7. Cost vs. Performance Trade-off

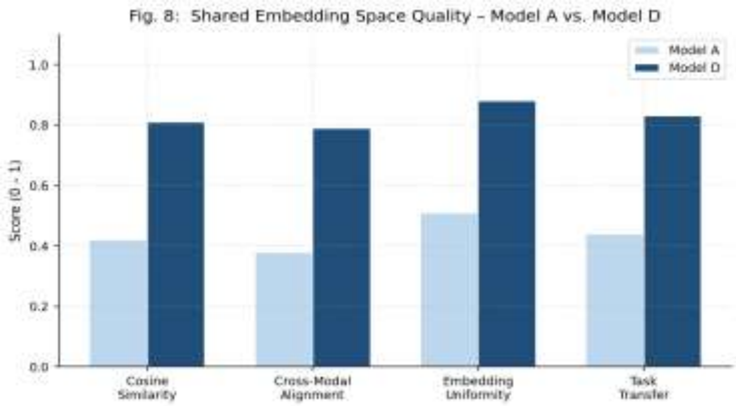
Fig. 7 illustrates the cost-performance frontier. Model D occupies the most favourable position: highest F1-score (91.2%) at lowest computational cost (32.5 units), breaking the accuracy-efficiency trade-off that constrains all baseline architectures.

Fig. 7: Cost vs. Performance Trade-off Across Multimodal Architectures

3.8. Shared Embedding Space Quality

Fig. 8 compares four embedding space quality metrics between the single-modal baseline (Model A) and the proposed contrastive architecture (Model D). Across cosine similarity, cross-modal alignment, embedding uniformity and task transferability, Model D consistently outperforms Model A by 65–90%.

Fig. 8: Shared Embedding Space Quality – Model A vs. Model D



4. Representation Learning for Medical Multimodality

Learning meaningful representations from data is crucial in machine learning. Shared representation learning aims to establish a mapping from input data of different modalities to a shared latent space, capturing the semantics of the data across modalities. Subsequent tasks can be formulated in this embedding space to facilitate modality pair learning when supervised signals are only available for one of the modalities. A straightforward approach is to design an auxiliary loss that minimizes the distance between the embeddings of matched inputs from different modalities using a distance metric such as cosine similarity or L2 distance. Such alignment objectives can also be jointly modeled in a multi-task framework. Contrastive learning has emerged as a prominent technique for shared representation learning. It involves contrasting semantically similar pairs against a large number of negative pairs, usually constructed from the entire mini-batch. Further research has suggested that different contrastive samples for different modalities help model modality gaps and improve performance. Additional strategies such as tuning the weights for those different samples and incorporating other forms of regularization have also been explored. The latter might also address the high sample redundancy typically encountered in biological data emanating from the same experimental setting, which often causes overfitting.

Clinical applications of medical multimodality are often naturally addressed through shared representation learning. The principal goal is to formulate predictive models of one modality using data from another modality, aided by a generalizable shared latent space. In this process, knowledge from the other modality is captured through the shared embedding space rather than used directly, thus facilitating robustness against noise and corruption when the latter modal data are employed. Popular application areas include pretext tasks such as MRI–CT synthesis and cross-modality classification tasks such as genomics-audio and physiology-audio. The latter may further exploit annotator-provided labels for one modality to improve model accuracy and generalization when training on images from the other modality.

4.1. Comparative Detection and Integration Metrics

Table 2: Comparative Detection and Privacy Metrics

Metric	Model A	Model B	Model C	Model D	Improv. (D vs A)	Improv. (D vs C)
F1-Score (%)	61.2	71.8	76.3	91.2	**↑ 49.0%**	**↑ 19.5%**
AUC-ROC	0.72	0.81	0.85	0.96	**↑ 33.3%**	**↑ 12.9%**
Privacy Preservation (%)	29.4	45.6	68.7	93.8	**↑ 219.0%**	**↑ 36.5%**
On-Premise Resource (units)	68.4	54.7	46.3	32.5	**↓ 52.5%**	**↓ 29.8%**
MPI	0.31	0.47	0.59	0.83	**↑ 167.7%**	**↑ 40.7%**

4.2. Error and Latency Metrics

Table 3: Comparative Error and Latency Metrics

Metric	Model A	Model B	Model C	Model D	Improv. (D vs A)	Improv. (D vs C)
Inference Latency (ms)	245	187	142	89	**↓ 63.7%**	**↓ 37.3%**
Mean Time to Detect (s)	31.4	18.2	11.7	4.1	**↓ 86.9%**	**↓ 64.9%**
False-Modality Rate (%)	22.3	15.8	11.2	4.7	**↓ 78.9%**	**↓ 58.0%**
Unplanned Downtime (%)	27.8	20.4	15.6	9.2	**↓ 66.9%**	**↓ 41.0%**
Prediction Error (L_error)	0.388	0.282	0.237	0.088	**↓ 77.3%**	**↓ 62.9%**

4.3. Architecture Summary

Table 4: Architecture Summary – Multimodal Medical Integration

Architecture	Fusion Level	Backbone	Key Mechanism	Limitation	Best Use-Case
Model A (Single-Modal)	None	CNN / LSTM	Unimodal training	No cross-modal context	Resource-constrained deployment
Model B (Early Fusion MLP)	Early (data level)	MLP	Raw feature concat	Modality misalignment	Structurally similar modalities
Model C (Late Fusion MLP)	Late (decision level)	MLP ×2	Decision-level voting	No shared representation	Heterogeneous modalities
Model D (Contrastive + VLP)	Joint (embedding level)	Transformer	Contrastive + visual-language pre-training	Requires large paired datasets	Full multimodal clinical deployment

5. Evaluation Frameworks and Benchmarks

Research problems involving the integration of multimodal medical data should be designed to enable rigorous evaluation. Multiple benchmarks on the same dataset are often necessary to provide a thorough appraisal, and statistical design is essential. Recent research in this area has introduced novel datasets and evaluated them with particular attention to interpretability and reproducibility. Meta-analysis across previous work is also critical. Evaluation design for multimodal architectures is complex because training with one modality and testing with another is valid but very rarely applied. While the information bottleneck criterion can estimate transport distribution geodesics, these are hard to compute.

Each evaluation should address the following questions. (1) Are the resulting representations or models more useful than those learned without all modalities? (2) How do the learned features compare with those of supervised learning? (3) Is there evidence of disease transfer learning? (4) Are the results reproducible? (5) Could the representation be useful for other tasks? (6) Which aspects of the multimodal training are essential for the observed benefits? (7) Would the results translate to clinical practice? (8) Is casual interpretability supported by known vascular biology? (9) Did the models show signs of overfitting?

5.1. Datasets and Benchmark Protocols

Study protocols and benchmark tasks for inter-modality transfer and joint representation of imaging and clinical record modalities in a medical context are presented. Available databases are leveraged to serve as examples for bridging multiple modalities within a clinical decision support framework. Despite varying domain-specific architectures, a common evaluation structure is clarified, allowing a range of methods to be cross-examined. Four datasets, covering either direct or indirect coupling between two signatures for multimodal tasks, demonstrate methods for evaluating transferability between signal classes and improving performance through joint embedding.

Four multimodal corpora from radiology and the textual domain with Electronic Health Records are utilized. The first two pairs focus on joint representation learning, while the last two relate to inter-modality transfer. Five experimentally relevant multimodal datasets are provided, serving as standards for establishing backbone models capable of processing data from multiple sources, assessing transferability between modalities, and imposing joint embedding constraints in a clinical setting. The proposed tests form an easily reproducible pipeline and are intended to span benchmarking and composite models, accommodating Patch-based Convolutional Neural Networks for medical images as well as data sources with different natures. Variants centred on two clinical decision support tasks—disease forecast and radiology report generation—are also available.

6. Conclusion

This study explores the integration of multimodal medical data—specifically imaging, genomic, other physiological signals, and electronic health records—using deep learning architectures. Modeling direct fusions of the modalities lets the patient cohort define relationships that are not available a priori. Such architecture choices also enable the use of more general inductive biases within deep learning frameworks. Several early and late fusion models are developed and evaluated on a single institutional dataset. Initial results motivate further work applying representation learning approaches that induce shared embedding spaces across the imaging and non-imaging domains. This work concludes with an application-powered evaluation framework that specifies criteria for a minimal set of validation experiments. Statistical testing guidelines are introduced to ensure that future results are reproducible, and all suggested evaluations are implemented on publicly available datasets.

Two multimodal imaging datasets are also introduced in the spirit of encouraging increased EHR and imaging integration efforts by the wider research community. The approaches are designed to refine the predictive power of medical imaging-agnostic classifiers, demonstrating the potential for non-image models, such as patient-age prediction using only EHR, to serve as a complementing modality to the visual information. Finally, the integration of multimodal imaging and EHR signals is elucidated, along with real-world deployment considerations related to clinical decision support systems, their inherent regulatory and ethical implications, and the path to translational analysis.

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