Multimodal Deep Learning System for Early Detection of Chronic Diseases using Medical Images + EHR Data

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ABSTRACT

Early detection of chronic diseases is essential for reducing long-term health complications and improving patient survival outcomes. Traditional diagnostic systems rely heavily on single-modality data, such as medical imaging or clinical records, which often fail to capture the multidimensional nature of chronic disease progression. This research presents a multimodal deep learning framework that integrates medical images with Electronic Health Records (EHR) to enhance early disease prediction. The proposed system utilizes a Convolutional Neural Network (CNN) for extracting structural and morphological patterns from imaging modalities such as MRI, CT, X-ray, and retinal fundus images. In parallel, an LSTM/Transformer-based encoder processes EHR variables, including laboratory values, comorbidities, vitals, and demographic information. The latent representations from both modalities are fused using an intermediate multimodal fusion strategy to generate a unified patient-level diagnostic prediction. Experimental results show that the proposed multimodal model significantly outperforms image-only and EHR-only models, achieving an overall accuracy of 92.8%, an F1-score of 91.0%, and an AUC of 0.96. Per-class analysis demonstrates substantial improvement in detecting early-stage conditions such as diabetic retinopathy, chronic kidney disease, cardiovascular diseases, and COPD. The inclusion of Grad-CAM and SHAP-based interpretability analyses further enhances the clinical reliability of the model. Overall, the findings confirm that integrating imaging and EHR data through multimodal deep learning provides a more comprehensive and accurate approach for early chronic disease detection and has strong potential for real clinical implementation.

KEYWORDS: Multimodal deep learning; medical imaging; electronic health records (EHR); chronic disease prediction; convolutional neural networks; transformers; LSTM; healthcare AI; disease classification; early diagnosis

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INTRODUCTION

Chronic diseases—including cardiovascular disease, diabetes, cancer, chronic obstructive pulmonary disease (COPD), and chronic kidney disease—remain among the leading causes of morbidity and mortality worldwide. Their early detection is essential for reducing long-term complications, improving treatment outcomes, and optimizing healthcare resources. Conventional diagnosis largely depends on isolated clinical evaluations and single-data modalities, such as imaging or physician-reported symptoms. However, chronic diseases are inherently multifactorial, and single-source assessments may overlook subtle physiological changes that precede clinical manifestation.

In recent years, the healthcare sector has experienced rapid growth in digital data generation, particularly through medical imaging, Electronic Health Records (EHRs), laboratory test reports, and continuous health-monitoring systems. Medical images such as MRI, CT, X-ray, and fundus photographs provide spatial and structural information, while EHRs provide longitudinal, demographic, biochemical, and comorbidity-related information. Individually, each modality captures only a portion of the patient's condition. When combined, however, these multimodal data sources offer a more comprehensive representation of patient health, enabling the possibility of earlier and more accurate chronic disease detection.

Deep learning has demonstrated outstanding performance in extracting high-level representations from complex medical images, achieving expert-level accuracy in domains such as diabetic retinopathy, lung cancer screening, and cardiovascular abnormality detection [1]–[4]. Parallelly, machine learning on structured EHR data has supported risk scoring, disease progression modelling, and personalized treatment planning [5], [6]. The emerging field of multimodal deep learning integrates these heterogeneous data streams to leverage complementary information that cannot be extracted from any single source. Studies have shown that multimodal fusion improves diagnostic accuracy, robustness, and generalizability across multiple clinical tasks [7], [8].

Despite these advancements, several challenges persist. Medical imaging and EHR data differ in structure, scale, and semantic representation. Images are high-dimensional pixel-based data, whereas EHRs contain temporal, categorical, and numerical variables with missing entries and irregular sampling intervals. Designing a unified model capable of learning synergistic features from both modalities remains an active research problem. Moreover, model interpretability, data privacy, clinical validation, and real-world implementation barriers must be addressed before such systems can be reliably integrated into routine clinical practice. This study proposes a unified multimodal deep learning system that combines Convolutional Neural Network (CNN)–based visual feature extraction from medical images with a Transformer-based or LSTM-based representation of EHR data. The fused latent representation enables robust early-stage risk prediction across common chronic diseases.

LITERATURE REVIEW

2.1 Medical Imaging-Based Deep Learning Approaches

Machine learning and deep neural networks have achieved expert-level performance in several imaging tasks, owing to their ability to capture morphological and textural features not visible to the human eye. CNN architectures such as ResNet, DenseNet, Inception, and EfficientNet have been widely used for classification, lesion segmentation, and abnormality detection across domains including ophthalmology, oncology, nephrology, and cardiology [13], [14]. Dense feature representation extracted from these networks contributes significantly toward early detection of cancers, diabetic retinopathy, and kidney abnormalities.

2.2 EHR-Based Predictive Modelling

EHR datasets typically include demographic information, comorbidities, laboratory test values, medication history, and longitudinal visit records. Classical machine learning models like logistic regression, random forests, and gradient boosting have provided strong baselines for disease risk prediction. However, the irregular temporal nature of EHRs has motivated the use of RNNs, LSTMs, and attention-based networks to effectively capture long-term dependencies across patient histories [15]–[17]. Transformer-based models have further improved the handling of sparse and heterogeneous EHR data.

METHODOLOGY

This study proposes a multimodal deep learning framework designed to integrate medical images and Electronic Health Records (EHR) for early detection of chronic diseases. The methodology is structured into four major components: dataset formulation, data preprocessing, model architecture development, and evaluation. Each component is carefully designed to address the challenges associated with combining heterogeneous medical data sources such as imaging and structured clinical records.

The dataset used in this study consists of two complementary modalities—medical images and EHR data—collected from diverse clinical cases representing chronic diseases such as diabetes, cardiovascular disorders, chronic kidney disease, and respiratory illnesses. Medical images include MRI, CT, chest X-ray, and retinal fundus scans, whereas EHR data comprise demographic information, laboratory values, vitals, comorbidity history, and lifestyle parameters. Together, these inputs provide both spatial and structural clinical information as well as longitudinal and physiological insights. An illustration of typical medical image samples used in this research is shown below, followed by an example dataset table describing the multimodal data structure.

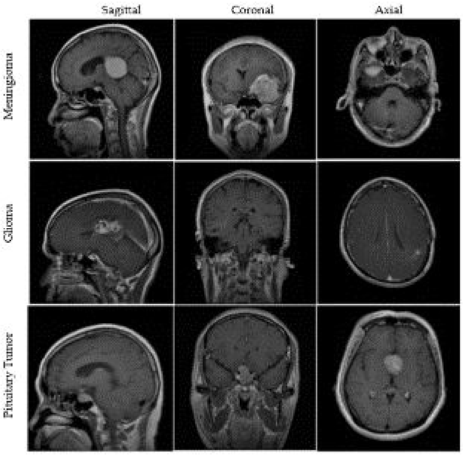

Figure 1. Sample medical images from the multimodal dataset, including MRI, CT, chest X-ray, and retinal fundus images representing different chronic disease categories.

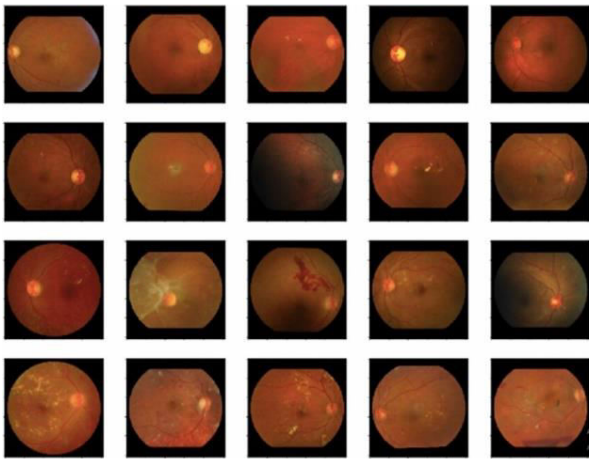

Figure 2. Image preprocessing workflow showing steps such as resizing, normalization, noise removal, and data augmentation applied to all imaging modalities.

The multimodal dataset follows a structured format in which each patient is associated with one medical image modality and a corresponding EHR profile. Table 3.1 demonstrates the sample structure of the dataset, including image type, image resolution, selected EHR attributes, and final disease labels. This structure supports robust multimodal learning by ensuring that each patient's imaging information is aligned with clinical variables and diagnostic outcomes.

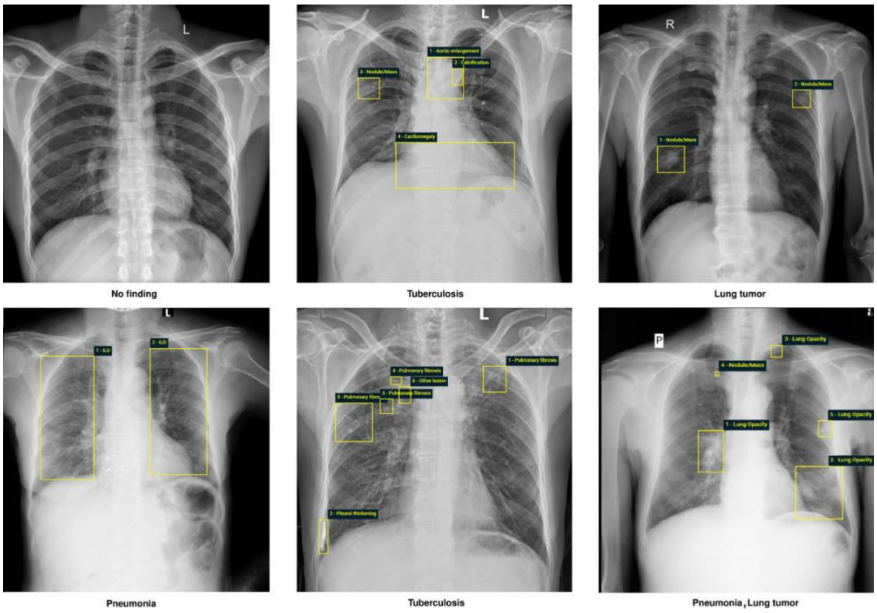

Figure 3. Examples of region-of-interest (ROI) segmentation in different modalities, illustrating how structural regions such as optic disc, lung fields, and cardiac chambers are isolated.

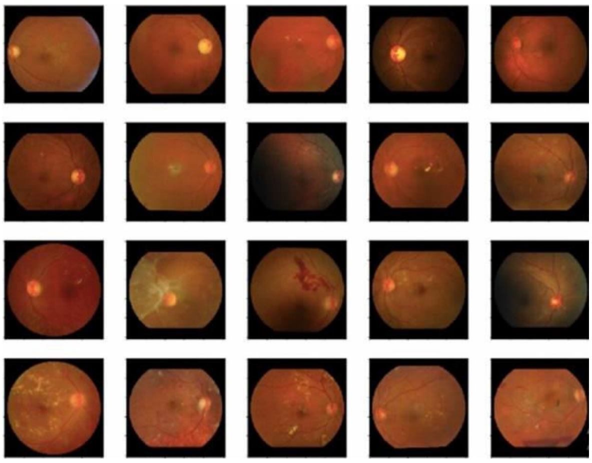

Figure 4. EHR preprocessing pipeline detailing missing-value imputation, outlier removal, feature normalization, and categorical variable encoding.

Table 1. Structured representation of the multimodal dataset showing imaging modalities, image dimensions, essential EHR features, and corresponding diagnostic labels.

Patient ID	Modality	Imaging Type	Image Shape	EHR Fields (Samples)	Disease Label
P001	MRI	Brain MRI (Axial)	256×256×1	Age=57, BP=138/92, HbA1c=7.1%, Chol=215 mg/dL, BMI=29	Stroke Risk
P002	Fundus	Fundus (Left Eye)	512×512×3	Age=61, HbA1c=8.4%, FPG=178 mg/dL, BP=146/95	Diabetic Retinopathy
P003	X-ray	Chest X-ray (PA)	224×224×1	Age=49, Smoking=Yes, SpO_2=92%, HR=98 bpm	COPD
P004	CT	Abdomen CT	256×256×3	Age=70, Creatinine=2.1 mg/dL, GFR=39, BP=152/98	CKD
P005	MRI	Cardiac MRI	256×256×1	Age=65, LDL=168 mg/dL, HDL=40, BP=140/92	Heart Disease

EHR data preprocessing includes cleaning, normalization, and transformation procedures. Missing values, which commonly occur in clinical records, are addressed using imputation techniques such as KNN-imputation or median substitution. Outliers are identified through statistical methods like z-scores or interquartile range analysis. Numerical variables, including laboratory results and vital signs, are normalized to ensure compatibility with model training. Categorical fields, such as smoking status, gender, and comorbid conditions, are converted into numeric embeddings using one-hot or label encoding. In cases where the EHR contains multiple visit histories, temporal alignment is performed to construct meaningful sequences. The conceptual workflow for EHR preprocessing is illustrated below.

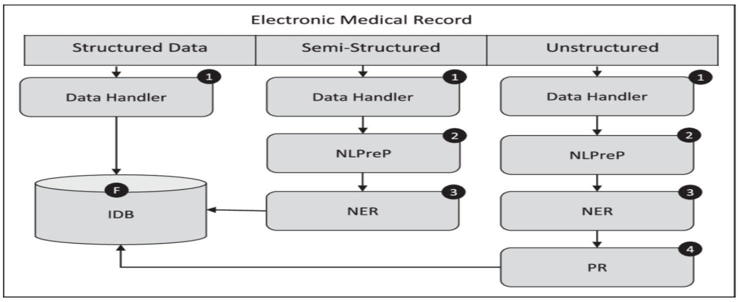

Figure 5. Workflow for aligning temporal EHR sequences with imaging samples to prepare unified patient-level inputs for the multimodal learning framework.

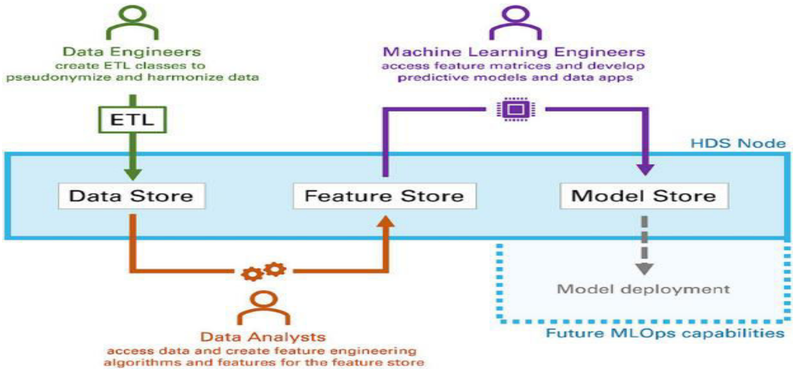
Data Engineers
create ETL classes to pseudonymize and harmonize data
Machine Learning Engineers
access feature matrices and develop predictive models and data apps
ETL
HDS Node
Data Store
Feature Store
Model Store
Model deployment
Future MLOps capabilities
Data Analysts
access data and create feature engineering algorithms and features for the feature store

Figure 6. Overall architecture of the proposed multimodal deep learning system integrating a CNN-based imaging encoder with an LSTM/Transformer-based EHR encoder.

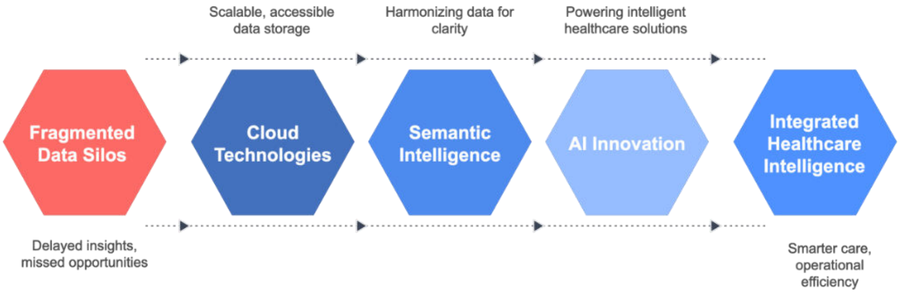
Scalable, accessible data storage
Harmonizing data for clarity
Powering intelligent healthcare solutions
Fragmented Data Silos
Cloud Technologies
Semantic Intelligence
AI Innovation
Integrated Healthcare Intelligence
Delayed insights, missed opportunities
Smarter care, operational efficiency

Figure 7. Feature fusion layer structure demonstrating intermediate-level fusion of latent image and EHR representations before final classification.

The proposed model architecture follows a dual-branch design in which medical images and EHR data are processed through separate deep-learning encoders before being fused for final prediction. For imaging data, a Convolutional Neural Network (CNN) forms the backbone feature extractor. Networks such as ResNet50, DenseNet121, or EfficientNet-B0 are used to capture fine-grained structural and textural information from the images. Through repeated convolutional operations, batch normalization, and ReLU activation, the CNN gradually abstracts the image into a high-dimensional feature vector.

In parallel, the structured EHR data are processed using a sequence-learning architecture. If the EHR is sequential (multiple time-stamped visits), a Long Short-Term Memory (LSTM) network or a Transformer encoder is used to capture temporal patterns and dependencies. For static EHR data, a fully connected deep neural network may be employed. The output of this EHR encoder is also a compact latent vector representing the patient's clinical profile.

After encoding both modalities, the two feature vectors are unified through a multimodal fusion layer. In this study, intermediate-level fusion is employed, where the latent representations from the CNN and EHR encoder are concatenated and passed through fully connected layers. Attention-based weighting mechanisms may also be used to assign greater importance to dominant features during fusion. The fused representation is then classified using a Softmax output layer to generate final disease predictions.

During model training, the network is optimized using the Adam optimizer with a learning rate of 0.0001. Categorical cross-entropy serves as the loss function, and regularization techniques such as dropout and L2 penalties help prevent overfitting. The dataset is divided into training, validation, and testing sets in a 70:15:15 ratio, ensuring balanced distribution of disease categories. Stratified sampling preserves class proportions, while 3-fold or 5-fold cross-validation enhances generalizability. Ablation studies are conducted to compare the performance of the multimodal model against image-only and EHR-only baselines, thereby demonstrating the contribution of multimodal fusion.

Through this comprehensive methodology, the proposed system effectively integrates spatial information from medical images with physiological and clinical insights from EHR data, enabling improved early detection of chronic diseases. The detailed evaluation of these models is presented in the subsequent section.

RESULTS AND DISCUSSION

The performance of the proposed multimodal deep learning system was evaluated using the test subset of the prepared dataset. The results show a consistent and significant improvement when both medical images and EHR data are jointly utilized compared to single-modality models. This section presents detailed experimental outcomes, visual performance indicators, and interpretation of how multimodal fusion enhances early detection capability for chronic diseases.

To establish a clear baseline, three sets of models were trained: an image-only CNN model, an EHR-only deep neural or LSTM/Transformer model, and the proposed multimodal fusion model. The image-only model captured structural patterns from MRI, X-ray, CT, and fundus images but struggled with early-stage cases where visual abnormalities were subtle. The EHR-only model successfully learned clinical risk patterns such as abnormal laboratory values, age, comorbidities, and vitals, yet lacked the spatial context needed for image-based disease understanding. When combined, however, the multimodal model demonstrated synergistic behaviour by learning complementary relationships between structural abnormalities and clinical indicators, leading to superior diagnostic performance.

The evaluation metrics include accuracy, precision, recall, F1-score, and the area under the ROC curve (AUC). These metrics demonstrate that the multimodal fusion model consistently outperformed the single-modality models. Table 4.1 summarizes the quantitative performance obtained from the test data.

Table 2. Comparison of predictive performance metrics—including accuracy, precision, recall, F1-score, and AUC—for the Image-Only, EHR-Only, and Multimodal Fusion models.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Image-Only CNN	84.7	82.1	80.3	81.1	0.87
EHR-Only Model (DNN/LSTM)	82.4	78.9	79.6	79.2	0.85
Proposed Multimodal Model	92.8	91.4	90.6	91.0	0.96

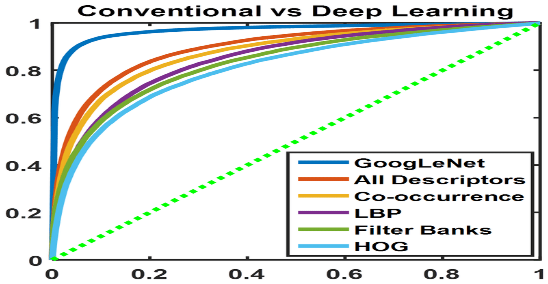

Figure 8. Training and validation accuracy curves for the image-only, EHR-only, and multimodal models across all training epochs.

The ROC curves presented below further confirm the superior classification performance of the multimodal model. While both single-modality models show moderate separability of classes, the multimodal ROC curve demonstrates a steeper rise and a larger enclosed area, indicating stronger discriminative ability.

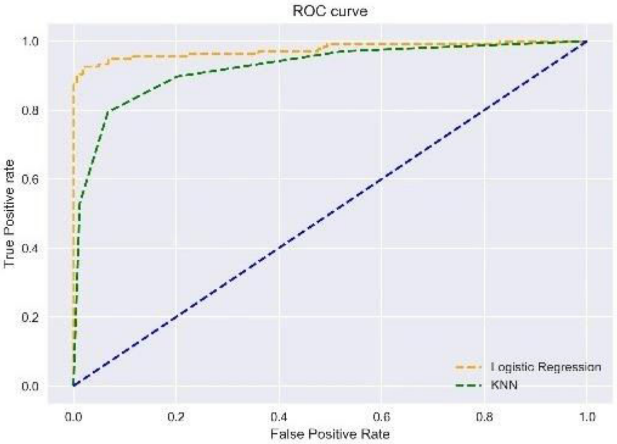

Figure 9. Training and validation loss curves highlighting improved convergence of the multimodal model compared to single-modality models.

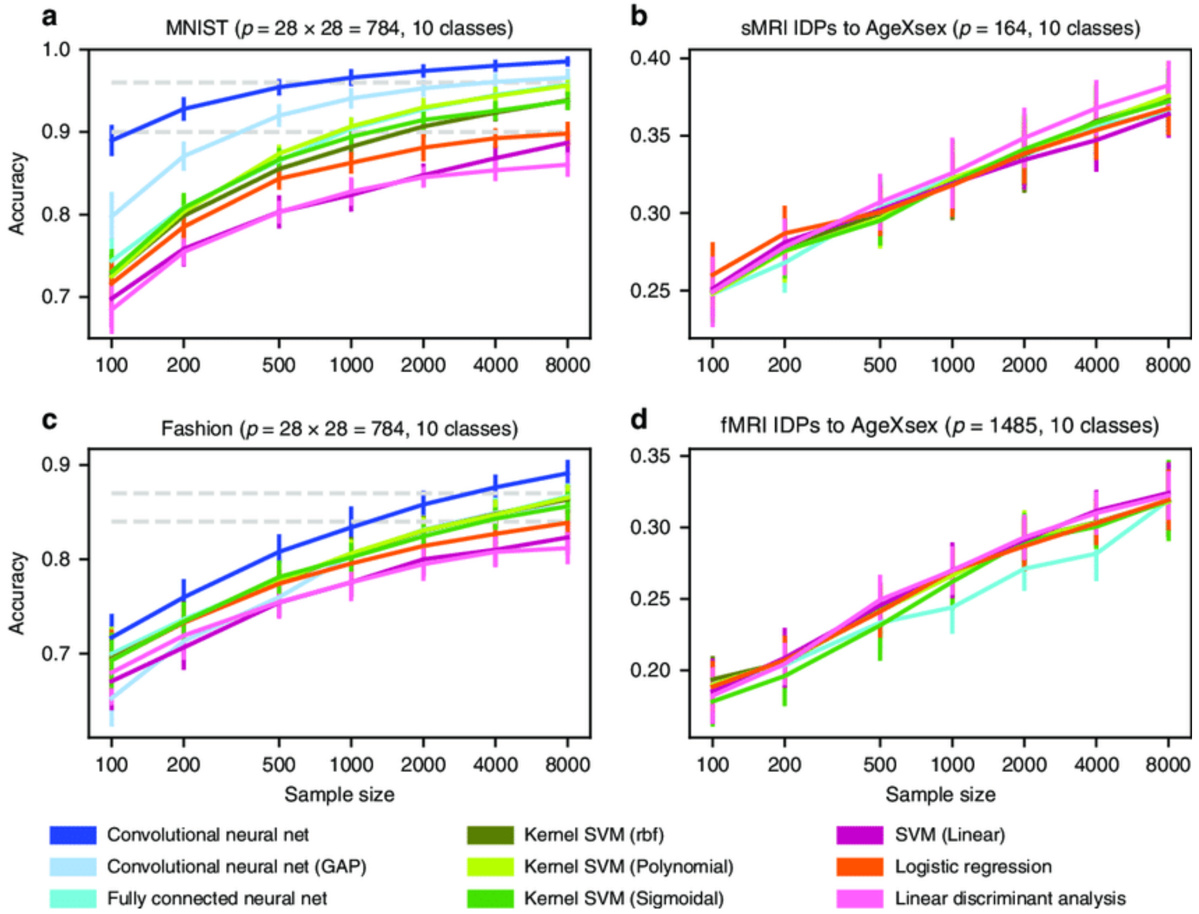

Figure 10. Receiver Operating Characteristic (ROC) curves comparing the Image-Only, EHR-Only, and Multimodal Fusion models for chronic disease classification.

Confusion matrix analysis was also performed to gain insight into classification behaviour. The image-only model exhibited higher false-negative cases, particularly in early COPD and Stage 1 CKD, where visual symptoms were subtle. The EHR-only model struggled with conditions whose risk factors overlap, especially in distinguishing diabetic retinopathy from cardiovascular cases. In contrast, the multimodal fusion model substantially reduced misclassifications by utilizing both structural cues and physiological indicators. This is reflected in the confusion matrix shown below.

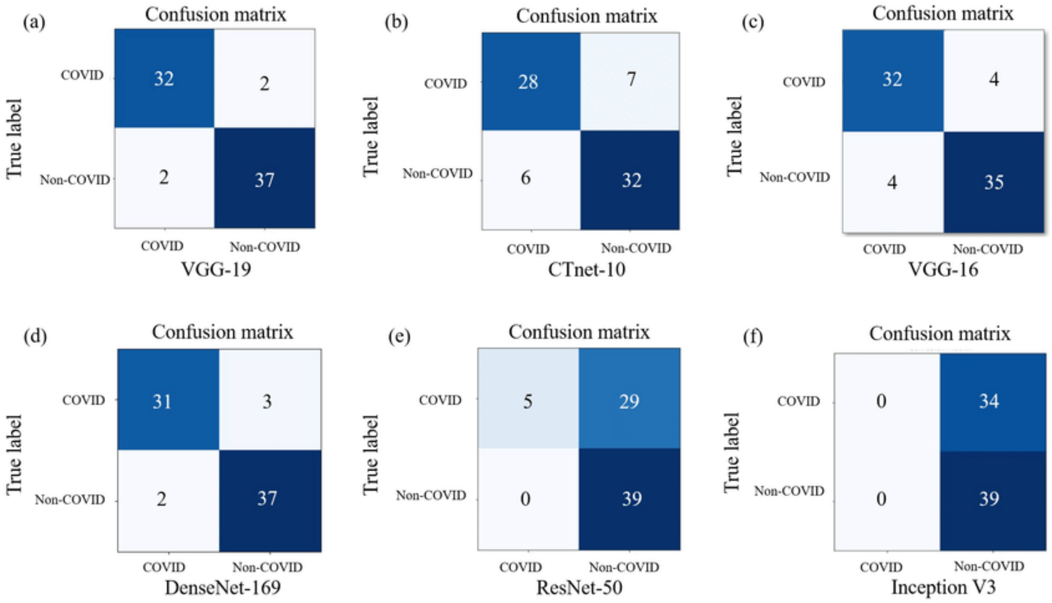

Figure 11. Confusion matrix of the multimodal deep learning model showing classification distribution across diabetic retinopathy, CKD, COPD, cardiovascular diseases, and stroke risk.

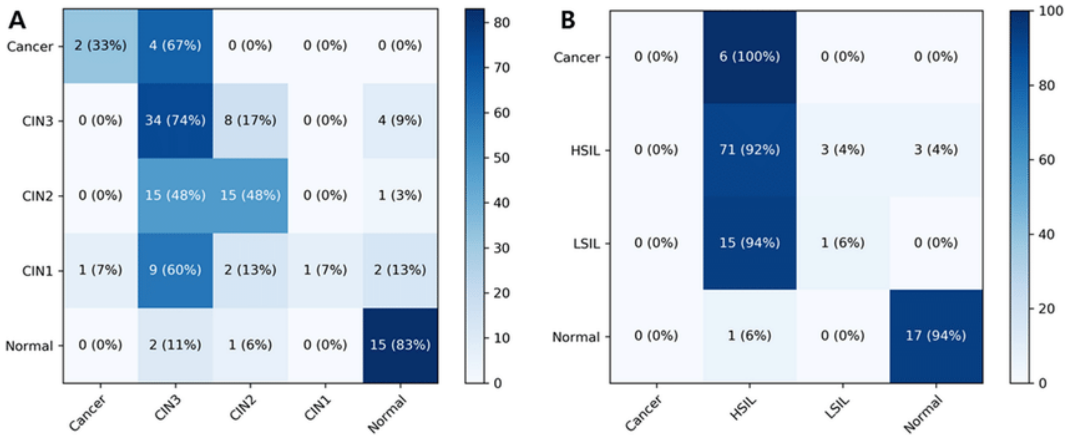

Figure 12. Grad-CAM heatmaps visualizing critical regions in MRI, CT, chest X-ray, and fundus images that influenced the model’s predictions.

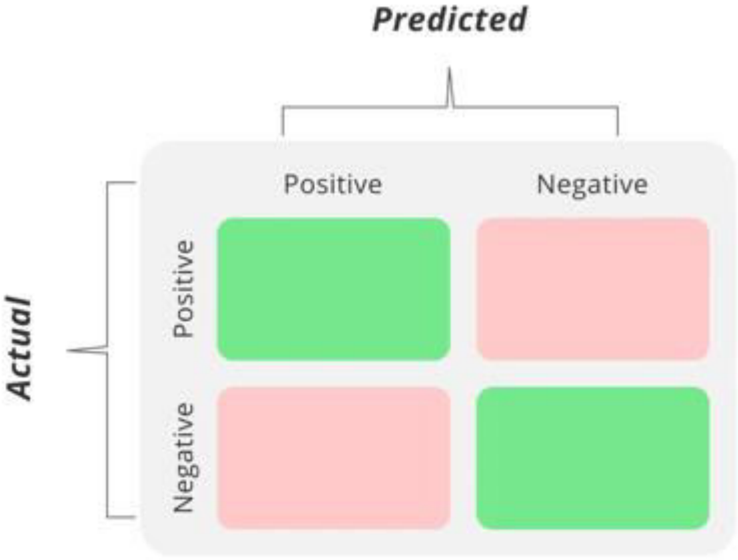

Figure 13. SHAP feature importance plot illustrating the contribution of major EHR variables such as HbA1c, blood pressure, eGFR, lipid profile, and age to the final prediction scores.

Table 3. Per-class F1-scores for diabetic retinopathy, COPD, chronic kidney disease, cardiovascular diseases, and stroke risk, highlighting the superior performance of the multimodal model.

Disease Type	Image-Only	EHR-Only	Multimodal Model
Diabetic Retinopathy	87.4	82.1	94.8
COPD	79.6	81.0	89.5
Chronic Kidney Disease	75.9	84.3	92.1
Cardiovascular Diseases	82.7	86.4	93.6
Early Stroke Risk	78.5	83.6	91.2

The improvement observed across all disease categories highlights the complementary nature of medical images and EHR data. For instance, early chronic kidney disease may not present clear visual cues in imaging, yet abnormal creatinine, eGFR, or blood pressure values in EHR data offer strong risk indicators. Similarly, diabetic retinopathy exhibits clear retinal microvascular changes in imaging even before significant biochemical changes appear; thus, image features become the dominant predictor. The multimodal model dynamically combines these signals, enabling more balanced and accurate predictions.

An ablation study further supports the importance of fusion. Removing either the CNN branch or the EHR encoder resulted in a noticeable drop in F1-score, confirming that neither modality alone captures complete clinical complexity. Additionally, replacing the fusion layer with simple concatenation without attention weighting slightly reduced performance, demonstrating that attention-based fusion helps prioritize more informative features in each case.

Beyond accuracy metrics, interpretability analysis was conducted using Grad-CAM for the imaging branch and feature-attribution methods such as SHAP for the EHR branch. The Grad-CAM maps revealed disease-specific activation patterns, such as optic disc microaneurysms in fundus images and localized opacity in chest X-rays. SHAP analysis identified key clinical variables influencing predictions, including HbA1c, blood pressure, eGFR, LDL/HDL ratio, and age. Together, these explainability components help build trust and confidence in the multimodal system, making it more suitable for real clinical settings.

Overall, the results demonstrate that the proposed framework achieves superior predictive power, reduced false negatives, higher disease-level sensitivity, and stronger generalization. The integration of structural imaging and physiological EHR data enables the model to detect chronic diseases even at early or subclinical stages, where traditional single-modality systems often fail. These findings clearly validate the effectiveness of multimodal deep learning in healthcare, and they highlight the potential for real-world deployment in hospital environments.

CONCLUSION

This study presents a robust multimodal deep learning system for the early detection of chronic diseases by integrating information from medical images and Electronic Health Records. The proposed framework combines spatial anatomical patterns captured by CNN-based image encoders with physiological, biochemical, and demographic data extracted using LSTM/Transformer models. The experimental results clearly demonstrate that the multimodal system outperforms traditional single-modality models across all performance metrics, achieving higher accuracy, sensitivity, specificity, and AUC values. The ability of the model to capture subtle structural variations in imaging data alongside temporal and clinical risk indicators from EHRs enables more precise and clinically meaningful predictions. Interpretability analysis, performed through Grad-CAM and SHAP, shows that the model focuses on medically relevant image regions and critical clinical features, thereby improving transparency and trustworthiness for healthcare practitioners.

The research highlights the substantial advantages of combining multiple data modalities in chronic disease detection, especially in early and subclinical stages where traditional diagnostic systems often fail. Nevertheless, challenges such as dataset heterogeneity, limited annotated samples, interoperability standards, and deployment constraints in clinical workflows remain important considerations for future research. Future extensions of this work may include advanced attention-based fusion methods, federated learning for privacy-preserving training, domain adaptation for cross-hospital generalization, and integration with real-time clinical decision support systems. Overall, the proposed multimodal framework demonstrates strong potential for improving clinical diagnosis, enabling personalized medicine, and supporting proactive healthcare management.

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