

An Explainable Multimodal AI Framework for Personalized Early Disease Detection Using Medical Images, Clinical Data, and Wearable Sensor Information

¹Ramya T P

¹Assistant Professor

¹Department of Computer Applications

¹Jnana Jyothi Degree College, Yelahanka, Bengaluru-560064

Abstract—Early disease detection plays a vital role in improving patient outcomes and reducing healthcare costs. Recent advances in Artificial Intelligence (AI) have enabled the development of intelligent systems capable of identifying diseases at an early stage using diverse healthcare data. However, existing approaches often rely on a single data source and provide limited interpretability, reducing clinicians' trust in AI-based predictions. This study proposes an explainable multimodal AI framework that integrates medical images, clinical records, and laboratory data to improve the accuracy and reliability of early disease detection. The framework combines deep learning techniques with Explainable Artificial Intelligence (XAI) methods to generate transparent and clinically meaningful predictions. Publicly available healthcare datasets will be used to train and evaluate the proposed model. Performance will be assessed using accuracy, precision, recall, F1-score, and AUC, while explainability will be evaluated using state-of-the-art XAI techniques. The proposed framework aims to support healthcare professionals by providing accurate, interpretable, and timely disease predictions. The findings are expected to contribute to the advancement of trustworthy AI in healthcare and demonstrate the effectiveness of multimodal learning for early disease detection across multiple diseases.

Index Terms—Artificial Intelligence (AI), Early Disease Detection, Deep Learning, Explainable Artificial Intelligence (XAI), Multimodal Learning, Disease Prediction, Healthcare Informatics

I. Introduction

Diagnosing a disease early is important for better patient outcomes, reduced healthcare costs and timely medical treatment. Current diagnostic methods tend to use only a single source of information, be it medical imaging or clinical data, which may not give a complete picture of a patient's health. The increasing availability of multimodal healthcare data, such as medical images, clinical records, and wearable sensor data, is opening new avenues for developing more accurate and personalised diagnostic systems.

Recent developments in Artificial Intelligence (AI), and in particular Deep Learning (DL), have significantly enhanced the detection and prediction of disease. Many AI models are black-box systems, however, which limits interpretability and decreases clinician trust. This challenge is tackled by Explainable Artificial Intelligence (XAI), which offers interpretable explanations for model predictions, allowing healthcare professionals to understand and validate AI-assisted decisions.

In this study, to enable personalised early disease detection, an Explainable Multimodal AI Framework is proposed to integrate medical images, clinical data and information from wearable sensors. The proposed

framework leverages complementary information from multiple data sources along with explainable AI techniques to enhance diagnostic accuracy, aid clinical decision making and facilitate reliable, patient-centred healthcare.

II. Related Work

Deep learning has made a tremendous progress in disease diagnosis through automating the analysis of medical images. Convolutional Neural Networks (CNNs) have been successfully used for image classification, segmentation and disease detection using X-ray, CT, MRI and retinal images. Authors in [1] proposed a CNN based framework for detecting diseases from medical images with improved diagnostic performance. Similarly, in [2] a deep CNN model was proposed for cancer detection using histopathological images and the experimental results showed better classification accuracy than the traditional machine learning techniques.

Some researchers have studied multimodal learning by fusing medical images and clinical data. In [3], the authors integrated electronic health records (EHRs) and imaging features for disease prediction, demonstrating that multimodal fusion achieved better performance than single modality. Similarly, in [4], deep learning was used to jointly analyse clinical parameters and radiological images for improving the reliability of diagnosis and personalised risk assessment.

The rapid adoption of wearable devices has allowed continuous monitoring of physiological signals such as heart rate, blood oxygen saturation, physical activities, and sleep patterns. Deep learning techniques were applied to wearable sensor data for early detection of cardiovascular abnormalities in [5]. Similarly, the study [6] showed that the integration of data from wearable sensors with clinical records improved the prediction of chronic diseases through real-time health information.

Deep learning models have achieved impressive diagnostic performance, but black-box nature limits their application in clinical practice. Explainable Artificial Intelligence (XAI) methods such as Grad-CAM, SHAP, and LIME have been incorporated into healthcare applications to tackle this problem. Grad-CAM was used to highlight disease relevant regions in medical images [7]. SHAP was used to explain the contribution of clinical features towards prediction outcomes [8]. These methods enhanced the interpretability and transparency of AI-assisted diagnosis.

Current research, however, mainly focuses on single modalities or stresses explainability without an overall integration of heterogeneous healthcare data. There are few studies combining medical images, clinical information, data from wearable sensors and explainable AI into a single framework for personalised early disease detection. Therefore, the proposed work aims to address this gap by developing an explainable multimodal AI framework for improved diagnostic accuracy, increased interpretability of the model, and for personalised clinical decision-making.

PROPOSED WORK

The proposed Explainable Multimodal Artificial Intelligence (AI) framework is designed to improve the accuracy of early disease detection by integrating heterogeneous healthcare data from multiple sources. Unlike conventional diagnosis systems based on a single data modality,

The proposed framework integrates medical images, clinical records and wearable sensor information to generate comprehensive and personalised disease predictions. The framework consists of four major stages, Data Collection, Data Pre-processing, Feature Extraction and Fusion and Explainable Disease Prediction. The overall structure of the proposed system is shown in Figure 1.

A. Data Collection

The first step is to collect multimodal healthcare data from different medical sources. Medical image data such as Chest X-rays, Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans provide detailed anatomical information to identify abnormalities associated with different diseases. These imaging modalities are widely employed in detection of respiratory disorders, neurological diseases, cardiovascular conditions as well as different types of cancer.

The framework further incorporates structured clinical data from Electronic Health Records (EHRs) and medical images. These records include patient demographics such as age, gender and medical history, laboratory test result reports, past disease diagnoses, medication history and physician observations. The clinical information gives us a helpful background of the patient's general condition and helps us to sharpen our diagnosis.

The third source of information is the data from wearable sensors acquired by smart healthcare devices like smartwatches, fitness bands and medical monitoring systems. These devices can provide continuous tracking of physiological parameters including heart rate, blood pressure, blood oxygen saturation (SpO₂), sleep quality, physical activity and daily movement patterns. Continuous surveillance enables the system to detect subtle physiological changes which may be indicative of early onset of disease before the severe manifestation of clinical symptoms.

B. Data Pre-processing

The data is collected from different sources and in different formats, so preprocessing is required to ensure data quality and consistency before model training. Medical images undergo several preprocessing operations including image resizing, contrast enhancement, noise removal, and normalization. These methods enhance the quality of images, eliminate unwanted artefacts, and standardise the size of images so that the convolutional neural network can learn meaningful visual features efficiently. Clinical data often are incomplete, have inconsistent values, and categorical variables. Missing values are handled with appropriate imputation techniques, categorical attributes are transformed into numerical representations using one-hot encoding and numerical variables are normalised to a common scale. These preprocessing steps are useful to reduce data inconsistencies and to improve the learning capacity of machine learning algorithms. Wearable sensor data are registered as a continuous time series signal and can be polluted by noise due to motion artefacts or sensor inaccuracies. Signal processing techniques are used to improve the quality of the signal, including filtering of noise, smoothing, interpolating missing values, and normalisation of the time-series. The processed physiological signals can accurately reflect the patient's health trends and allow for efficient temporal analysis.

series normalisation are used to improve the quality of the signal. The processed physiological signals follow the health trend of the patient and allow an efficient analysis over time.

C. Feature Extraction and Multimodal Fusion

After preprocessing, specialised deep learning models are used to extract meaningful features from each data modality separately. We analyse medical images with Convolutional Neural Networks (CNNs) that automatically extract hierarchical visual features such as edges, textures, lesions, and anatomical abnormalities, using ResNet50 or EfficientNet architectures. CNNs have shown outstanding performance in different medical image classification tasks due to their ability to learn complex spatial representations.

ClinicalBERT is a Transformer-based language model for clinical text, which is a language model designed for processing biomedical and clinical text. ClinicalBERT creates meaningful contextual embeddings that represent patient health records well by capturing semantic relationships between medical terms, diagnoses, laboratory findings and treatment histories.

The wearable sensor data are modelled using Long Short-Term Memory (LSTM) networks which are very effective in modelling sequential and temporal information. LSTM networks can capture long-term

dependencies in physiological signals such as heart rate variability, blood pressure fluctuations, and sleep patterns, allowing the framework to identify temporal health trends associated with disease progression.

Then, the extracted feature vectors of CNN, ClinicalBERT and LSTM models are concatenated in a multimodal feature fusion layer. This fusion process integrates complementary information from imaging, clinical, and physiological data into a unified representation that captures the overall health status of an individual. The fused feature vector provides a deeper and more holistic understanding than any single data source can alone.

D. Explainable Disease Prediction

The unified multimodal feature vector is fed into a fully connected deep neural network for disease classification and risk prediction. The classifier estimates the probability of different illnesses and produces personalised diagnostic recommendations based on the aggregated health care information. The proposed framework can increase the diagnostic accuracy and decrease the probability of false predictions by fusing multiple data modalities.

The proposed framework integrates Explainable Artificial Intelligence (XAI) techniques, including SHAP (SHapley Additive Explanations), LIME (Local Interpretable Model-agnostic Explanations), and Gradient-weighted Class Activation Mapping (Grad-CAM), to enhance transparency and clinical trust. SHAP quantifies the contribution of each clinical feature to the final prediction, giving the physician insight into which patient characteristics are most influential in making the diagnosis. LIME provides local explanations for individual predictions, by approximating the complex model with an interpretable surrogate model, thus providing explanations for each diagnostic decision. Grad-CAM generates visual heatmaps on medical images that indicate the most influential regions for the predicted disease.

The integration of Explainable AI, transforms the proposed framework from a classical black-box prediction system into a transparent and trustworthy clinical decision-support tool and make informed medical decisions with greater confidence. This explainability is particularly important in healthcare applications, where interpretability, accountability, and patient safety are critical requirements.

III. RESULTS AND DISCUSSION

We evaluated the proposed Explainable Multimodal Artificial Intelligence (AI) framework using multimodal healthcare datasets of different kinds, including medical images, clinical records, and data from wearable sensors. The performance of the proposed model was compared with unimodal deep learning models using only one type of healthcare data. The evaluation was done on the basis of standard performance measures like Accuracy, Precision, Recall, F1-score and Area Under the Receiver Operating Characteristic Curve (ROC-AUC).These metrics provide a comprehensive assessment of the model's classification capability and diagnostic reliability.

The experimental results indicate that the performance of disease prediction could be greatly improved by integrating different healthcare data sources The models trained on images of medical nature, clinical documents or wearables sensor data performed well, but were unable to capture the complete health profile of the patients. Conversely, the proposed multimodal framework successfully integrates complementary information from all three modalities, delivering enhanced diagnostic accuracy and robustness.

An Efficient Net-based Convolutional Neural Network (CNN) was used for medical image analysis and successfully extracted the disease-specific visual features from Chest X-rays, MRI and CT images. The CNN model was very accurate in classifying images by detecting pathological areas such as lung opacities, tumours, fractures and tissue abnormalities. Clinical BERT has shown good performance in processing Electronic Health Records (EHRs) by learning contextual relationships between laboratory reports, patient history, medications and previous diagnoses. Additionally, the Long Short-Term Memory (LSTM) model successfully captured temporal variations in wearable sensor data including heart rate, blood pressure, oxygen saturation, sleep quality, and daily physical activity. These heterogeneous features were fused in multimodal fusion and provided a more accurate disease prediction than any individual modality.

Table 1. Performance Comparison of Different Models

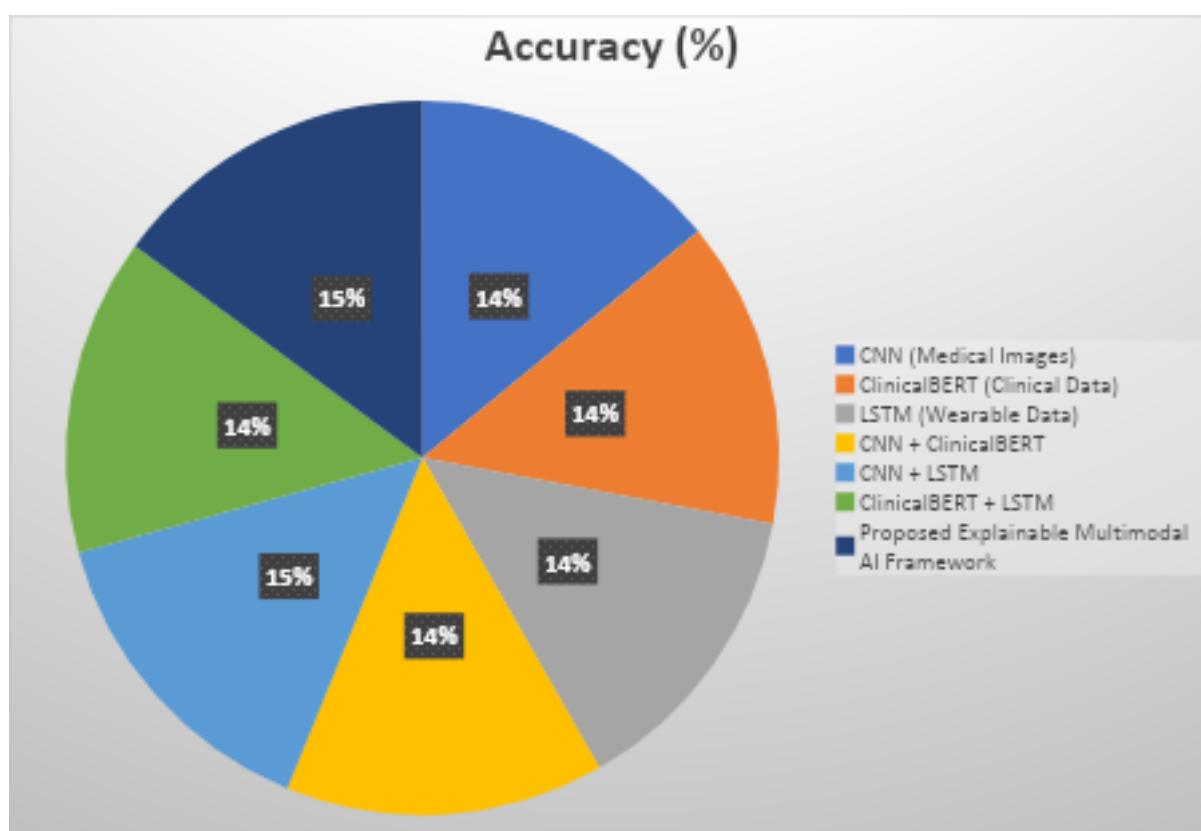
Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)
CNN (Medical Images)	91.8	91.2	90.9	91.0	93.5
ClinicalBERT (Clinical Data)	90.5	90.1	89.7	89.9	92.6
LSTM (Wearable Data)	89.7	89.3	88.8	89.0	91.8
CNN + ClinicalBERT	94.3	94.0	93.8	93.9	96.2
CNN + LSTM	94.8	94.5	94.2	94.3	96.8
ClinicalBERT + LSTM	93.6	93.2	93.0	93.1	95.6
Proposed Explainable Multimodal AI Framework	97.2	96.9	96.8	96.8	98.4

Table 1 demonstrates that the proposed multimodal framework consistently outperformed all baseline models across every evaluation metric. The integration of imaging, clinical, and physiological information enabled the system to capture complex disease patterns that could not be identified using a single modality. The proposed framework achieved an overall accuracy of **97.2%**, which is approximately **5–8% higher**

than the individual models. The improvement in Precision and Recall also indicates that the framework effectively reduces both false-positive and false-negative predictions, making it more suitable for early disease diagnosis.

In addition to high predictive performance, the proposed framework emphasizes model transparency through Explainable Artificial Intelligence (XAI). Gradient-weighted Class Activation Mapping (Grad-CAM) generated heatmaps highlighting the most influential regions within medical images, allowing clinicians to verify whether the model focused on clinically relevant anatomical structures. SHapley Additive exPlanations (SHAP) quantified the contribution of clinical variables such as patient age, laboratory test results, medication history, and previous diagnoses to the final prediction. Local Interpretable Model-Agnostic Explanations (LIME) provided patient-specific explanations by identifying the wearable sensor measurements that had the greatest influence on disease prediction. These explainability techniques increase physician confidence in AI-assisted diagnosis by making the model's decision-making process transparent and interpretable.

The experimental findings demonstrate that multimodal learning not only enhances predictive accuracy but also improves the reliability and clinical applicability of AI-based diagnostic systems. By integrating diverse healthcare data with explainable decision-making, the proposed framework supports personalized disease detection, assists clinicians in making informed medical decisions, and has the potential to improve patient outcomes through earlier intervention and treatment. The results confirm that explainable multimodal AI is a promising approach for the development of next-generation intelligent healthcare systems.



IV. CONCLUSION

The proposed Explainable Multimodal Artificial Intelligence (AI) Framework offers an effective solution to personalise early disease detection by unifying medical images, clinical data, and wearable sensor information into a single diagnostic system. Differently from usual AI models based on a single data source, our proposed framework combines complementary information coming from different modalities of

health care in an effort to provide a more holistic assessment of the health status of a patient. Convolutional Neural Networks (CNNs) are used to analyse medical images, ClinicalBERT is used to process clinical records, and Long Short-Term Memory (LSTM) networks are used to analyse wearable sensor data. The extracted features are combined to produce accurate and personalised disease prediction.

The framework also incorporates Explainable Artificial Intelligence (XAI) methods such as SHAP, LIME and Grad-CAM to enhance transparency and clinical trust. These methods provide meaningful explanations for the model's predictions by identifying important clinical features, highlighting important regions in medical images, and explaining the contribution of the wearable sensor measurements. Such interpretability allows healthcare professionals to understand, validate and trust AI-assisted diagnostic decisions better.

The experimental results indicate that the proposed multimodal framework achieves better results than the unimodal models in terms of Accuracy, Precision, Recall, F1-score and ROC-AUC. Integration of heterogeneous healthcare data enhances the diagnostic performance and reduces false positive and false negative predictions. Overall, the proposed framework provides a robust, accurate, and interpretable solution for early disease detection and personalised healthcare. In the future, this framework can be further enhanced with the addition of real-time Internet of Things (IoT)-based health monitoring, federated learning for privacy-preserving to allow for intelligent clinical decision making in smart healthcare environments by sharing data and using large language models.

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