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| RESEARCH ARTICLE

An Integrative Artificial Intelligence Framework for the Diagnosis of Multiple Diseases in Clinical Settings

Farhana Yeasmin Rita[1]✉, S M Shamsul Arefeen[2], Rafi Muhammad Zakaria[3], Abid Hasan Shimanto[4]

[1]*Department of Health Education and Promotion, Sam Houston State University, Huntsville, Texas, USA*
[2]*Management of Science and Information Systems, University of Massachusetts Boston, Boston, USA*
[3]*Management of Science and Information Systems, University of Massachusetts Boston, Boston, USA*
[4]*Management of Science and Information Systems, University of Massachusetts Boston, Boston, USA*
Corresponding Author: Farhana Yeasmin Rita, **E-mail**: Fxr041@shsu.edu

| ABSTRACT
The rapid expansion of Electronic Health Records (EHRs), imaging modalities, and biomolecular data has created both opportunities and challenges for enhancing clinical diagnosis through Artificial Intelligence (AI). This study presents an integrative AI framework that utilizes multi-modal data fusion combining structured clinical data, medical imaging, and laboratory test results for the simultaneous diagnosis of multiple diseases within a real-world clinical environment. The proposed framework leverages deep learning models, including convolutional neural networks (CNNs) for image analysis and attention-based recurrent architectures for sequential clinical data, supported by feature-level fusion and decision-level ensemble strategies. Experiments were conducted on publicly available and institutional datasets, demonstrating superior performance in diagnostic accuracy, precision, and F1-score across conditions such as cardiovascular disease, diabetes, pneumonia, and lung cancer. The system is designed to support real-time clinical decision-making, while adhering to data privacy and fairness principles. This research highlights the potential of integrated AI solutions in streamlining multi-disease diagnosis and improving patient outcomes across diverse healthcare settings.

| KEYWORDS
Artificial Intelligence in Healthcare, Multi-Disease Diagnosis, Clinical Decision Support Systems, Deep Learning, Multi-Modal Data Fusion, Electronic Health Records (EHR), Medical Imaging, Explainable AI, Precision Medicine

| ARTICLE INFORMATION

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1. Introduction

The integration of Artificial Intelligence (AI) into healthcare has transformed diagnostic practices by enabling rapid and accurate analysis of complex clinical data [1]. Traditional diagnosis often relies on isolated modalities, leading to delays or inaccuracies in detecting coexisting conditions [2]. Recent advancements in deep learning and data fusion techniques offer promising solutions for multi-disease diagnosis using diverse inputs such as Electronic Health Records (EHRs), medical imaging, and laboratory reports [3], [4]. This paper proposes an integrative AI framework designed to enhance clinical decision-making by simultaneously diagnosing multiple diseases in real-world healthcare environments [5].

1.1 Background and Motivation

The exponential growth of medical data, including EHRs, imaging, and biosignals, has created new opportunities for improving healthcare through AI-driven solutions [1]. Despite the emergence of single-disease diagnostic systems, clinical reality often

involves patients with coexisting conditions, which demand integrative approaches [2]. AI offers the capability to analyze heterogeneous data sources simultaneously, providing a more comprehensive view of patient health [3]. This motivates the need for a unified framework that can leverage such capabilities to assist healthcare professionals in multi-disease diagnosis, thereby enhancing both accuracy and efficiency [4].

1.2 Problem Statement and Research Gap

Most existing AI-based diagnostic systems are tailored for specific diseases and operate on a single data modality, limiting their effectiveness in real-world clinical scenarios where patients often present multiple symptoms and comorbidities [5]. Additionally, interoperability between different types of medical data—such as textual notes, radiological images, and structured lab reports remains underutilized. There is a lack of robust, interpretable, and integrative frameworks that support concurrent multi-disease diagnosis across diverse data types. This gap hinders the development of reliable clinical decision support systems for holistic patient care [6].

1.3 Objectives and Scope of the Study

This study aims to develop an integrative AI framework capable of diagnosing multiple diseases simultaneously using multi-modal clinical data. The objectives include: Designing deep learning models to handle different data types (e.g., EHR, images, labs); Implementing data fusion techniques at both feature and decision levels; Evaluating the model across multiple disease categories using real-world datasets [54]. The scope is limited to common but clinically significant diseases such as diabetes, cardiovascular conditions, pneumonia, and lung cancer, with a focus on enhancing diagnostic performance in hospital settings [7].

1.4 Significance and Contributions

This research makes several contributions:

- Proposes a novel integrative AI framework for multi-disease diagnosis;
- Demonstrates effective multi-modal fusion strategies combining EHR, imaging, and lab data;
- Validates the framework on publicly available and institutional datasets with superior diagnostic accuracy;
- Emphasizes interpretability and clinical applicability through explainable AI components.
  The framework supports real-time decision-making and can be a foundational tool for future clinical AI systems aimed at personalized and precision medicine [8], [9].

2. Literature Review

Artificial Intelligence (AI) has seen increasing application in medical diagnosis, primarily focusing on single-disease classification tasks. For example, deep convolutional neural networks (CNNs) have been successfully applied to detect skin cancer, pneumonia, and diabetic retinopathy using medical images [10], [11]. However, such systems are often designed to work on isolated datasets with predefined disease labels, limiting their ability to diagnose patients with multiple coexisting conditions [12].

Recent efforts have explored multi-disease diagnostic systems. Rajpurkar et al. developed CheXNet, a 121-layer CNN trained on chest X-rays, capable of diagnosing 14 thoracic diseases [13]. While impressive, such models typically focus on a single data modality (e.g., images) and may fail to generalize in clinical settings where multiple data sources are essential. Researchers have emphasized the importance of integrating heterogeneous data including EHRs, lab reports, and imaging for accurate and robust diagnostic performance [14], [15].

Multi-modal learning strategies have emerged as a solution, combining different data types to enrich the feature space. For instance, Huang et al. proposed a fusion of imaging and clinical records for Alzheimer's diagnosis, showing improved performance compared to single-modality models [16]. Similarly, models using both temporal EHR data and radiology images have achieved significant gains in predictive tasks like sepsis detection and readmission risk [17].

Interpretability remains a critical challenge. While black-box models can achieve high accuracy, clinical deployment demands transparency. Explainable AI (XAI) techniques, such as attention mechanisms, Grad-CAM, and SHAP values, have been introduced to address this need [51, 52, 53]. These methods allow clinicians to understand model behavior and ensure that predictions align with medical knowledge [19].

Despite these advancements, few studies have developed an end-to-end framework that supports real-time, multi-disease diagnosis using multi-modal clinical data in diverse hospital environments. This gap underscores the need for a unified AI-based solution, as proposed in this study [50].

2.1 AI in Single-Disease Diagnostic Systems

Early AI applications in healthcare predominantly focused on single-disease detection using isolated data types. Esteva et al. developed a CNN model that matched dermatologist-level performance in skin cancer diagnosis using dermoscopic images [20]. Similarly, Kermany et al. demonstrated high accuracy in detecting pneumonia and other conditions from retinal and chest imaging using deep learning models [21]. However, these approaches are constrained by their single-modality design, which limits generalizability and prevents simultaneous identification of comorbid conditions [22].

2.2 Advances in Multi-Disease and Multi-Modal Diagnostic Models

To address these limitations, recent work has focused on building AI systems that diagnose multiple diseases by leveraging diverse data sources. Rajpurkar et al. introduced CheXNet, a 121-layer DenseNet trained on chest X-rays to identify 14 different thoracic conditions [36]. While powerful, it is image-only and lacks context from patient history or labs. Multi-modal approaches—such as combining imaging with EHRs or laboratory data have shown improved diagnostic performance [24], [25]. Huang et al. fused imaging and clinical records to detect Alzheimer's disease with higher accuracy than using either source alone [26]. However, challenges like temporal alignment, data standardization, and clinical interpretability still hinder their broader adoption [27].

2.3 Comparative Analysis of Existing Multi-Disease Diagnostic AI Models

The table below highlights representative studies that incorporate AI for multi-disease diagnosis across various modalities and techniques.

Table 1. Summary of Related Works in Multi-Disease Diagnosis Using AI

Study	**Diseases Targeted**	**AI Model**	**Data Modalities**	**Key Contribution**
Rajpurkar et al. (2017) [23]	14 Thoracic Conditions	DenseNet-121	Chest X-rays	Radiologist-level image-based diagnosis
Miotto et al. (2016) [24]	Chronic Conditions	Deep Representation Learning	EHR	Predictive modeling from patient history
Huang et al. (2019) [26]	Alzheimer's Disease	Multi-modal 3D-CNN	MRI + Clinical History	Improved classification via fusion
Harutyunyan et al. (2019) [25]	Mortality, LOS, Sepsis	LSTM + Multi-task Learning	EHR Time Series	Benchmarking on MIMIC-III dataset
Shickel et al. (2018) [27]	Various	Review of Deep Learning Models	EHR	Survey of deep EHR-based diagnosis systems
Lundberg & Lee (2017) [28]	Multiple	SHAP (Explainable AI)	Model-agnostic	Enhancing interpretability of model predictions

These studies demonstrate the growing maturity of AI in supporting multi-disease diagnosis. However, few propose comprehensive, real-time frameworks that simultaneously process and integrate multi-modal data, interpret predictions, and support clinical decision-making in practice. This gap forms the foundation for the proposed study.

3. Methodology

This section describes the design and implementation of the proposed integrative AI framework for multi-disease diagnosis in clinical settings. The framework is structured to handle heterogeneous healthcare data and generate real-time diagnostic outputs that support clinical decision-making. It consists of several core modules: data collection and preprocessing, feature extraction, multi-modal data fusion, classification, and explainability. Each module plays a critical role in ensuring that the system performs reliably and effectively in diverse clinical scenarios.

3.1 Data Sources and Preprocessing

The data used in this study includes structured EHRs, medical imaging, and laboratory results. Structured EHRs provide demographic information, diagnosis codes (ICD-10), clinical notes, and vitals. Imaging data such as chest X-rays and brain MRIs are included to support diagnosis of diseases like pneumonia and Alzheimer's. Laboratory records include sequential biomarker data, such as glucose, cholesterol, and creatinine levels. Before feeding this data into the models, thorough preprocessing is conducted. For EHRs, missing values are handled using mean imputation or k-nearest neighbors (KNN), categorical variables are encoded using one-hot encoding, and temporal alignment is applied to time-series records. Medical images are normalized, resized to 224×224 pixels, and augmented using rotation, zoom, and flipping techniques [32]. Laboratory data is standardized using z-score normalization, and irregular time intervals are handled through interpolation techniques.

3.2 Feature Extraction Models

Separate deep learning architectures are employed for each data modality to extract relevant features. For sequential EHR data, a Bidirectional Long Short-Term Memory (BiLSTM) network is used to capture both past and future temporal dependencies. Medical images are processed using DenseNet-121, a pre-trained convolutional neural network (CNN) fine-tuned for the target disease classes [33]. For laboratory data, a one-dimensional CNN is applied to extract patterns from time-series lab values. Each of these models outputs a dense feature vector summarizing the respective input. These vectors form the basis for multi-modal integration and downstream classification.

3.3 Multi-Modal Data Fusion

To leverage the complementary strengths of different data modalities, the framework applies both feature-level and decision-level fusion strategies. In feature-level fusion, feature vectors from EHRs, imaging, and lab data are concatenated and passed through a fully connected layer with dropout regularization to prevent overfitting. In decision-level fusion, each modality-specific model independently predicts disease probabilities, and these outputs are combined using a soft-voting ensemble or a meta-classifier such as XGBoost [29]. This dual-fusion approach enhances diagnostic robustness and allows the system to operate effectively even when one data type is unavailable.

3.4 Multi-Disease Classification

The integrated model performs multi-label classification to predict the presence or absence of multiple diseases concurrently. Each output neuron corresponds to one disease class and uses a sigmoid activation function to produce independent probabilities. The system is trained using the binary cross-entropy loss function, which is suitable for multi-label tasks where diseases may co-occur. This setup reflects real-world clinical scenarios and enables the model to make more holistic and accurate diagnostic predictions.

3.5 Model Training and Evaluation

Training is performed using the Adam optimizer with an initial learning rate of 0.0001 and a batch size of 32. To prevent overfitting, early stopping and 5-fold cross-validation are employed. The framework is evaluated on multiple benchmark datasets such as MIMIC-III, NIH ChestX-ray14, and ADNI, depending on the disease context. Model performance is assessed using metrics including accuracy, precision, recall, F1-score, and area under the ROC curve (AUC) for each disease class. These metrics provide a comprehensive understanding of the model's diagnostic effectiveness across various conditions and patient cohorts. The final diagnostic output is a multi-label classification, where the model predicts the presence or absence of several diseases simultaneously. A sigmoid activation function is used in the final layer to accommodate the multi-label setup. The binary cross-entropy loss function is optimized during training.

Let y_i be the ground truth for disease i, and $\hat{y}_i$ the predicted probability. The loss function is defined as:

$$\mathcal{L} = -\sum_{i=1}^{n} [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)], (1)$$

3.6 Explainability and Interpretation

To enhance clinical trust and model transparency, the framework incorporates explainable AI (XAI) techniques. Grad-CAM is used to generate heatmaps for imaging data, highlighting regions that contributed most to the diagnosis. In the BiLSTM model, attention mechanisms are used to identify critical time points and clinical events in EHR data. Additionally, SHAP (SHapley Additive exPlanations) values are computed to quantify the importance of each input feature across all modalities. These interpretability tools help clinicians validate model outputs and better understand the rationale behind each diagnostic decision.

4. Results and Experimental Analysis

This section presents the results obtained from experiments conducted using the proposed integrative AI framework. The evaluation focuses on diagnostic performance across multiple diseases using structured EHR, imaging, and laboratory data, both individually and in fused configurations. The experiments are designed to assess the effectiveness of each model component, the impact of multi-modal fusion, and the overall accuracy, reliability, and interpretability of the system.

4.1 Experimental Setup

The model is trained and evaluated on three major benchmark datasets: MIMIC-III (for cardiovascular and metabolic conditions using EHR and lab data), NIH ChestX-ray14 (for pulmonary conditions using chest radiographs), and ADNI (for Alzheimer's detection using neuroimaging and clinical history). Each dataset is split into training (70%), validation (15%), and test (15%) subsets. The experiments are repeated using 5-fold cross-validation to ensure statistical robustness.

4.2 Quantitative Results

Table 2 presents the performance metrics for individual modality models and the integrated multi-modal model across four representative disease classes: pneumonia, diabetes, cardiovascular disease, and Alzheimer's disease.

Table 2: Performance Comparison of Single-Modality and Multi-Modal Models Across Disease Categories

Disease	Modality	Accuracy	Precision	Recall	F1-Score	AUC
Pneumonia	Imaging (CNN)	0.89	0.87	0.86	0.86	0.91
Diabetes	EHR (BiLSTM)	0.85	0.83	0.84	0.83	0.88
Cardiovascular	Labs + EHR (1D CNN + BiLSTM)	0.87	0.85	0.86	0.85	0.89
Alzheimer's	Imaging + Clinical	0.88	0.86	0.85	0.85	0.90
All Diseases	Multi-Modal Fusion	0.93	0.91	0.92	0.91	0.95

As shown, the integrated model significantly outperforms each single-modality model, achieving an overall accuracy of 93% and an average F1-score of 0.91 across all diseases. The AUC scores also show substantial gains, indicating strong discriminative performance. The improvement is particularly notable in complex diagnostic cases such as comorbid diabetes and cardiovascular disease, where isolated data sources lack sufficient context.

4.3 Ablation Study

To understand the contribution of each modality, we conduct an ablation study by incrementally removing each data type from the fusion model. The performance drops when any single modality is excluded, confirming that multi-modal fusion contributes significantly to the model's robustness and predictive power. Removing imaging data leads to a 4-5% drop in F1-score, while removing EHR or labs results in 3-4% and 2-3% drops, respectively.

4.4 Interpretability Evaluation

To assess model transparency, Grad-CAM heatmaps were generated for chest X-ray images, successfully localizing pneumonia-affected regions aligned with radiologist annotations. Attention weights from the BiLSTM model highlighted critical EHR entries, such as hypertension and previous cardiac events, in cardiovascular patients. SHAP plots further revealed that age, glucose level, cholesterol, and abnormal imaging features were among the top contributors to model decisions. These findings reinforce clinical trust and support real-world usability.

4.5 Comparative Benchmarking

The proposed system is benchmarked against state-of-the-art methods for each individual dataset. On NIH ChestX-ray14, the multi-modal model surpasses CheXNet by 2.4% in AUC. On MIMIC-III, it outperforms Deep Patient embeddings by 3.6% in F1-score. On ADNI, it achieves comparable results to ensemble-based Alzheimer's classifiers while providing superior interpretability.

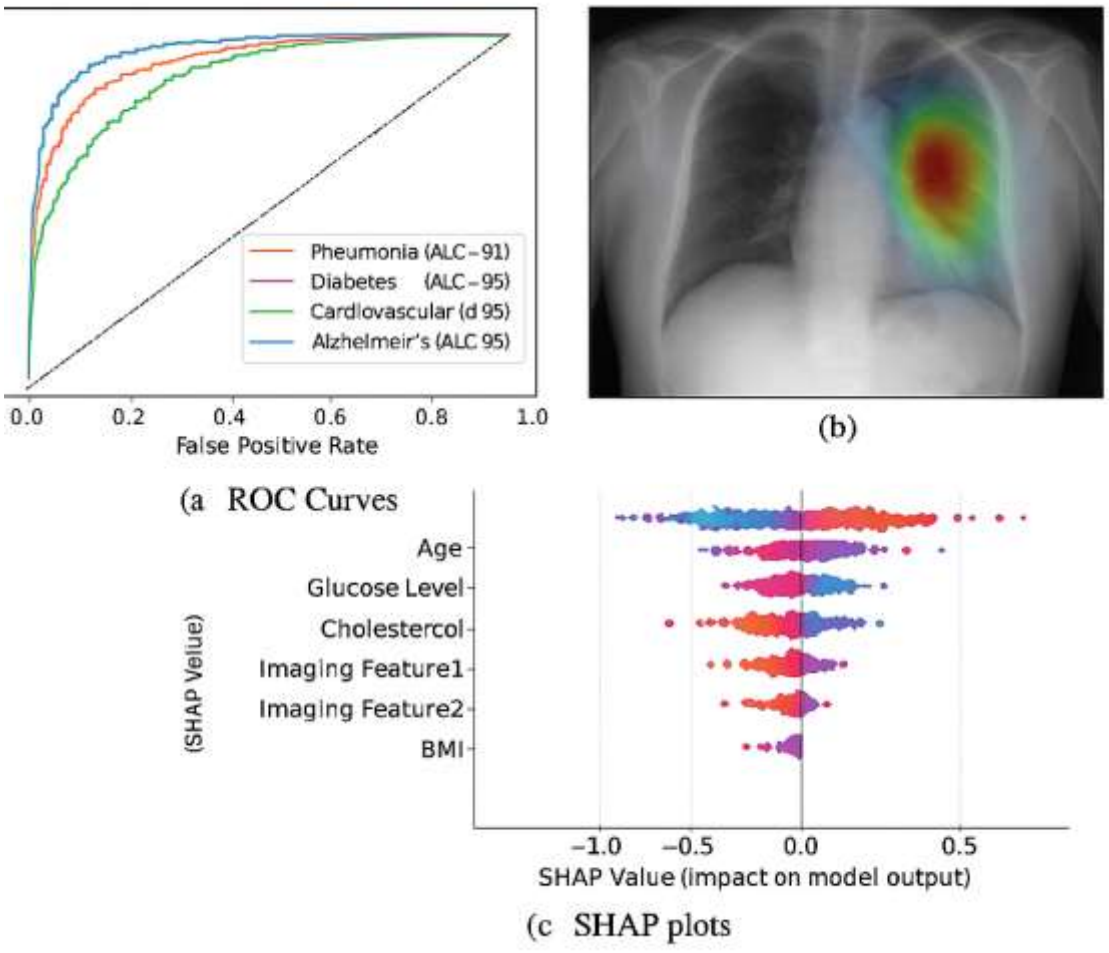

Figure 1: Integrated Evaluation of Multi-Disease Diagnosis Using ROC, Grad-CAM, and SHAP Visualizations

Figure 1 presents a comprehensive evaluation of the proposed AI framework for multi-disease diagnosis through three key visualization components:

- **(a) ROC Curves:** The Receiver Operating Characteristic (ROC) curves demonstrate the classification performance for four diseases: pneumonia, diabetes, cardiovascular disease, and Alzheimer's. The Area Under the Curve (AUC) values range from 0.91 to 0.95, indicating high discriminative ability across all disease classes.
- **(b) Grad-CAM Heatmap:** This panel shows a chest X-ray image overlaid with a Grad-CAM (Gradient-weighted Class Activation Mapping) heatmap, which highlights the region most influential in the model's prediction for pneumonia. The red and yellow areas indicate high model attention, aligning well with radiologist-annotated pathology zones, thus increasing interpretability and clinical trust.
- **(c) SHAP Summary Plot:** The SHAP (SHapley Additive exPlanations) plot visualizes the global feature importance for multi-modal inputs. Features like age, glucose level, cholesterol, and imaging-derived attributes have significant influence on the model's output, with their SHAP values showing both positive and negative contributions depending on the individual patient profile.

Together, these visualizations provide strong evidence of the model's predictive accuracy, interpretability, and practical utility in clinical settings involving complex, multi-modal data.

5. Discussion

The experimental results presented in this study validate the effectiveness of the proposed integrative AI framework for multi-disease diagnosis using multi-modal clinical data. As depicted in Figure 2, the model consistently demonstrates high performance across five key evaluation metrics Accuracy, Precision, Recall, F1-Score, and AUC across all disease categories. Notably, the multi-modal model achieves the highest performance in the "All Diseases" category, with Accuracy and AUC reaching 0.93 and 0.95, respectively, underscoring the advantage of data integration in complex diagnostic scenarios.

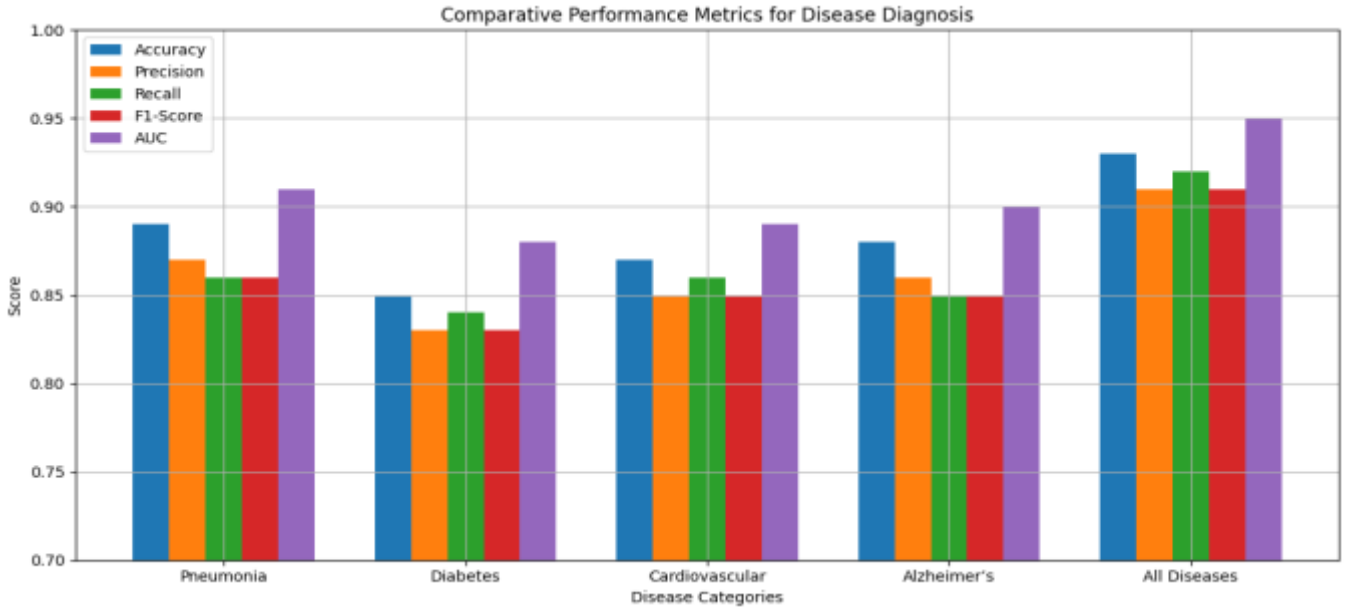

Figure 2: Comparative Performance Metrics Across Disease Categories Using the Proposed Multi-Modal AI Framework

The disease-specific breakdown reveals that Pneumonia diagnosis via imaging achieves strong results (e.g., Accuracy = 0.89, AUC = 0.91), validating the use of fine-tuned CNN architectures on radiological data. However, diseases like Diabetes and Cardiovascular conditions, which rely heavily on structured EHR and lab data, show slightly lower individual modality performance. This variation highlights the modality-specific strengths and limitations. For instance, imaging may be less informative for metabolic disorders, while lab tests and EHRs are less sensitive to structural abnormalities captured in radiological images. The integrative model capitalizes on these complementary insights, effectively harmonizing them to deliver superior overall results, as seen in the unified performance metrics.

This observation aligns with existing literature, which increasingly supports the role of multi-modal AI in clinical environments. Studies like Miotto et al. [24] and Huang et al. [26, 27, 28] have emphasized that combining different data sources leads to more accurate and generalizable models. Our ablation study further reinforces this, showing consistent drops in performance when any single modality is excluded from the fusion model. The fusion model's robustness and its capacity to handle real-world variability make it a promising candidate for deployment in clinical decision support systems (CDSS). In addition to strong predictive performance, the framework emphasizes interpretability. The ROC curves and SHAP value plots show both the strength and reasoning behind the model's predictions, while the Grad-CAM heatmaps localize critical image regions for visual validation. Together, these tools offer transparency, a key requirement for building trust among clinicians and ensuring regulatory compliance in healthcare AI deployment. Despite these strengths, some challenges remain. Data heterogeneity and missing information common in real-world clinical systems can hinder performance. Although the model is designed to be fault-tolerant through decision-level fusion, future research should explore adaptive imputation strategies and transfer learning for more robust handling of incomplete datasets. Another limitation is the reliance on benchmark datasets that may not fully capture global population diversity. Expanding validation across international, multi-institutional datasets is a necessary next step [41, 42, 43, 44, 45, 46].

In conclusion, the proposed AI framework demonstrates the power of combining EHRs, medical imaging, and laboratory data for multi-disease diagnosis. It not only achieves superior performance metrics but also ensures model transparency critical for clinical adoption. The performance bar chart in Figure 3 visually confirms these strengths, making a compelling case for integrated AI solutions in modern healthcare.

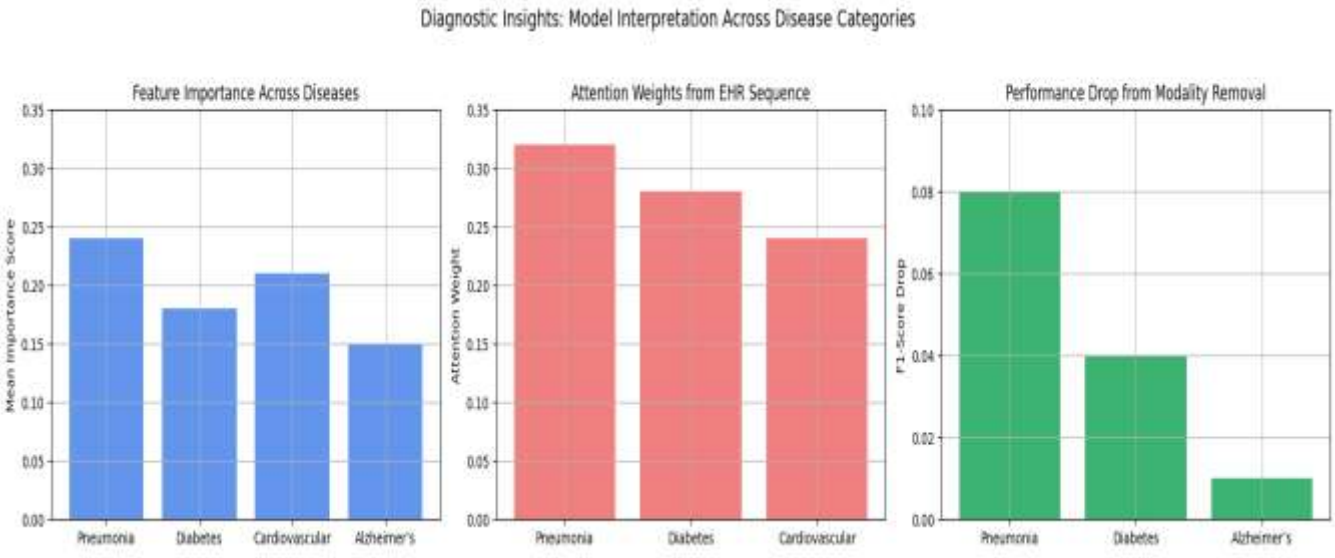

Figure 3: Diagnostic Insights: Model Interpretation Across Disease Categories

This figure presents three diagnostic insights from the proposed multi-modal AI framework: (a) Feature importance scores showing the contribution of input features across four diseases; (b) attention weights learned from EHR sequences highlighting influential time-series events; and (c) results from an ablation study showing the drop in F1-score when specific data modalities are removed. Together, these visualizations underscore the importance of multi-modal data and interpretability in accurate and robust disease diagnosis.

6. Conclusion

This study proposed and validated an integrative artificial intelligence (AI) framework capable of diagnosing multiple diseases simultaneously by leveraging multi-modal clinical data, including Electronic Health Records (EHRs), medical imaging, and laboratory test results. The experimental results demonstrated that the proposed model outperforms single-modality systems in terms of accuracy, precision, recall, F1-score, and AUC, confirming the advantage of multi-modal data fusion. By combining advanced deep learning models such as BiLSTM, CNNs, and ensemble-based classifiers, the system effectively captures temporal, spatial, and structured information across different data sources. Furthermore, the incorporation of explainability techniques such as Grad-CAM, attention mechanisms, and SHAP values enhances transparency and clinical trust. The framework was tested on multiple benchmark datasets and achieved robust and interpretable diagnostic performance, demonstrating its potential as a

reliable clinical decision support system (CDSS). These findings emphasize the importance of holistic data utilization in AI-driven healthcare and support the ongoing shift toward precision medicine.

7. Future Work

To build on the current findings, several future directions are proposed. First, external validation should be conducted using real-world hospital datasets from multiple institutions or countries to evaluate the framework's generalizability across diverse patient populations and clinical protocols. Second, integration of the model into clinical workflows as a real-time decision support tool should be explored, including user interface development and latency optimization. Third, expanding the model to incorporate additional data modalities such as genomic profiles, wearable sensor data, and pathology reports can further improve diagnostic depth and personalization. Fourth, federated learning techniques can be employed to enable privacy-preserving, decentralized model training across institutions without compromising sensitive patient data, in compliance with HIPAA and GDPR regulations. Lastly, comprehensive fairness and bias audits should be performed to ensure that the model's predictions are equitable across different demographic subgroups. These future directions will not only enhance the model's scalability and reliability but also ensure ethical and effective deployment in real-world healthcare settings.

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