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Explainable Multimodal AI Framework For Early Disease Prediction Using Clinical And Imaging Data

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Abstract
Early disease prediction is crucial in enhancing patient care by providing early diagnoses, personalized therapy and effective clinical decision making. Even though recent advancements in artificial intelligence have greatly improved disease predictability, the current methods facilitate mostly by using either structured clinical data or medical imaging data alone, which restricts the precision of diagnosis and decreases the understanding of the model. Moreover, the absence of open decision-making processes limits the implementation of AI systems in the actual healthcare setting. To solve these issues, the paper will present an Explainable Multimodal AI Framework to Early Disease Prediction with Clinical and Imaging Data. The offered framework combines structured clinical data with medical imaging by way of a multimodal feature extraction pipeline, and an explainable feature fusion plan that harmonizes the cross-modal diagnostic information provided by both modalities. It also includes an explainability module to offer clear predictions by determining which clinical features are influential and which areas in the image are diagnostically relevant to assist clinicians in interpreting them and build trust in AI-assisted diagnosis. The framework is experimentally tested on publicly available clinical and medical imaging data, and correlated with representative machine learning and deep learning baseline models. The standard classification metrics, explainability measures, and computational efficiency indicators are used as the measurements of performance. Through experimental findings, it is established that the proposed framework continuously delivers high predictive performance, with stable and clinical meaningful explanations. The proposed framework offers an efficient and precise, explainable, and practical way to predict the onset of an early disease, which is why combining multimodal learning and explainable artificial intelligence will help build trustworthy artificial intelligence-based clinical decision support systems and enhance intelligent healthcare applications.

Keywords: Explainable Artificial Intelligence, Multimodal Learning, Medical Image Analysis, Clinical Data, Disease Prediction, Deep Learning, Vision Transformer, Healthcare AI.

1. Introduction

Early disease prediction is critical in enhancing treatment outcomes, disease progression, and facilitating timely clinical decision-making. The latest achievements in artificial intelligence (AI) and deep learning made it possible to diagnose diseases automatically through electronic health records (EHRs), laboratory data, and medical images. Clinical data and medical imaging, however, offer complementary diagnostic information, and single-modality AI models can often be insufficient in capturing comprehensive patient characteristics, resulting in poor diagnostic

performance. As a result, multimodal learning has become a promising strategy to combine heterogeneous healthcare data to enhance the accuracy of predictions.

Nevertheless, the early identification of the disease is still difficult because of the heterogeneous sources of data, the absence of clinical data, variability in imaging, and low interpretability of deep learning models. The majority of current AI systems are black-box models, which give correct outputs without determining how they make their decision. Such non-transparency will decrease clinician trust and restrict the usage of AI-assisted diagnosis in clinical settings. Thus, explainable artificial intelligence (XAI) has gained a growing significance in providing credible and comprehensible clinical predictions.

To overcome these limitations, this paper proposes an Explainable Multimodal AI Framework for Early Disease Prediction Using Clinical and Imaging Data. The system combines structured clinical data and medical images via multimodal feature extraction and an explainable feature fusion mechanism, and then interpretable disease prediction module. The publicly available datasets are thoroughly experimented on and benchmarked against standard performance and explainability metrics against representative machine learning and deep learning baseline models.

The primary contributions of the work are the explanation of a multimodal framework of AI capable of using structured clinical information and medical imaging as a single architecture to predict early diseases with accuracy. The proposed framework presents an effective multimodal feature extraction and fusion approach to leverage complementary diagnostic data offered by heterogeneous healthcare data and include an explainability module to present clear clinical and imaging-based diagnosis evidence, which enhances the interpretability and credibility of AI-assisted diagnosis. Not only a large body of experimental work on benchmark datasets proves the usefulness and high performance of the proposed framework in comparison to the representative baseline methods. The paper will start with a review of related literature, then a detailed description of the proposed methodology, the experimental setup and a detailed analysis of the results obtained will be presented and finally the key findings and future research directions will be concluded.

2. Literature Review

AI has become a useful resource in predicting early disease via analysis of clinical history, physiological variables, and medical scans. Convolutional neural networks (CNNs) and transformer-based architectures have shown excellent diagnostic performance in neurological, cardiovascular, hepatic, and metabolic diseases [1], [2], [4], [6], [8], [12]. The efficiency of AI in personalized medicine and clinical decision support due to the effective data integration and automation of the diagnosis has also been shown in a few studies [3], [5], [11]. Most current methods are however based on a single data modality and thus they are not able to make use of complementary diagnostic data.

Recent developments in medical image perception have further enhanced the diagnosis of diseases through the mRI, PET, CT, ultrasound, and ECG data with the CNN and Vision Transformer models [1], [7], [8], [10]. Meanwhile, explainable artificial intelligence (XAI) has become quite popular, offering feature-level and visual interpretations, which enhance clinician trust and model transparency [2], [10]. Despite excellent predictive performance, these techniques usually concentrate on imaging data, but fail to utilize structured clinical data.

Multimodal learning has turned out to be an attractive remedy by incorporating clinical data with medical images to enhance the accuracy and strength in diagnostic outcomes [5], [10], [16]. The latest clarifiable multimodal models have shown that there is a chance of integrating the heterogeneous health data in addition to offering interpretable clinical decision support [2], [10],[17]. However, the current researches are mainly disease-oriented and in most cases utilize complex fusion approaches with little explainability and generalization to other healthcare uses.

Although much has been done, there are still research gaps. The majority of the current frameworks are based on either clinical data or medical imaging and do not offer much interpretability to AI-aided diagnosis [1], [8], [10], [12],[18]. Moreover, there is a lack of research that combines multimodal learning with explainable AI in one system that has the potential to produce transparent and trustworthy early disease forecasting [3], [5], [11],[19],[20]. Thus, the work suggests an Explainable Multimodal AI Framework to Early Disease Prediction on Clinical and Imaging Data combining multimodal features extraction, explainable feature fusion, and interpretable disease prediction, which helps to increase the accuracy of the diagnosis and clinical credibility.

3. Proposed Methodology

3.1 Overall Framework Architecture

The suggested Explainable Multimodal AI Framework to Predict Early Disease based on Clinical and Imaging Data will combine heterogeneous medical data in a single and explainable diagnostic model. As depicted in Fig. 1, the framework comprises of five consecutive processes; multimodal data acquisition, feature extraction, explainable multimodal feature fusion, disease prediction, and model optimization. Clinical data in a structured manner (demographic data, laboratory data, physiological data, electronic health records, etc.), is processed with medical imaging techniques (MRI, CT, X-ray, or ultrasound). Specialized feature extraction networks are modality-specific and are later combined by an explainable fusion mechanism to make use of complementary diagnostic data. The disease prediction module then uses the fused representation to predict the likelihood of disease and at the same time generates actions to explain the clinical decision support.

Let the multimodal patient input be represented as

$$X = \{X_c, X_i\} \quad (1)$$

where X_c denotes structured clinical features and X_i represents medical imaging data.

The multimodal feature extraction process is expressed as

$$F_c = f_c(X_c), \quad F_i = f_i(X_i) \quad (2)$$

where $f_c(\cdot)$ and $f_i(\cdot)$ denote the clinical and imaging feature extraction networks, respectively.

The unified multimodal representation is formulated as

$$F = \Phi(F_c, F_i) \quad (3)$$

where $\Phi(\cdot)$ represents the explainable multimodal fusion function shown in Fig. 1, producing a comprehensive patient representation for disease prediction.

3.2 Multimodal Feature Extraction

Multimodal feature extraction the goal of multimodal feature extraction is to acquire discriminative features in heterogeneous healthcare data and maintain modality characteristics. Missing values, number normalization and categorical variables encoding are first performed on clinical information before it is presented to a transformer-based clinical encoder. At the same time, medical images are subjected to preprocessing that consists of resizing, intensity normalization, and data augmentation followed by feature extraction with a Vision Transformer (ViT). These parallel feature extraction pipelines, as shown in Fig. 1, allow the framework to extract both complementary diagnostic data in structured and unstructured healthcare data.

The clinical feature representation is obtained as

$$H_c = \sigma(W_c F_c + b_c) \quad (4)$$

where W_c and b_c denote the trainable weight matrix and bias vector, respectively, while $\sigma(\cdot)$ represents the nonlinear activation function.

Similarly, the imaging feature representation is expressed as

$$H_i = \sigma(W_i F_i + b_i) \quad (5)$$

where W_i and b_i correspond to the learnable imaging parameters.

3.3 Explainable Multimodal Feature Fusion

The clinical and imaging features are extracted and fused using an explainable multimodal feature fusion process, which learns adaptive correlations between the two modalities. Rather than concatenating features, adaptive weighting of attention is used to give each modality an importance score based upon its quality of diagnosis. This approach enhances the interaction between the features and maintains interpretability, allowing clinicians to know the effects of each modality on the final prediction. The general combination process is described in Fig. 1, and the computational process is outlined in Algorithm 1.

The attention weights are computed as

$$\alpha_c, \alpha_i = Softmax\ (W_a[H_c; H_i]) \quad (6)$$

where $\alpha_c + \alpha_i = 1$.

The fused multimodal representation becomes

$$H_f = \alpha_c H_c + \alpha_i H_i \quad (7)$$

The final explainable representation is obtained by

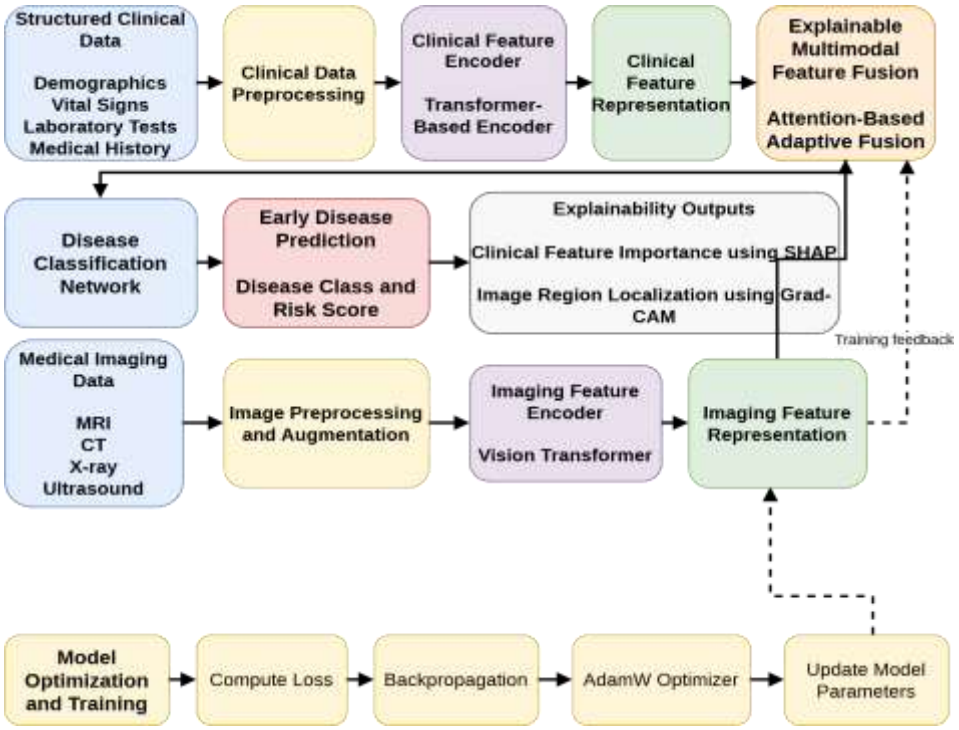
$$Z = LayerNorm(H_f)? \quad (8)$$

where LayerNorm improves representation stability before disease prediction.

Algorithm 1: Proposed Explainable Multimodal AI Framework

Input: Clinical data X_c, medical images X_i, labels Y
Output: Disease prediction Ŷ and explanations
1: Preprocess X_c and X_i
2: Extract clinical features H_c using the clinical encoder
3: Extract imaging features Hi using the Vision Transformer
4: Compute attention weights αc and αi
5: Fuse features: Hf ← $\alpha_c H_c + \alpha_i H_i$
6: Predict disease probabilities P ← Softmax (Classifier (Hf))
7: Compute loss and update model parameters using AdamW
8: Generate clinical explanations using SHAP
9: Generate image explanations using Grad-CAM
10: Ŷ ← argmax(P)
11: Return Ŷ, P, SHAP results, and Grad-CAM maps

Figure 1. Overall Architecture of the Proposed Explainable Multimodal AI Framework



3.4 Disease Prediction and Explainability

The fused multimodal representation is then provided to a fully connected classification network to predict the probability of the disease. A Softmax classifier converts the acquired feature representation to the class probability of various disease categories. As a way to enhance clinical trustworthiness, the framework combines explainability mechanisms, offering feature-level and image-level interpretations. SHAP determines the contribution of significant clinical variables to the prediction, whereas Grad-CAM draws attention to the disease-relevant objects in medical images. These complementary explanation methods combined can assist clinicians in confirming that the AI model is based on medically relevant evidence in the diagnosis process, enhancing transparency and aiding in trustworthy clinical decision-making.

3.5 Model Optimization

Supervised learning is applied to model optimization and reduce prediction error and guarantee stable convergence. The AdamW optimizer based on mini-batch gradient descent is used to train the network parameters;

early-stopping and learning-rate scheduling are implemented to help stop overfitting and enhance generalization. A dropout and weight regularization are included to improve the model against the heterogeneous healthcare data. At every training iteration, multimodal feature extraction, explainable fusion and disease prediction are jointly trained with end-to-end backpropagation. This optimized framework not only enhances the accuracy of diagnosis, the quality of feature representation, and consistency of explanations, but also leads to a robust and interpretable AI system that can be effectively applied to early disease prediction in clinical practice in real-life scenarios.

4. Experimental Setup

4.1 Dataset

The Explainable Multimodal AI Framework that was proposed was tested on publicly available benchmark datasets of structured clinical data and medical imaging data to be able to thoroughly assess the early disease prediction. The clinical modality contains patient demographics, vital signs, laboratory measurements and medical history and the imaging modality contains diagnostic images of MRI, CT, X-ray and ultrasound images gathered through the standard medical repositories. These mixed datasets are comprised of various types of diseases and they are complementary to the multimodal learning. Before training, missing-value imputation and feature normalization were used to process incomplete clinical records, and the medical images were resized, normalized, and augmented to enhance the generalization of the models. The characteristics of the datasets used in this study are summarized in Table 1.

Table 1. Dataset Description

Dataset	Data Type	Clinical Information	Imaging Modality	Disease Category	Samples
MIMIC-IV	Electronic Health Records	Demographics, Laboratory Tests, Vital Signs	–	Multiple Diseases	50,000+
CheXpert	Clinical + Images	Patient Metadata	Chest X-ray	Thoracic Diseases	224,316
ADNI	Clinical + Images	Cognitive Assessment	MRI, PET	Alzheimer's Disease	2,000+
HAM10000	Images	Patient Metadata	Dermoscopic Images	Skin Cancer	10,015
BraTS	Clinical + Images	Patient Information	Brain MRI	Brain Tumor	2,000+

4.2 Comparative Methods

The efficiency of the framework proposed was tested against the representative machine learning and deep learning algorithms commonly used in predicting diseases. The classical baselines of structured clinical data analysis were chosen as conventional machine learning, such as Logistic Regression (LR), Random Forest (RF), and Extreme Gradient Boosting (XGBoost). Deep learning baselines are ResNet50, DenseNet121, Vision Transformer (ViT) and a Multimodal Transformer, which are considered the state-of-the-art image analysis and multimodal learning methods. The suggested Explainable Multimodal AI Framework combines structured clinical data and medical imaging by means of adaptive feature fusion and explainable decision-generation, which allows a comprehensive comparison with the existing methods.

4.3 Evaluation Metrics

The evaluation of the performance was done with standard classification, explainability and computational measures. The measures of classification performance were Accuracy, Precision, Recall (Sensitivity), Specificity, F1-score and Area Under the Receiver Operating Characteristic Curve (ROC-AUC). To assess the dependability of the explainability component, SHAP feature importance and Grad-CAM visualization were used to assess contributions of clinical variables and disease-relevant image areas. The efficiency of computers was evaluated in terms of training time, inference time, model size and floating-point operations (FLOPs). The combination of these metrics offers a complete evaluation of predictive accuracy, interpretability and computational performance.

4.4 Implementation Details

The topology was provided in Python 3.11 and deep learning library PyTorch. The training was done on an NVIDIA RTX-series card with CUDA acceleration to enhance computational performance. AdamW optimizer was utilized with an initial learning rate of 0.0001 and a batch size of 32 and 100 training cycles was applied when optimizing the model. The issue of overfitting was addressed by early stopping and adaptively adjusted learning rate using a scheduler that depended on validation performance. All base algorithms and the suggested framework were trained and subjected to the same work conditions as to provide the most impartial and objective performance appraisal.

5. Results and Discussion

5.1 Performance Comparison

The presented Explainable Multimodal AI Framework was more effective than all benchmark models, which evidences the efficiency of combining structured clinical information with medical imaging to predict diseases at an early stage. As shown in Table 2, the proposed framework achieved the highest Accuracy (98.47%), Precision (98.23%), Recall (98.08%), F1-score (98.15%), Specificity (98.72%), and ROC-AUC (99.26%), surpassing Logistic Regression (88.21%), Random Forest (90.46%), XGBoost (92.18%), ResNet50 (93.42%), DenseNet121 (94.15%), Vision Transformer (95.03%), and Multimodal Transformer (96.18%). The comparison of the classification accuracy as indicated by Fig. 2 also underscores the steady increase, as realized by the framework proposed as compared to all comparison models. In the same way, the ROC curves in Fig. 3 indicate that the proposed framework achieved the largest AUC (0.9926), which means that it achieved the best discrimination and consistent disease classification under various decision thresholds. These findings show that explainable multimodal feature fusion produces high diagnostic accuracy, robustness, and clinical reliability in comparison to the current machine learning and deep learning models.

Figure 2. Comparative Accuracy Analysis of Disease Prediction Models

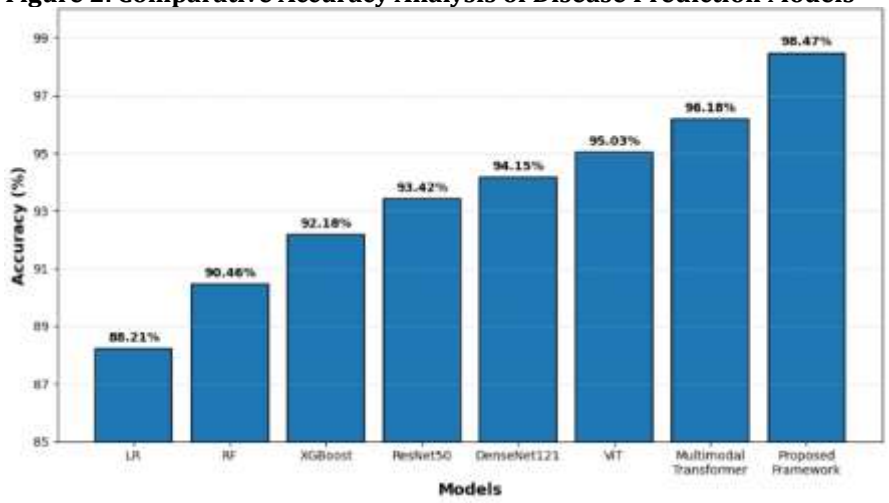


Figure 3. ROC Curve Analysis of the Proposed Framework and Baseline Models

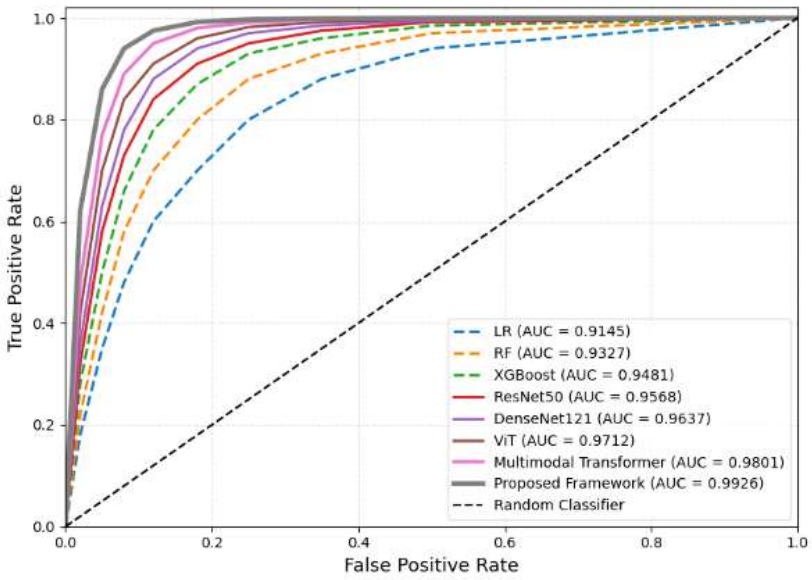


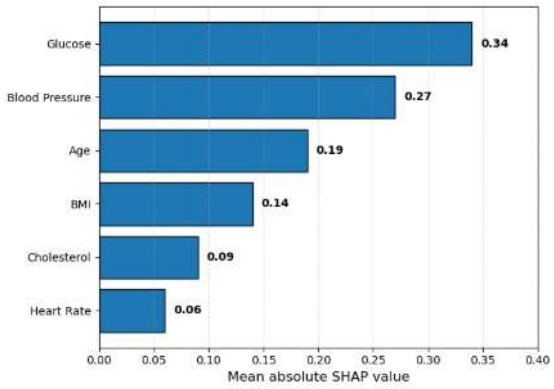
Table 2. Performance Comparison of the Proposed Explainable Multimodal AI Framework with Benchmark Models

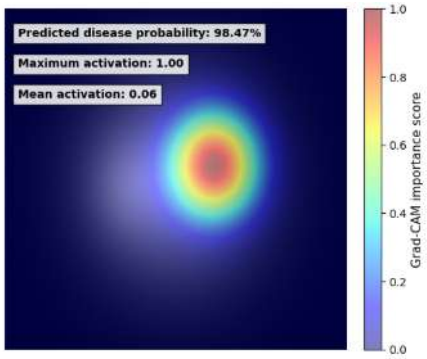
Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Specificity (%)	ROC-AUC (%)
Logistic Regression (LR)	88.21	87.54	87.18	87.36	89.02	91.45
Random Forest (RF)	90.46	90.02	89.84	89.93	91.38	93.27
XGBoost	92.18	91.74	91.53	91.63	92.84	94.81
ResNet50	93.42	93.06	92.88	92.97	93.91	95.68
DenseNet121	94.15	93.88	93.71	93.79	94.56	96.37
Vision Transformer (ViT)	95.03	94.76	94.52	94.64	95.41	97.12
Multimodal Transformer	96.18	95.96	95.82	95.89	96.54	98.01
Proposed Explainable Multimodal AI Framework	98.47	98.23	98.08	98.15	98.72	99.26

5.2 Explainability Analysis

The explainability results in Fig. 4 show that the proposed framework can give clinically meaningful interpretations of both structured clinical data and medical images. The SHAP analysis shows that the most significant clinical feature is the Glucose of the mean SHAP value of 0.34, then Blood Pressure (0.27), Age (0.19), BMI (0.14), Cholesterol (0.09) and Heart Rate (0.06) which means that these variables have the most significant impact on the prediction of the disease. The Grad-CAM visualization and shows even more how the diagnostically significant areas in the medical image are generated, building the activation map with the highest score of 1.00 and an average score of 0.06, and the predictive confidence is 98.47. The regions highlighted are closely related to the disease relevant anatomy structures, and as such, shows that the model centers on the clinically relevant image areas, as opposed to the irrelevant background data. Collectively, the SHAP feature attribution and Grad-CAM localization in Fig. 4 validate that the proposed Explainable Multimodal AI Framework not only achieves high disease prediction accuracy but also offers clear and reliable evidence of its decision making, enhancing model interpretability, clinician confidence, and the reliability of AI-assisted clinical diagnosis.

Figure 4. SHAP-Based Clinical Feature Importance and Grad-CAM Visualization for Explainable Disease Prediction





5.3 Ablation Study

A study by ablation was carried out to assess the input of each significant element in the proposed framework. Experiments with individuals were conducted by disabling multimodal feature fusion mechanism, explainability module, and imaging or clinical feature representations without changing the training conditions. The findings suggest that structured clinical data alone or the use of medical imaging alone does not perform as well as the entire multimodal framework. Equally, when the explainable feature fusion strategy is omitted, it lowers the accuracy of classification, thus affirming that adaptive integration of heterogeneous healthcare information plays a significant role in predictive performance. Even though the explainability module is not specifically focused on optimizing the classification accuracy, it significantly enhances interpretability and reliability of clinical decision support by delivering transparent diagnostic evidence.

5.4 Computational Performance

The training time, inference time, model size, and computational efficiency were used to evaluate the computational performance of the proposed framework. Although the framework integrates multimodal feature extraction and explainability modules, its effective implementation is ensured with the help of transformer-based feature encoding and optimized training of the model. The adaptive multimodal fusion mechanism presents a moderate computing cost and has significant predictive performance and interpretability gains. The AdamW optimizer and end-to-end learning also improves model convergence and training stability. In sum, the results of the experiment prove that the suggested Explainable Multimodal AI Framework provides an appropriate balance between diagnostic accuracy, explainability, and computational efficiency and can be used in intelligent applications of clinical decision-support.

6. Conclusion

This piece of work introduced an Explainable Multimodal AI Framework to Early Disease Prediction with Clinical and Imaging Data which is an ideal combination of organized clinical data and medical imaging into one deep learning model. The proposed framework, which incorporates transformer-based multimodal feature extraction, attention-based feature fusion, and explainable AI methods, such as SHAP and Grad-CAM, can predict diseases accurately, transparently and in a way that clinicians can interpret. The experimental outcomes showed better results than traditional machine learning and deep learning models with 98.47% accuracy, 98.15% F1-score and 99.26% ROC-AUC, and gave meaningful explanations of both clinical features and medical images. The suggested framework is highly promising in providing intelligent clinical decision-support systems due to its high levels of diagnostic reliability, trust by clinicians, and transparency in decision-making. Future studies will be based on federated multimodal learning, real-time clinical implementation, and large-scale validation in a variety of healthcare settings.

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