MULTI-MODAL MEDICAL DATA FUSION DIAGNOSTIC ASSISTANT

ABSTRACT

In today's fast-evolving healthcare landscape, accurate and timely diagnosis is crucial. With the exponential growth of digital health records, imaging technologies, and wearable devices, massive volumes of multi-modal medical data are generated every day. However, these data often remain siloed across systems and are interpreted separately by clinicians, which may lead to diagnostic delays or inaccuracies. The Multi-Modal Medical Data Fusion Diagnostic Assistant is a proposed AI-driven system that integrates various types of medical data—including imaging (CT, MRI), electronic health records (EHR), lab reports, and sensor data—into a unified platform. By applying machine learning and data fusion techniques, the assistant supports clinicians in diagnosing complex conditions more accurately and efficiently. This approach improves early detection, reduces diagnostic errors, and enables personalized treatment strategies, thereby transforming traditional diagnosis into a smarter, data-driven process.

INTRODUCTION

Modern medicine increasingly relies on the analysis of diverse and complex datasets. These include radiological images, pathology results, genetic information, and detailed patient histories. Yet, many hospitals and clinics still analyze these data streams independently, which creates gaps in understanding a patient's full medical context. Multi-modal data fusion is a method that combines different types of data into a single, interpretable model to provide a more holistic view of a patient's health.

The Multi-Modal Medical Data Fusion Diagnostic Assistant aims to revolutionize medical diagnostics by merging structured and unstructured data into a coherent platform. This includes image data from CT/MRI/X-ray, textual data from physician notes and EHRs, tabular data from lab results, and even time-series data from wearable health monitors. The system uses artificial intelligence to identify patterns and correlations across these data types, offering highly accurate, real-time decision support for clinicians.

This project is highly relevant in areas such as oncology, cardiology, and neurology—fields where early and accurate diagnosis significantly improves patient outcomes. With the support of advanced deep learning techniques and data fusion strategies, this assistant can dramatically enhance the quality and speed of diagnosis, helping to deliver smarter, more efficient healthcare.

DESIGN & OUTCOME

DESIGN

The design of the Multi-Modal Medical Data Fusion Diagnostic Assistant involves multiple integrated modules:

1. **Data Acquisition Layer**
   This component collects data from multiple sources: radiology departments (e.g., DICOM imaging files), hospital databases (EHR, HL7), lab systems, and external devices like fitness trackers or portable ECG monitors. The system ensures data is securely transferred and complies with health data regulations such as HIPAA.
2. **Preprocessing Unit**
   Each data type undergoes cleaning and transformation. Imaging data is standardized and normalized; text data from clinical notes is processed using Natural Language Processing (NLP) techniques; lab data is structured and cleaned for consistency. Noise reduction and missing data handling ensure higher reliability.
3. **Feature Extraction Engine**
   This module uses advanced AI models such as Convolutional Neural Networks (CNNs) for image feature extraction and NLP models like BERT or spaCy for extracting medical terms from clinical texts. Structured features are extracted from EHR and lab data.
4. **Data Fusion Layer**
   Fusion is performed using a hybrid method combining early, intermediate, and late fusion approaches. This allows the assistant to analyze features both at the input level and at the model decision stage, improving overall accuracy and flexibility across different cases.
5. **Diagnosis & Prediction Engine**
   Using supervised and unsupervised learning algorithms such as Random Forest, SVM, or Deep Neural Networks, the assistant processes the fused data to provide diagnostic predictions, severity scores, and risk classifications.
6. **User Interface and Visualization**
   The assistant presents results through an intuitive dashboard. Clinicians can see visualized scan images with marked regions of concern, summarized health data, timelines, and suggested next steps or alerts for abnormal findings.