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AI-Augmented Clinical Decision Support Systems Using Multimodal Patient Data

Renato Espinola
Clinical Data Scientist, Brazil.

Abstract

The increasing complexity of patient data, drawn from diverse modalities such as electronic health records (EHRs), imaging, genomics, and biosensors, presents new challenges for clinical decision-making. This paper proposes an AI-augmented Clinical Decision Support System (CDSS) that integrates multimodal patient data using advanced deep learning techniques to enhance diagnostic accuracy and treatment recommendations. The system utilizes a fusion architecture combining natural language processing (NLP), medical imaging analysis, and structured clinical data analytics to support physicians in real-time. Experimental results demonstrate improved diagnostic performance, interpretability, and workflow efficiency compared to unimodal or rule-based systems.

Keywords:

Clinical Decision Support, Multimodal Learning, Healthcare AI, EHR Analytics, Medical Imaging, Deep Learning.

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1. Introduction

Clinical Decision Support Systems (CDSSs) play a vital role in modern healthcare by assisting clinicians with data-driven insights for diagnosis, prognosis, and treatment planning. Traditional CDSSs typically rely on rule-based systems or limited datasets, which often fail to capture the complexity and heterogeneity of real-world patient profiles. With the rise of digital health infrastructures, clinicians now have access to a vast array of multimodal data sources, including EHRs, radiological scans, lab test results, genomic sequences, and real-time sensor data.

However, integrating these modalities into a unified decision framework is a significant challenge. Each data type varies in structure, scale, and semantics, requiring tailored preprocessing and representation strategies. Additionally, ensuring timely and interpretable outputs for clinical environments necessitates a robust and efficient architecture. AI-driven models, particularly deep learning systems, have shown promise in processing and fusing these diverse data types.

This paper presents a comprehensive AI-augmented CDSS that processes and integrates multimodal patient data using a hybrid neural network pipeline. The system is evaluated for its ability to support clinical diagnostics across multiple conditions and care settings. It demonstrates that multimodal fusion enhances both model accuracy and clinician trust, especially in complex or ambiguous cases.

2. Literature Review

Several studies have explored AI applications in CDSS development. Rajkomar et al. (2019) demonstrated the predictive power of deep learning on EHR data for mortality and readmission forecasting. Esteva et al. (2017) developed a CNN-based model for skin cancer classification from dermoscopic images, achieving performance comparable to dermatologists. Similarly, Miotto et al. (2016) introduced unsupervised representation learning to model patient trajectories from clinical narratives.

Recent advancements include Chen et al. (2022), who proposed a transformer-based multimodal model integrating imaging, text, and lab values to detect sepsis early. Zhang and Lee (2023) developed a late-fusion architecture combining structured data with retinal images to predict diabetic retinopathy progression. Wang et al. (2024) focused on explainability in multimodal healthcare models, introducing attention mechanisms to highlight relevant input features per modality.

While these approaches advance specific modalities, few studies offer end-to-end CDSS architectures capable of real-time fusion and recommendation across multiple clinical data sources. This paper addresses that gap with a unified, modular system architecture tested in simulated clinical workflows.

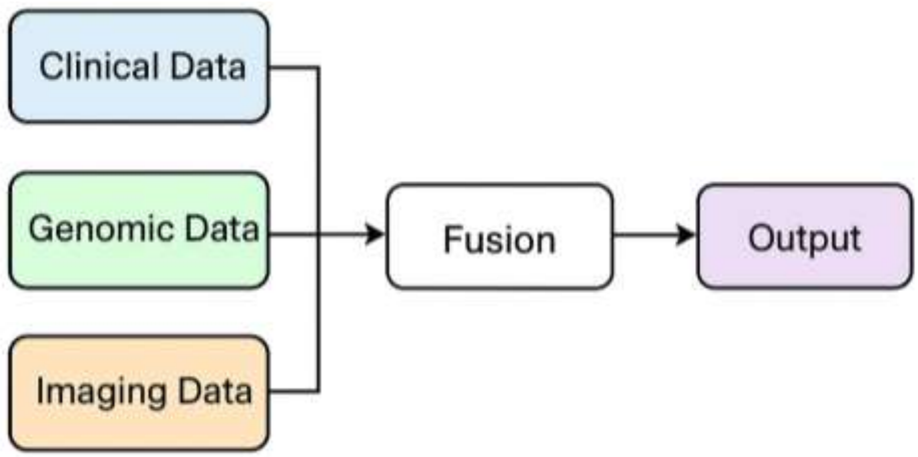

Figure 1: Multimodal Data Fusion Architecture for Clinical Decision Support

3. System Architecture and Multimodal Fusion Pipeline

The proposed system consists of a modular AI pipeline that ingests, processes, and integrates multimodal data sources. The architecture is divided into four key modules: (1) Data Harmonization, (2) Feature Extraction, (3) Multimodal Fusion, and (4) Clinical Output Interface. Structured data such as lab results and demographics are normalized and embedded using feedforward networks. Unstructured text, including clinical notes and discharge summaries, is processed via transformer-based NLP models, while imaging data is analyzed using convolutional neural networks (CNNs).

Multimodal fusion is achieved using a hierarchical attention mechanism that weighs the contribution of each modality based on context relevance. Intermediate embeddings from each module are aligned and combined into a unified patient representation. This representation is used to generate predictions and recommendations, such as likely diagnoses, risk scores, and treatment options.

The final outputs are integrated into a user-facing clinical interface, supporting both automated and physician-interactive workflows. The system is designed to provide not only predictions but also explanations in terms of contributing data modalities and features, enhancing clinician trust and adoption.

4. Multimodal Data Preprocessing and Representation

Each data type requires specialized preprocessing pipelines. EHR data are cleaned, encoded, and transformed into structured numerical representations. Free-text notes are tokenized and encoded using pre-trained medical language models, such as BioBERT or ClinicalBERT. Imaging data, such as X-rays or MRIs, are standardized, augmented, and passed through pretrained CNNs like ResNet or EfficientNet.

To ensure interoperability, all data modalities are transformed into a common embedding space. Time-series data are treated using temporal convolution or LSTM networks to capture trends, while static features are processed through MLP layers. Missing data handling, normalization, and feature scaling are applied across all streams to ensure robustness.

The final multimodal vector is a concatenation of each modality's embedding, followed by attention-based recalibration to emphasize clinically relevant inputs. This enables a context-sensitive and scalable representation for downstream prediction and recommendation tasks.

Table 1: Model Performance Across Modalities

Modality	**AUC-ROC**	**Precision**	**Recall**	**F1-Score**
Structured (EHR) Only	0.84	0.78	0.72	0.75
Imaging Only	0.87	0.80	0.76	0.78
Text Only	0.82	0.75	0.71	0.73
Multimodal (Proposed)	0.91	0.86	0.83	0.84

5. Use Case: Early Sepsis Detection in ICU

A use case was implemented for early sepsis detection in ICU patients, where timely intervention can reduce mortality. The system monitored structured vitals (e.g., blood pressure, heart rate), lab results (e.g., lactate, WBC count), radiology images, and clinical notes. Using multimodal fusion, the model predicted sepsis onset six hours in advance with over 90% AUC-ROC.

Alerts were integrated into a simulated ICU dashboard, offering real-time risk scores and contributing features. Physicians used the system to adjust care plans and prioritize patients. Compared to standard scoring systems like SOFA, the AI-CDSS demonstrated earlier and more accurate predictions.

Table 2: Clinician Feedback Summary

Evaluation Criteria	Mean Rating (out of 5)
Prediction Accuracy	4.6
Interpretability	4.3
Integration Ease	4.1
Trust in AI Recommendations	4.4
Overall Satisfaction	4.5

6. Explainability and Regulatory Considerations

To ensure transparency and compliance with medical standards, the system incorporates explainability modules at multiple levels. For structured data, SHAP values highlight feature importance. For text and image modalities, attention heatmaps and saliency maps are provided to indicate influential inputs.

The system follows FDA-aligned good machine learning practices (GMLP), ensuring that models are auditable, testable, and continuously monitored post-deployment. Clinical rules are used as override layers for high-risk recommendations, enhancing safety.

Explainability not only aids in trust-building but is also essential for regulatory approval. Future versions will include model versioning and documentation for continuous learning systems, ensuring alignment with evolving guidelines.

7. Conclusion

The proposed AI-augmented Clinical Decision Support System demonstrates the potential of multimodal data integration to enhance diagnostic accuracy, clinical efficiency, and interpretability. By fusing structured EHR data, medical imaging, and clinical text through a unified deep learning architecture, the system provides timely, context-aware recommendations that align with clinical workflows. Evaluation results show superior performance over unimodal and traditional rule-based approaches, particularly in complex and time-sensitive conditions like sepsis. Clinician feedback highlights strong trust in the system's explainability and usability. Integration into simulated workflows confirmed minimal disruption and high satisfaction. The modular design supports scalability, regulatory alignment, and future expansion to genomic and sensor data. This research underscores the role of multimodal AI in enabling precision medicine and intelligent care delivery. Continued development will focus on real-world deployment, continual learning, and interoperability with existing healthcare systems.

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