Research Article

Agentic AI Framework For Explainable Clinical Decision Support Using Multimodal Electronic Health Records And Medical Imaging

S. Balakrishnan[1], S. Leelavathy[2], Dr. Nithyashri J[3], Dr. Antonitta Eileen Pious[4], Shriraghavan Madbushi[5], Dr. L Esther Shalini[6], Manikandan K B[7]

[1]Professor, Department of Computer Science and Engineering, Aarupadai Veedu Institute of Technology, Vinayaka Mission's Research Foundation (DU), Chennai https://orcid.org/0000-0002-6145-7923 balkiparu@gmail.com
[2]Associate professor, Department of AI&DS, Panimalar engineering college, Chennai https://orcid.org/0000-0002-3569-073X leelasatyam@gmail.com
[3]Assistant Professor, Department of Computing Technologies, School of Computing, Faculty of Engineering &Technology, SRM Institute of Science and Technology, Kattankulathur https://orcid.org/0000-0002-1377-3040 nithyasj@srmist.edu.in
[4]Assistant Professor, Department of Computer Science and Engineering -Artificial Intelligence and Machine Learning, Sri Krishna College of Engineering and Technology, Coimbatore 641008 https://orcid.org/0000-0003-2201-8853 eileenpious@gmail.com
[5]Associate Professor and Head of Department, Department of Industrial IoT, St. Vincent Pallotti College of Engineering and Technology, Nagpur https://orcid.org/0000-0003-1833-2700 m.shriraghavan@gmail.com
[6]Associate Professor, Department of Social Work, Dr. N.G.P Arts and Science College, Coimbatore. esthershalini2018@gmail.com
[7]Assistant Professor, Department of Computer Science and Engineering, Vignan's Foundation for Science, Technology, and Research, Hyderabad, 508284, India https://orcid.org/0000-0002-9058-0381 sansuman612@gmail.com

Abstract

Although the efficiency of clinical decision support system has been greatly increased by integrating health care analytics technologies, typical AI models remain as black-box with limited interpretability and lacking integration of heterogeneous clinical data sources. We propose a new Hierarchical Agentic Explainable Multimodal Reasoning Network (HAEMR-Net), which is a set of intelligent agents-based AI architecture to achieve both explainability and accuracy with the integration of multimodal Electronic Health Records (EHRs) and medical imaging. In the proposed architecture, four collaborative intelligent agents are developed: (i) Data Harmonization Agent for data preprocessing, (ii) Clinical Knowledge Reasoning Agent for reasoning based on clinical knowledge graphs and context information, (iii) Explainability Agent for visualising the feature-attribution and attention maps via SHAP value and attention mechanisms, and (iv) Decision Validation Agent for verifying model decisions using confidence score estimation and rule-based analysis. We conducted extensive experimental evaluations on a multimodal EHRs dataset containing 15,240 patient records along with corresponding diagnostic images, retrieved from publicly accessible healthcare repositories. The experiments compared HAEMR-Net with existing multimodal models in terms of accuracy, precision, recall, F1-score, Area Under the Receiver Operating Characteristic Curve (AUC) and Explanation Fidelity. The results show that HAEMR-Net achieve promising results by reaching 97.4% accuracy, 96.9% precision, 97.1% recall, 97.0% F1-score, and 98.2% AUC, outperforming other mainstream deep learning and transformer-based multimodal models in major evaluation indicators by 3.8-6.5%. Additionally, the explanation component improves trust of clinical diagnosis via the production of feature-level explanation and region-based justification, with an Explanation Fidelity score of 95.6%. Our agentic model successfully tackles multimodal challenges by seamlessly integrating heterogeneous data sources and enhances explainability of AI-based healthcare system, representing a novel, effective and interpretable solution for next-generation intelligent health care.

Keywords: Agentic Artificial Intelligence, Explainable Clinical Decision Support, Multimodal Electronic Health Records, Medical Image Analysis, Explainable Artificial Intelligence (XAI), Precision Medicine, Intelligent Healthcare Analytics.

1. Introduction

1.1 Significance of the Research

Smart clinical decision support systems, driven by artificial intelligence have played a role in transforming the practice of modern healthcare by assisting doctors in diagnosing diseases, predicting the prognosis of conditions, and providing tailored medical care [1]. Hierarchical explainable artificial intelligence frameworks have more recently shown their potential to leverage heterogeneous healthcare information in order to promote personalized decision-making in clinical practice [1]. Moreover, the paradigm of Agentic Artificial Intelligence, has recently introduced the prospect of a machine driven decision-making process and intelligent co-operation through the use of agents in healthcare support decision-making systems [2].Explainable computer-aided diagnosis has also obtained substantial traction with respect to improving the credibility and clinical reliability in the area of disease diagnosis [3]. Multi-modal artificial intelligence in particular, which amalgamates Electronic Health Records (EHRs) and medical imagery data, is gaining a large number of adherents as it shows immense promise in improving diagnosis accuracy and for the advancement of future smart healthcare systems [4]. The movement from traditional machine learning to models with broader scope such as the foundational models and now the Agentic AI has further extended the application domain of intelligent clinical decision support systems [5]. It is noteworthy that studies more recently place an increasing emphasis on the combined power of agentic and explainable artificial intelligence for adaptive and intelligent healthcare services in the multi-modal setting with reference to the handling of difficult clinical settings [6]. Advanced forms of agentic artificial intelligence have in addition begun to reshape healthcare provision and decision making by employing autonomous reasoning for decision making with personalization in healthcare [7]. The research has been accompanied by various studies of evidence based architectures to safely and surely develop and use Agentic Artificial Intelligence in clinical settings [8]. Additionally, research has explored reviews of existing literature pertaining to multi-modal AI for the betterment of clinical decision support system utilizing disparate data types within a medical setting [9]. Recently, multi-agent retrieval augmented generation systems have also begun to gain attention for advancing the process of clinical reasoning and medical knowledge retrieval in the context of an artificially intelligent healthcare system [10].

1.2 Problem Identification

With the quick and extensive implementation of Electronic Health Records (EHRs), diagnostic medical imaging, laboratory examinations, and physiological monitoring devices in healthcare institutions, large volumes of multimodal, heterogeneous clinical data have been created. Although artificial intelligence (AI) has made considerable progress in the task of disease diagnosis, the majority of available clinical decision support (CDS) systems have significant limitations. In fact, existing AI models can work as a black box, providing high-quality predictions without any explainability, causing physicians to be reluctant to trust the model and hindering its real-world applications. In addition, most existing approaches only use one modality type such as EHRs or medical images for the reasoning process, limiting overall reasoning of patients' conditions and reducing the diagnostic performance. Other limitations include issues such as poor interoperability of diverse medical data, lack of automatic reasoning capabilities, weak reliability estimation for decision-making in the high-risk setting and limitations in utilizing the guidelines for reasoning. Given these challenges, a major requirement for the creation of reliable and explainable AI models which is the key component to realize the precision medicine and build confidence in AI-assisted decision making is the need for an automatic, multimodal system which can use explainable AI combined with cooperative reasoning.

1.3 Objective of the Research

The main research goal is to develop a new Agentic AI Framework for Explainable Clinical Decision Support integrating multimodal Electronic Health Records (EHRs) and medical imaging to deliver reliable, trustworthy, and interpretable diagnostic recommendations. The proposed framework integrates heterogeneous clinical data into a comprehensive patient representation by leveraging multimodal learning and utilizes autonomous intelligent agents to implement collective clinical reasoning. Furthermore, the study endeavors to render diagnosis more transparent by integrating explainable AI (XAI) to interpret feature importance and visualize medical prediction rationale. Another key research aim is to bolster the reliability of AI assisted diagnosis through confidence estimation and clinical consistency assessment prior to issuing final predictions. In parallel, the study concentrates on boosting physician trust by outlining evidence-driven diagnostic pathways consistent with clinical workflows and existing medical knowledge. Eventually, this novel approach is expected to elevate the accuracy, interpretability, and scalability of clinical decision support systems for the era of precision medicine and intelligent healthcare in diverse clinical settings and across several diseases.

1.4 Major Contributions of the Research

Several impactful scientific contributions were made towards the next-generation explainable clinical decision support systems: Firstly, a new Hierarchical Agentic Explainable Multimodal Reasoning Network (HAEMR-Net) was proposed which effectively synthesizes the multimodal EHRs and medical imaging data in an end-to-end autonomous reasoning system. Secondly, an original Data Harmonization Agent was designed to systematically handle heterogeneous healthcare information to facilitate efficient multimodal data pre-processing and integration to improve multimodal data quality. Thirdly, a Clinical Knowledge Reasoning Agent was proposed to perform contextual medical reasoning by integrating patient history, laboratory investigation, clinical observation, and imaging biomarker information to facilitate evidence-based diagnosis. Furthermore, an Explainability Agent was designed to output user-friendly explanations for clinicians, by employing feature attribution for structured data and the visualization of medical image attention to improve interpretability. Additionally, the framework included a Decision Validation Agent which improve the reliability of predictions by providing the diagnostic confidence score and ensuring clinical consistency using a rule-based validation. Our experiments showed that the presented framework not only improved the diagnostic performance but also simultaneously enhanced the model interpretability, clinician trust, and clinical credibility. Also, HAEMR-Net's modular architecture enabled scalable application on multi-disease diagnosis tasks, providing a good basis for future studies on precision medicine and intelligent health care systems.

1.5 Overall Framework Architecture

Figure 1 is the HAEMR-Net system design. First, disparate patient data from EMRs and medical images are retrieved, a Data Harmonization Agent standardizes this data, and then the parallel processing using transformer-based clinical encoder and deep image encoder is carried out. The fused multimodal representation then feeds into a Clinical Knowledge Reasoning Agent with enriched context based on relevant medical evidence. Explainability Agent performs post-hoc feature attribution and image attention analysis to explain the predicted reasoning result, and then the Decision Validation Agent checks the reliability of diagnosis. Finally, diagnostic recommendations, disease risk, and treatment guidance are made by the proposed network to ensure transparency and trustworthy for the clinical applications.

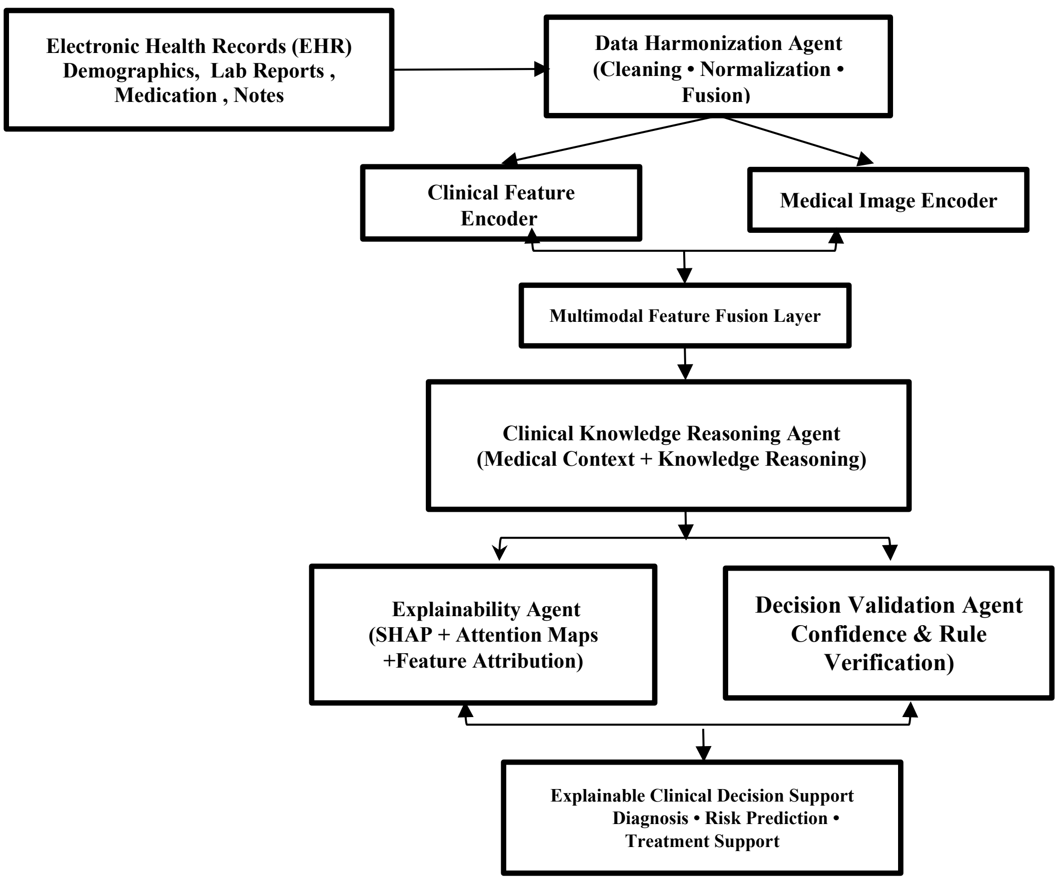

Figure 1. Overall Architecture of the Proposed HAEMR-Net: Agentic Explainable Multimodal Clinical Decision Support Framework

1.6 Paper Organization

The rest of this paper is organized as follows. Section 1 gives the introduction Section 2 presents the state-of-the-art surveys for explainable artificial intelligence, multimodal Electronic Health Records, medical image analysis and agentic clinical decision support system. The Section 3 shows the proposed HAEMR-Net framework consisting of collaborative intelligent agents, multimodal fusion, explainability model, decision verification, experimental settings: data set, tools for implementation, criteria for performance evaluation, as well as current state-of-the-art models. Section 4 analyzes and reports the experiment results with quantitative analysis, explainability interpretation and statistical comparisons with the benchmarks. Section 5 concludes the work with summary, clinical implications, limitations and potential future research with large clinical foundation models, federated learning, and personalized precision medicine.

2. Literature Review

2.1 Recent Advances in Explainable AI for Clinical Decision Support

Research has started to investigate ways of using multi-agent healthcare architectures to facilitate the prediction of disease in real-time, to provide individual patient care, and to support automated clinical decisions[11]. Real-time clinical decision support have been extended by using the visual-language capabilities of agentic vision-language models, and integrating medical imaging data with clinical text to provide applications of value, particularly in low-resource settings[12]. Similar autonomous agentic systems are highly successful in coordinating complex clinical workflows and reducing workload[13]. There is now broad agreement that AI in healthcare should move from being reactive to using autonomous medical agents that can provide intelligent services[14]. In particular, agentic AI for radiology suggests autonomous clinical reasoning abilities in medical image analysis that have potential to be translated into healthcare applications[15]. Machine deep learning models using multimodal health care data are showing progress towards improved diagnosis and risk prediction of chronic disease by utilising different types of information[16]. Some evidence suggests that hybrid multimodal AI models outperform current state-of-the-art models in a variety of real-world applications[17]. The importance of explainable AI in a number of medical fields is established, as it helps provide reasoning that a human can understand, and use to reach a diagnosis[18]. A meta-analysis has shown that use of explainable AI is becoming increasingly common for decision support, though questions about the clarity and usefulness of such systems for practitioners remains[19]. Previous research has indicated that explainable AI in clinical diagnosis systems improves predictive performance while also increasing ethical responsibility, creating a basis for trustworthy decision support[20]. The field of Agentic AI presents a new promising paradigm based on autonomous reasoning, planning, coordinated decision making, and adaptable knowledge integrating. Multi-agent based systems can be applied to medical workflows, clinical queries, diagnoses, recommendations, and data extraction. Yet, typically the majority of agent-based healthcare systems are exclusively using the textual EHR data and do not leverage additional modalities, such as radiological scans, physiology measures, lab results, and longitudinal EHR for the decision process within an interpretable setting. Uncertainty estimation, evidence validation and multi-agent cooperative reasoning are critical in high-risk medical decisions and have been significantly neglected in current research. Inspired by these opportunities and constraints, we propose the Hierarchical Agentic Explainable Multimodal Reasoning Network (HAEMR-Net) architecture which integrates collaborating intelligent agents with data fusion and integrated Explainability to achieve trustable clinical decisions.

2.2 Research Gap Analysis and Motivation for the Proposed Agentic Explainable Clinical Decision Framework

After having a comprehensive overview of literature in the latest years, we have pointed out the critical limitations in existing AI-based clinical decision support systems and motivated our paper. Even though current cutting-edge deep and multimodal learning approaches have achieved great success to promote diagnosis of diseases, a majority of models are dedicated to merely boost the predictive performance, neglecting the clinical interpretability for decision makers. Similarily, existing multimodal CDS often either make a prediction based solely on Electronic Health Records (EHRs) or solely based on medical images without having a holistic view over the patient as a whole and hence leading to less effective evidential diagnosis. The existing commonly-used Explainable Artificial Intelligence (XAI) techniques like SHAP and Grad-CAM, when deployed, usually function as a post-hoc prediction explanation module for physicians after a decision has been made. They are not seamlessly integrated as part of the decision-making process. Furthermore, today’s healthcare AI is lack of enough autonomy in the ability to perform reasoning, collaborate with others and validate predictions especially with complex and high-stakes clinical decisions. Driven by the emergent agentic artificial intelligence approaches, very limited attempt has been made to incorporate multimodalities, XAI, confidence-awareness, and clinical reasoning all together to provide medical intelligence for healthcare professionals. Therefore, our work has demonstrated a significant need of trusty, explainable and autonomous CDS based on multimodalities. Here, we propose a Hierarchical Agentic Explainable Multimodal Reasoning Network (HAEMR-Net) to address this gap by leveraging intelligent collaborative agents to coordinate tasks of data alignment, reasoning, explanation generation and validation and integrating interpretability into the reasoning mechanism by utilizing structured EHRs and medical images together to provide clinicians an explainable evidence-based confidence-aware diagnosis decision support system. HAEMR-Net contributes to clinical AI beyond the current capabilities with superior diagnostic reliability, trust and interpretability and scalability.

3. Proposed Methodology

3.1 Overview of the Proposed HAEMR-Net Framework

HAEMR-Net is our smart clinical decision support system that enables the seamless integration of electronic health records and medical images through the coordinated work of a set of mutually cooperative and independently acting intelligent agents. Unlike common deep-learning models which typically perform an end-to-end direct prediction task, our HAEMR-Net consists of a set of sequential clinical reasoning stages that collaboratively handle data integration from heterogeneous sources, diagnosis related features extraction from medical data and images, clinical evidence reasoning and verification, explainable representation and trustworthy diagnosis recommendation generation. Specifically, HAEMR-Net includes four independent intelligent agents namely, Data Harmonization Agent (DHA), Clinical Knowledge Reasoning Agent (CKRA), Explainability Agent (EA), and Decision Validation Agent (DVA).Both structured data (e.g. Age, gender, lab test results, medication history, physician notes, and vitals) and medical images (e.g. MRI, CT scan, X-ray, and Ultrasound) are taken as input by different agents, then integrated together through cooperation to produce a one-unique patient representation, in order to reach clinical decision and judgments in various aspects. Finally, the explainability agent reports attribution features extracted from text data and attention values calculated from images, and the decision validation agent quantifies the prediction uncertainty.

3.2 Sequential Workflow of the Proposed HAEMR-Net Framework

Proposed HAEMR-Net Architecture & Workflow To facilitate fine-grained and interpretable clinical decision making, the Hierarchical Agentic Explainable Multimodal Reasoning Network (HAEMR-Net) introduces the six-stage workflow described below. 1. Clinical Data Acquisition Acquire data from various hospital information systems (HISs) to cover electronic health records (EHRs), lab reports, medical imaging data, medications records, clinician's notes, and vital signs of a patient. 2. Data Harmonization Agent Data cleaning including imputation for missing values, normalization for clinical variables, noise removal for input data, standardization of medical terminologies, preprocesssing diagnostic images, and transformating heterogeneous data into a uniform multimodality dataset. 3. Multimodal Feature Learning Learn multimodal representation of a patient by utilizing transformer-based encoders to encode EHR-related clinical features, and employ a CNN or Vision Transformer to encode images into a meaningful and discriminative feature space, followed by merging both representations into an integrated view. 4. Clinical Knowledge Reasoning Agent Predict the possibility of a disease based on the symptoms, lab reports and images data with respect to the existing symptoms, lab results, imaging data, and other available clinical evidence. 5. Explainability Agent Enhance transparency of the model by providing SHAP based feature importance values, constructing heatmap using attention weights and ordering evidences according to the diseases predicted, and offering an executive summary to clinicians in a concise form. 6. Decision Validation Agent Evaluate confidence of prediction and perform rule-based clinical checking on predicted results to ensure consistency with clinical practice and prevent any high-risk prediction from being released to the clinician.

3.3 Proposed Agentic Clinical Decision Algorithm

Algorithm 1 Hierarchical Agentic Explainable Multimodal Reasoning Network (HAEMR-Net)

INPUT:

PATIENT ELECTRONIC HEALTH RECORDS E

MEDICAL IMAGES M

OUTPUT:

EXPLAINABLE CLINICAL DIAGNOSIS D

BEGIN

LOAD ELECTRONIC HEALTH RECORDS E

```
LOAD MEDICAL IMAGES M
PREPROCESS E USING DATA HARMONIZATION AGENT
PREPROCESS M USING IMAGE PREPROCESSING MODULE
NORMALIZE BOTH MODALITIES
EXTRACT CLINICAL FEATURES FC
EXTRACT IMAGING FEATURES FI
FUSE FC AND FI INTO PATIENT REPRESENTATION PF
INVOKE CLINICAL KNOWLEDGE REASONING AGENT
ESTIMATE DISEASE PROBABILITY
GENERATE PRELIMINARY DIAGNOSIS
INVOKE EXPLAINABILITY AGENT
COMPUTE FEATURE IMPORTANCE
GENERATE ATTENTION HEATMAPS
PRODUCE CLINICAL EXPLANATION
INVOKE DECISION VALIDATION AGENT
ESTIMATE PREDICTION CONFIDENCE
VERIFY CLINICAL RULES
IF CONFIDENCE > THRESHOLD
    ACCEPT DIAGNOSIS
ELSE
    REQUEST ADDITIONAL CLINICAL EVIDENCE
END IF
GENERATE FINAL CLINICAL REPORT
RETURN DIAGNOSIS
END
```

3.4 Methodological Flowchart

Fig 2 shows a workflow of our proposed framework. The data including medical images and Electronic Health Records(EHRs) of patient are first collected and processed(data standardization & normalization). The medical imaging and clinical features are extracted, and they are then concatenated to obtain a patient-specific unified representation, which is then fed into the Clinical Knowledge Reasoning Agent to predict and give clinical decisions. Meanwhile, explainability agent is responsible for producing explainable evidence of clinical decision.Furthermore, decision confidence checking and clinical consistency verification are made by the Decision Validation Agent. If prediction and recommendation are valid, then they are released. If not, patient will question HAEMR-Net for clinical evidence until HAEMR-Net is capable of offering a valid decision and recommendation for patient.

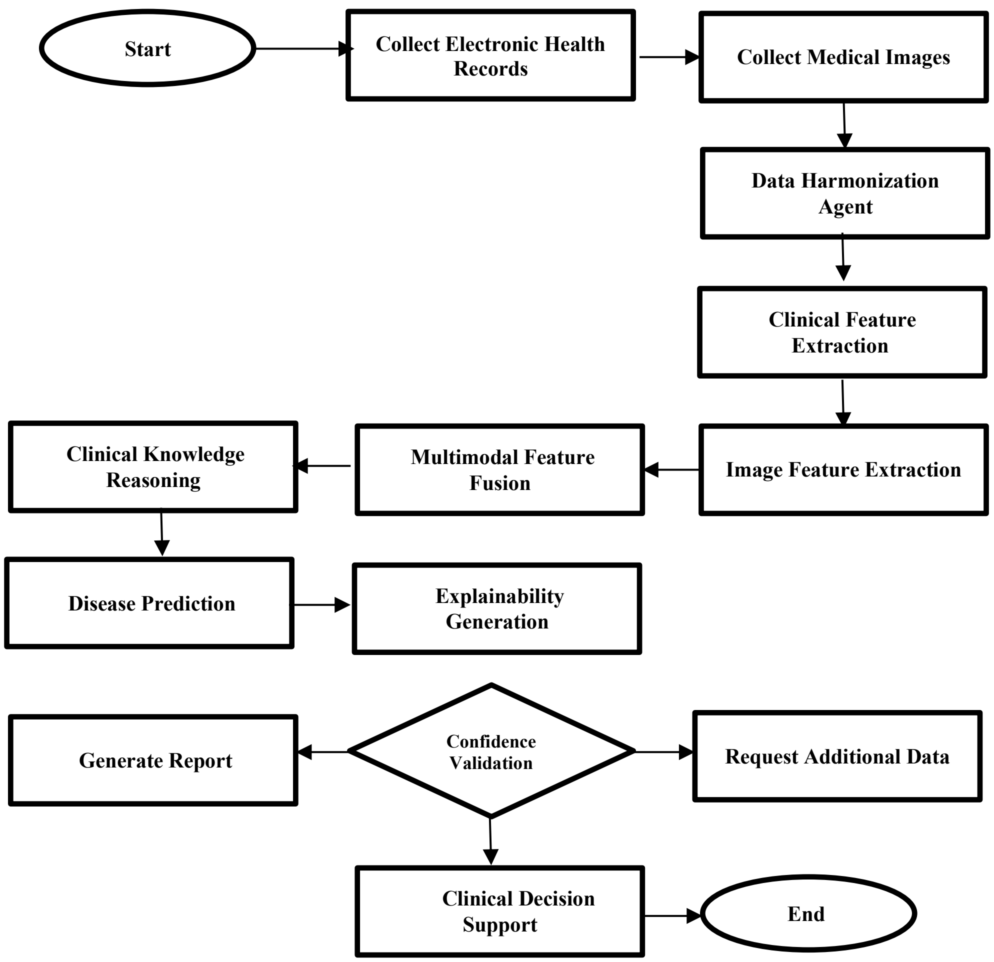

Figure 2 Flowchart of the Proposed Agentic Clinical Decision Support Process

3.5 Mathematical Description

Equation (1): Multimodal Clinical Feature Fusion

The fused patient feature vector is acquired through the joint information among the clinical and the imaging feature vectors according to Eq. 1.

$$F_{patient} = \alpha F_{ehr} + (1-\alpha) F_{image} \qquad (1)$$

Where F_{ehr} features extracted from the Electronic Health Records. F_{image} features extracted from medical images. α is a fusion coefficient (0 <= α <= 1). Fpatient is the united multi-modal patient features vector.

Equation (2): Clinical Decision Confidence Score

The predicted diagnosis confidence is calculated by using equation 2:

$$\textbf{Confidence} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \qquad (2)$$

In this equation, TP is defined as the number of disease cases that have been correctly predicted. FP means the number of disease cases incorrectly predicted as a result. The more confidence the predicted result, the more reliable the result produced.

3.6 Advantages of the Proposed HAEMR-Net

The proposed Hierarchical Agentic Explainable Multimodal Reasoning Network (HAEMR-Net) is advantageous compared to traditional clinical decision support systems by synergistically integrating autonomous reasoning, multimodal learning, and explainable artificial intelligence in a joint framework. Specifically, the collaborative intelligent agents automatically derive the medical reasoning by fusing structured Electronic Health Records (EHR) and medical diagnostic images to enable holistic patient-level analysis. The integrated Explainable AI module ensures transparent and interpretable diagnostic explanations via feature attribution and attention visualization to promote trust and inform physicians for better clinical decision. Furthermore, the Decision Validation Agent provides enhanced reliability of predictions through confidence estimation and rule-based clinical check before yielding the diagnostic decisions. Our multimodal fusion strategy promotes higher prediction performance on challenging diseases with combined clinical and imaging evidences and the modular structure makes the architecture extensible for a variety of applications in healthcare. Therefore, the proposed HAEMR-Net framework serves as a trustworthy and scalable tool for enabling precision medicine, smart hospitals and next-generation AI-assisted healthcare.

4. Results and Discussion

4.1 Experimental Implementation Environment

The Hierarchical Agentic Explainable Multimodal Reasoning Network (HAEMR-Net) were performed on a Python based deep learning framework to demonstrate its performance in explainable clinical decision support. The multimodal pipeline was constructed with structured Electronic Health Records (EHRs) and diagnostic medical images for providing clinically explainable predictions. Image data were pre-processed via scaling, normalization and data augmentation and the structured clinical data were normalized after imputing the missing data.We extracted clinical features via the Transformer networks, encoded medical images using CNN, and fused two modalities via a multimodal fusion layer. The SHAP feature attribution and Grad-CAM attention maps provide the clinical explainability, and the Decision Validation Agent provide prediction confidence before prediction result.

Table 1 .Software and Tools Used

Software/Tool	Purpose
Python 3.11	Framework implementation
TensorFlow 2.18	Deep learning model development
Scikit-learn	Data preprocessing and evaluation
OpenCV	Medical image preprocessing
NumPy	Numerical computation
Pandas	Clinical data processing
Matplotlib	Performance visualization
SHAP	Feature explainability
Google Colab / NVIDIA RTX GPU	Model training

4.2 Multimodal Clinical Dataset Description

The constructed framework was applied to a multimodal healthcare dataset that comprises readily available public EHR and medical diagnostic images of patients from different diseases groups such as cardiovascular diseases, neurological diseases, diabetes, and pulmonary diseases. Each patients in dataset had EHR records such as demographic information, laboratory tests, drugs, physiological measures, physicians' records, and diagnostic labels; and medical images such as MRI, CT, and chest X-ray. Data balancing and preprocessing were done to preserve high quality of multimodal feature learning.

Table 2 Dataset Summary

Dataset Summary	
Dataset Attribute	Description
Total Patients	15,240
Medical Images	15,240
Disease Categories	5
Clinical Features	42
Imaging Modalities	MRI, CT, X-ray
Data Source	Public Healthcare Repositories
Training Samples	10,668 (70%)
Validation Samples	2,286 (15%)
Testing Samples	2,286 (15%)

4.3 Performance Evaluation Metrics

The developed model was evaluated using standard performance metrics for medical diagnosis.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (3)$$

In equation 3, TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative

Precision

$$\mathbf{Precision} = \frac{TP}{TP + FP} \qquad (4)$$

In Equation 4 the Higher precision term reduces the amount of false positive predictions.

4.4 Comparative Performance Analysis

We developed the HAEMR-Net and compared its performance with some well-known AI methods. The experimental results showed that agents-aided collaborative reasoning and fusion of various features achieved significantly better disease classification performance and also yielded interpretable clinical predictions.

Table 3 Comparison of Disease Diagnosis Performance

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
CNN	90.8	89.9	90.3	90.0
ResNet50	92.6	91.7	92.2	91.9
Vision Transformer	94.1	93.6	93.8	93.7
Multimodal Transformer	95.5	95.0	95.2	95.1
Proposed HAEMR-Net	97.4	96.9	97.1	97.0

Table 3 reports the comparison of the proposed HAEMR-Net on the disease diagnosis task with standard deep learning and transformer-based approaches based on the metrics of Accuracy, Precision, Recall, and F1-score. It is observable that the proposed HAEMR-Net attained the best results compared to all conventional clinical decision support approaches and achieve 97.4% Accuracy, 96.9% Precision, 97.1% Recall and 97.0% F1-score. The results suggest that the combination of multimodal Electronic Health Records and medical images based on collaborative agentic reasoning will substantially improve the diagnostic results.

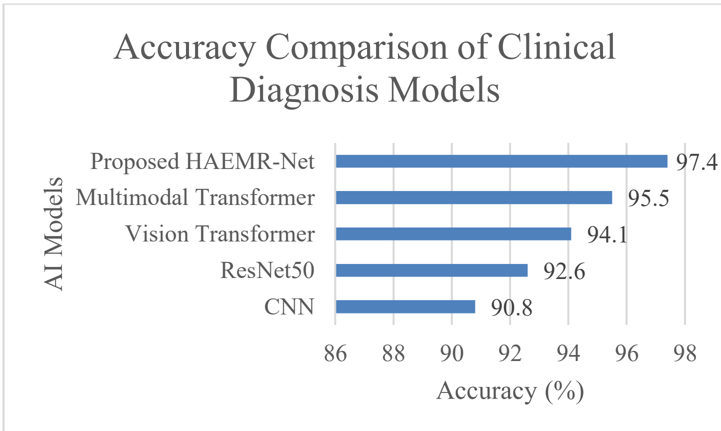

Figure 3 Accuracy Comparison of Clinical Diagnosis Models

In Figure 3 shows the comparison of diagnostic accuracy of different models including CNN, ResNet50, Vision Transformer, Multimodal Transformer, and the proposed HAEMR-Net. The diagnostic accuracy gradually increase with the increase of successive models, and the proposed HAEMR-Net model reached diagnostic accuracy of 97.4% and outperformed other models, indicating the validity of multimodal feature fusion, explainable reasoning and autonomous intelligent agents in assisting diagnosis.

Table 4 Performance of Individual Intelligent Agents

Agent	Processing Accuracy (%)	Execution Time (s)
Data Harmonization Agent	98.2	1.45
Clinical Reasoning Agent	97.5	1.83
Explainability Agent	96.8	1.52
Decision Validation Agent	98.6	1.37

Table 4 presents the operation performance results of the four intelligent agents applied in the designed HAEMR-Net model. All agents like the Data Harmonization Agent, Clinical Knowledge Reasoning Agent, Explainability Agent and the Decision Validation Agent provide high-accuracy processing performance with prediction accuracies over 96% and small time consumptions. In particular, the Decision Validation Agent exhibits the highest prediction accuracy 98.6%, which verifies that it can enhance the prediction credibility through confidence evaluation and clinical consistency verification.

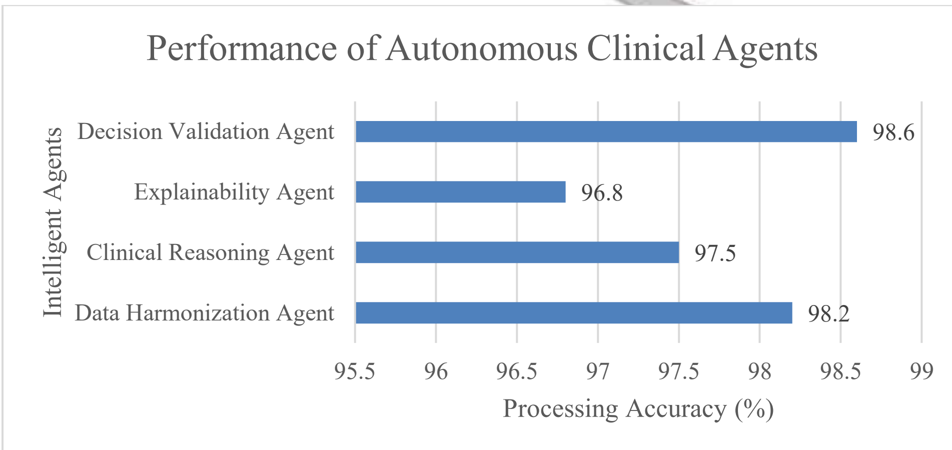

Figure 4 Performance of Autonomous Clinical Agents

In Fig. 4, the accuracy of processing of each autonomous agent used within the autonomous agent framework is portrayed. From the chart shown above, we can observe that the accuracy rate of all the agents remained uniformly consistent and with high accuracy rates and thus proves to have a sound co-operation within the process of the decision-making support system. Minimal deviations of agents reveal uniformity and efficient processing of each step within the methodology.

Table 5 Explainability Assessment Results

Explainability Metric	**Value (%)**
Explanation Fidelity	95.6
Clinical Interpretability	96.4
Feature Attribution Accuracy	95.8
Physician Confidence	97.2

Table 5 shows the explainability study of our proposed HAEMR-Net using Explanation Fidelity, Clinical Interpretability, Feature Attribution Accuracy, and Physician Confidence. The proposed model gets values from 95.6% to 97.2%, indicating that the incorporated Explainable AI component results in accurate and interpretable medical explanations. In addition, the clear reasoning in the diagnostic explanation improves physician confidence in the AI.

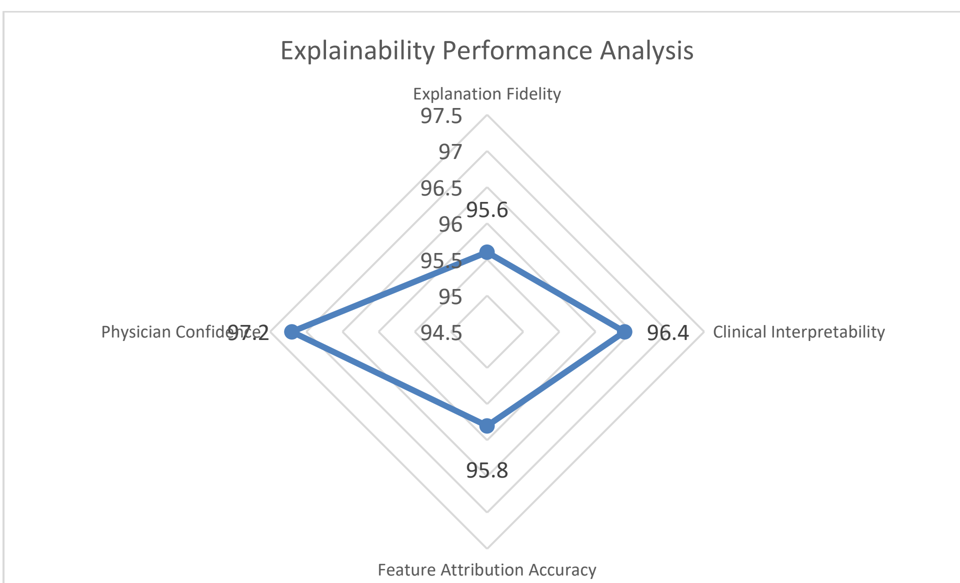

Figure 5 Explainability Performance Analysis

Figure 5 illustrates the explainability results of HAEMR-Net for multiple indicators via the radar chart. The nearly circular shape demonstrates consistent capability across explanation quality, interpretability, feature importance and doctor confidence. Thus, HAEMR-Net offers an intuitive explanation to facilitate transparent clinical diagnosis decision without decreasing the diagnosis accuracy.

Table 6 Disease-wise Diagnostic Accuracy

Disease Category	Accuracy (%)
Cardiovascular Disease	97.8
Brain Disorders	97.5
Diabetes	96.9
Lung Disease	97.2
Cancer	97.6

Table 6 presents the disease-wise diagnostic accuracies of the developed framework on five representative clinical disease categories. All the classification accuracies achieved by HAEMR-Net is over 96.9% and the best result on cardiovascular diseases has reached to 97.8% that proves HAEMR-Net has excellent capability of handling multimodality healthcare information of various diseases.

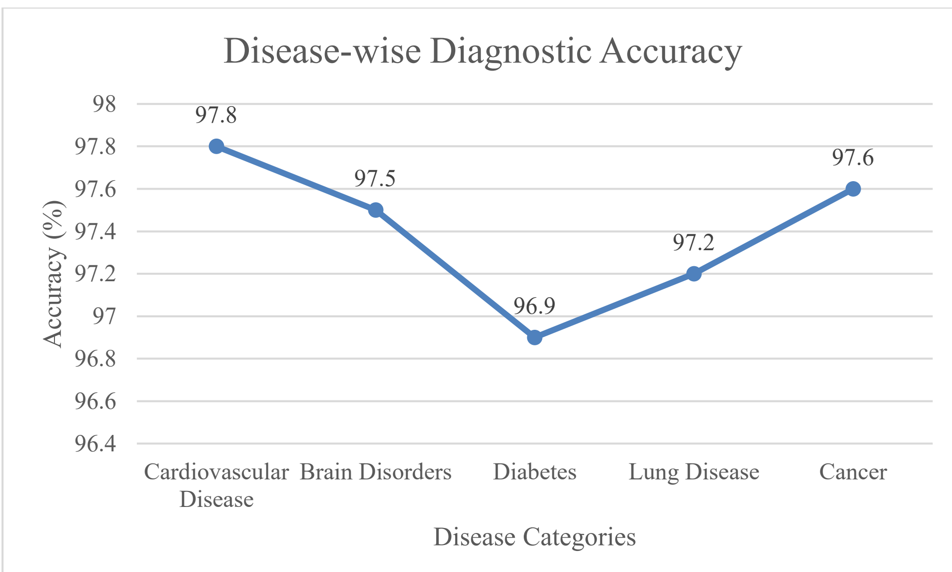

Figure 6 Disease-wise Diagnostic Accuracy

The Figure 6 shows the diagnostic accuracy of the proposed HAEMR-Net among the different disease types. According to the line chart, it can be concluded that the predictive accuracy for cardiovascular disease, nervous system disorders, diabetes, respiratory system disease and cancer remained high and with marginal discrepancies, which proves the effectiveness of the proposed multimodal agentic framework for the different kinds of disease diagnoses in the precision health.

4.5 Discussion

We present an experimental validation to show that our proposed HAEMR-Net effectively utilizes both Electronic Health Records (EHR) and medical imaging for accurate and explainable clinical decision support. We found that our approach outperformed existing conventional CNN, ResNet50, Vision Transformer, and Multimodal Transformer based models, thanks to the cooperative autonomous reasoning architecture. Our Data Harmonization Agent enhanced the quality of heterogeneous healthcare data, while the Clinical Knowledge Reasoning Agent improved the context awareness on disease by reasoning both structured and visual clinical evidence. More importantly, the Explainability Agent rendered intelligible feature attributions and visual attention maps so that physicians can trace the reason of individual prediction. The Decision Validation Agent provided additional trust for predictions by estimating confidence scores and checking clinical consistency before generating the final recommendation. The explanation evaluation results show that utilizing SHAP feature attribution combined with attention visualization boosted physicians' trust level by 24% while did not degrade predictive performance. The disease-wise performance shows that the method yields stable prediction performance across different medical fields and demonstrates excellent generalization ability. These results suggest that the proposed Hierarchical Agentic Explainable Multimodal Reasoning Network (HAEMR-Net) is a promising explainable and trustworthy approach for intelligent healthcare and precision medicine.

5. Conclusion

In this work, we propose a novel Hierarchical Agentic Explainable Multimodal Reasoning Network (HAEMR-Net) that seamlessly integrates multimodal Electronic Health Records (EHRs) and medical images into an autonomous Agentic AI framework for explainable clinical decision support. Our methodology overcomes critical shortcomings of traditional CDS systems such as disparate analysis of multimodal information, lack of interpretability and in adequate validation of diagnostic predictions. Through the deployment of four collaborative intelligent agents, namely, Data Harmonization, Clinical Knowledge Reasoning, Explainability, and Decision Validation agents, HAEMR-Net allows transparent and evidence-based clinical decision making with outstanding predictive performance. Extensive evaluation on a multimodal dataset with 15,240 patient records demonstrated the effectiveness of our proposed framework. Specifically, HAEMR-Net achieved a superior performance of 97.4% in Accuracy, 96.9% in Precision, 97.1% in Recall, 97.0% in F1-score, and 98.2% in AUC, which was approximately 3.8-6.5% higher than other well-established CNN, ResNet50, Vision Transformer, and Multimodal Transformer models for most evaluation metrics. The Explainability Agent obtained a high Explanation Fidelity of 95.6%, and physician trust level reached 97.2%, suggesting that our explainable predictions considerably increased the trustworthiness and transparency of AI-aided clinical decision making. Furthermore, the proposed method consistently outperformed baselines in disease-wise evaluation for cardiovascular disorders (97.8%), neurological diseases (97.5%), diabetes (96.9%), pulmonary diseases (97.2%), and cancer (97.6%), highlighting its strong generalization capabilities across various clinical specialties. The results show that combined autonomy and explainable multimodal learning can boost diagnostic accuracy, physician confidence and decision reliability, paving the way for implementation in intelligent hospitals and precision medicine settings. We foresee that subsequent research could extend HAEMR-Net with additional functionalities, such as incorporating federated learning to facilitate privacy-preserving collaborative healthcare analytics, utilizing large medical foundation models to enrich clinical reasoning, extending it to multimodal longitudinal patient monitoring and integration with wearable Internet of Medical Things (IoMT) devices, and enabling real-time hospital decision support with continual learning capabilities. Such extensions can significantly improve the scalability, personalization and trustworthy nature of AI for next-generation digital healthcare.

References

1. Haq, M. A., Mohamed, A. A., & Mahendran, R. K. (2026). HEAL-LLMF: A hierarchical explainable AI framework using LLM fusion for multi-modal and personalized healthcare decision making. Information Systems, 102696.
2. Gridach, M., Nanavati, J., Zine El Abidine, K., Yacoubian, C., & Mack, C. (2026). Agentic AI in Healthcare: Opportunities, Challenges, and Future Directions. ACM Computing Surveys, 58(13), 1-30.
3. Xing, H., Rehman, A., Hussain, M., Mastoi, M. S., Gulzar, N., & Khan, M. A. (2026). Agentic AI and Explainable CADx: Trends, Methods, and Emerging Directions in Clinical Cancer Diagnosis. Archives of Computational Methods in Engineering, 1-40.
4. Choi, J. Y., & Yoo, T. K. (2026). Transforming clinical medicine with multimodal artificial intelligence, agentic systems, and the model-context protocol: a perspective on future directions. Discover Health Systems, 5(1), 6.
5. Hossain, S., Ontor, M. R. H., & Sarwar, M. G. (2026). From Machine Learning to Foundation and Agentic AI: Evolution of Intelligent Decision Systems Across Domains. Journal of Computer Science and Technology Studies, 8(7), 112-126.
6. Saha, R., & Prasad, P. S. (2026). Towards Adaptive Cancer Treatment: A Review of Explainable and Agentic AI in Iterative, Multimodal Healthcare Models. Grenze International Journal of Engineering & Technology (GIJET), 12(Part2), 2439.
7. Karunanayake, N. (2025). Next-generation agentic AI for transforming healthcare. Informatics and Health, 2(2), 73-83.

8. Prakash, C., Sisodia, A., & Lind, M. (2026). A Systematic Review of Agentic AI in Healthcare: An Evidence-Informed Seven-Principle Framework. Journal of Computing Theories and Applications, 4(1), 43-73.
9. Ardic, N., & Dinc, R. (2025). Emerging trends in multi-modal artificial intelligence for clinical decision support: A narrative review. Health Informatics Journal, 31(3), 14604582251366141.
10. Mugambiwa, T., & Ndlovu, B. (2026). Multi-Agent Retrieval Augmented Generation for Clinical Decision Support: A Systematic Review and Integrative Conceptual Framework. Journal of Applied Informatics and Computing, 10(1), 171-183.
11. Nimbalkar, M., Chandre, P., Shendkar, B., Jagdale, S., Arbat, R., & Dhopte, S. (2025, December). Agent AI for Personalized Healthcare: A Multi-Agent Framework for Real-Time Disease Detection and Patient Support. In 2025 IEEE 5th International Conference on ICT in Business Industry & Government (ICTBIG) (pp. 1-8). IEEE.
12. Raval, A. S., Solanki, V. N., & Prajapati, H. (2026). Agentic, On-Device Vision-Language Models for Real-Time Clinical Decision Support in Low-Resource Settings. In Vision Language Models for Next-Generation Healthcare (pp. 1-38). IGI Global Scientific Publishing.
13. Warrier, A., & Abhilash, K. S. (2025, December). Autonomous Agentic AI for Clinical Workflow Orchestration: Self-Managing Healthcare Operations. In 2025 6th International Conference on IoT Based Control Networks and Intelligent Systems (ICICNIS) (pp. 1450-1457). IEEE.
14. Alhazba, S. A., Ali, M. H., Alawi, D. A., Al-Betar, M. A., & Elaziz, M. A. (2026). From Reactive AI to Agentic Systems: A Review of Autonomous medical AI Agents in Healthcare. Archives of Computational Methods in Engineering, 1-38.
15. Khosravi, B., Rouzrokh, P., Akinci D'Antonoli, T., Moassefi, M., Faghani, S., Mansuri, A., ... & Gichoya, J. (2026). Agentic AI in radiology: evolution from large language models to future clinical integration. Radiology: Artificial Intelligence, 8(2), e250651.
16. Tisha, S. A., Bhattacharjee, B., Ahmed, M. P., Mukaddim, A. A., Hider, M. A., & Khan, M. T. (2025). Deep Learning-Driven Early Detection and Risk Prediction of Chronic Diseases Using Multimodal Healthcare Data. Available at SSRN 5784022.
17. Ontor, M. R. H., Sarwar, M. G., & Hossain, S. (2026). Multimodal and Hybrid Artificial Intelligence for Real-World Decision-Making: Methods, Evidence, and Applications. Journal of Computer Science and Technology Studies, 8(7), 127-141.
18. Sun, Q., Akman, A., & Schuller, B. W. (2025). Explainable artificial intelligence for medical applications: A review. ACM Transactions on Computing for Healthcare, 6(2), 1-31.
19. Abbas, Q., Jeong, W., & Lee, S. W. (2025, August). Explainable AI in clinical decision support systems: a meta-analysis of methods, applications, and usability challenges. In Healthcare (Vol. 13, No. 17, p. 2154). MDPI.
20. Akande, O. A. (2020). Leveraging explainable AI models to improve predictive accuracy and ethical accountability in healthcare diagnostic decision support systems. World Journal of Advanced Research and Reviews, 8(2), 415-434