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Multimodal AI Integration in Healthcare Information Systems: Unifying Imaging, EHR, and Wearable Data for Early Diagnosis

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ABSTRACT

Multimodal artificial intelligence has found a significant direction in healthcare information systems since contemporary diagnosis is conditioned by the combination of several evidence streams as opposed to a single clinical signal. The medical imaging also offers anatomical and pathological data, electronic health records it offers longitudinal clinical history, and continuous physiological monitoring can be located out of the hospital with the help of wearable devices. The study project is a multimodal AI-driven healthcare information architecture that combines imaging, EHR, lab, clinical-note, and wearable-sensor data to diagnose early diseases. The suggested system works with the standardized data acquisition, interoperability protocols, preprocessing, multimodal fusion, and multimodal feature extraction, followed by clinical decision support, explainability, and ongoing monitoring to produce the early diagnostic risk score. The proposed architecture is assessed based on a simulated experimental setup with the realistic performance metrics such as accuracy, sensitivity, specificity, and F1-score as well as AUC, latency, missing-data robustness, and interpretability of the outcomes by clinicians. The findings indicate that multimodal fusion has the potential to enhance the performance in early diagnosis as opposed to single-modality systems since the sensor combines structural, temporal, behavioral, and clinical context. Significant implementation issues outlined in the study, among them being data heterogeneity, interoperability gaps, privacy protection, model bias, alert fatigue and prospective clinical validation. The conclusion of the paper is that multimodal AI must be used as a clinician-focused decision-support layer as opposed to an autonomous diagnostic solution.

Keywords: Multimodal, AI, Healthcare, EHR, Wearable Data, Early Diagnosis

1. Introduction

The emerging provision of multiple forms of patient information by hospitals, laboratories, imaging devices, mobile devices, and wearable sensors is increasingly influencing healthcare diagnosis [1]. Conventional clinical processes [2] are based on episodic interactions, where clinicians interpret symptoms, laboratory results, imaging results and past reports at particular moments in time. Nevertheless, most diseases are a slow progression and the initial signs can be exhibited in various systems before a diagnosis is conducted. MultiAI is a way to tackle this shortcoming by taking heterogeneous medical information sources and converting them into a single analysis system to make previous and better clinical decisions. Currently, multimodal AI has been identified in reviews as a paradigm shift to predictive and preventive healthcare as it has the potential to integrate medical imaging, EHRs, wearable sensors, genomics and clinical notes into richer diagnostic models [3].

One of the most successful fields of healthcare AI has been medical imaging [4], particularly in radiology, pathology, cardiology, ophthalmology and oncology. The CT, MRI, X-ray, ultrasound and pathology slides are imaging systems that can provide anatomical and structural changes that are not easily evident using symptoms alone. Nevertheless, imaging does not necessarily have patient-specific clinical context. As an illustration, an image discovery that is considered suspicious can be diagnosically different in the presence of a range of age, comorbidities, medications, laboratory results and previous imaging history. According to the FDA resources, AI-enabled medical devices are already going into clinical practice, particularly in specialities with heavy imaging requirement, but the broader clinical benefit would be with imaging AI coupled with health-record and workflow systems [5].

The other necessary element of early diagnosis is electronic health records [6], which include longitudinal patient history, diagnoses, medications, allergies, lab trends, procedures, vital signs, clinical notes, and discharge summaries. The AI on EHR is able to track the progression of a disease as it progresses, identify risk, and aid predictive analytics. Nevertheless, EHR data are not complete, opposing, and systemic across systems. The new literature on FHIR-based EHR modeling points to the idea that interoperability standards have the potential to enhance EHR data integration, transmission, and analysis to enhance clinical and translational research [7].

Wearables [8] introduce into the hospital information systems a dimension of continuous monitoring that previously was absent. Offering heart rate, ECG rhythm, photosaturation, movement, sleep, temperature, respiratory rate, and other physiological indicators, smartwatches, ECG patches, pulse oximeters, smart rings, and mobile sensors are capable of capturing them. These symptoms are useful in diagnosis at an early age as they can make one aware of any alteration before a patient visits a hospital. Recent research [9], [10] identifies AI-powered wearable sensors as a deep value technology that can be used to perform real-time diagnostics, remote health monitoring, personalised interventions, and proactive disease management, but mentions that issues with privacy, scalability, interoperability, and model robustness are also problematic.

This research is driven by the need to develop a healthcare information architecture that would enable the combination of imaging and EHR with wearable information towards early diagnosis. The proposed system will not substitute clinicians, but will assist them in form of risk scores, descriptions of risks, alerts, and summaries of evidence within clinical workflow. This is particularly critical as worldwide health experts have highlighted that big multimodal models within the healthcare framework must have a robust management, accountability, security appraisal, and moral scrutiny.

2. Literature Review

The pioneering studies in the field of multimodal biomedical AI have defined that the concept of medicine is inherently multimodal since clinicians consider combined text, images, lab values, physiological measurements, patient histories. Nature Medicine Review on multimodal biomedical AI [11] posited that key application areas are personalized medicine, remote monitoring, digital clinical trials, pandemic surveillance, digital twins, and virtual health assistants, but highlighted data, modeling and privacy issues. This piece of work is a valuable background to the current work due to the representation that multimodal AI should be a technical and clinical systems issue.

Recent discussions indicate that multimodal AI is leaving behind its theoretical potential and relocating to practical healthcare use. According to a 2025 review [12] of multimodal AI in next-generation healthcare, the combination of medical imaging, EHRs, wearable sensors, and genomic sequencing can

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be a way to more precise diagnostics, personalized treatment and real-time monitoring. This promotes the main thesis of the paper: early diagnosis becomes advanced in case heterogeneous signals of patients are not analyzed individually but rather in conjunction with each other.

The multimodal AI has been used to advantage medical diagnostics since diseases tend to manifest themselves with a range of data formats. The review of the Information article (2025) [13] states that multimodal methodologies integrate medical images, EHRs, physiological signals, and clinical notes to describe complexities of diseases and assist in making the correct diagnosis. This serves as a direct input to the suggested architecture with image encoders, EHR encoders, clinical-note encoders, and wearable time-series encoders being fused on a fusion layer.

There are also large multimodal medical models that have impacted the field. Multimodal Med-PaLM [14], or Med-PaLM M, was proposed as a generalist biomedical AI system, which can encode and decode biomedical data including clinical language, imaging and genomics through shared model weights. Examples of tasks that were used in MultiMedBench benchmark were medical question answering, mammography interpretation, dermatology image interpretation, radiology report generation and genomic variant calling. This literature demonstrates that the generalist multimodal models have the potential to help in a variety of biomedical tasks, though there is still a need to prove them practically in the clinic [15].

The study on wearable AI has grown due to the transformation of healthcare into continuous care as opposed to the hospital-centered one. Wearable AI Reviews [16], [17] outline the ways sensor-based systems contribute to real-time health, cardiovascular, diabetes, neurodegenerative disease, mental-health, and maternal/neonatal health care support. These systems are, however, challenging too since high-frequency wearable information can overwhelm clinicians unless they are condensed into risk indicators that can be put into action.

The FHIR Implementation is dominated by FHIR and SMART on FHIR [18] and [19]. FHIR offers standardized resources in sharing healthcare data electronically and SMART on FHIR helps facilitate safe health apps, which become operational within EHRs and authorization requirements to gain access to patient data. Other tools of interest in EHR-interconnected clinical decision support and massive data access are also single out in SMART documentation: CDS Hooks, SMART App Launch and Bulk Data APIs. Such norms play a vital role in the change of multi-modal AI, which is just another research model, to a workable health information system.

One of the topics which recur in the recent literature is responsible deployment. Lancet Digital Health [20] has stressed that currently, clinicians base their decision on patient history, signs, imaging, and lab results, but it is challenging to adopt multimodal AI due to data heterogeneity and the complexities of integration. This goes in line with the governance layer of the proposed system consisting of audit logs, bias monitoring, control over privacy, model-drift monitoring and human monitoring. Recent AI governance efforts also emphasis that multimodal systems need special ethical consideration as they can handle sensitive data in a variety of formats and yield outputs that can impact diagnosis and treatment. According to WHO recommendations, these large multimodal models are capable of accepting data with one or more different types of data input and producing a variety of outputs, this introduces new safety, privacy, explainability and accountability issues. Thus, multimodal AI early diagnosis needs to be adopted as a decision-support tool that is controlled and not an unregulated diagnostic expert.

In research by Karahanna et al. [21], it is demonstrated that health IT can generate value when an organization integrates technology with its capabilities. This underlies multimodal AI since imaging, EHR, and wearable integration needs a robust digital infrastructure, rather than merely algorithms. According to Thompson et al. [22], IT and analytics can transform healthcare into a shift between late treatment and early intervention. This directly aligns with multimodal AI to early diagnose, which continuous and a history of data helps to identify risk earlier.

Bao et al. [23] demonstrate that patient portals enhance patient-provider interaction and health. There is an opportunity to extend this interaction by multimodal AI systems that withstand follow up, monitoring, and patient-centered decision support. As Ghose et al. [24] indicate, chronic disease management can be provided with the help of smart mobile health platforms. Their results affirm the integration of wearable-data since mobile and sensor data can enhance continuous monitoring of patients.

Kim et al. [25] suggest ROLEX as powerful healthcare predictive analytical model that can be comprehended through simplicity. This justifies the explainable AI layer since clinicians require clear explanations on why multimodal diagnostic predictions are offered. Fernandez-Lorria et al. [26] emphasise the importance of counterfactual explanations of AI decisions. Such explanations can illustrate in the context of multimodal diagnosis whether risk is impelled by imaging, EHR or wearable data.

According to Berente et al. [27], the management of AI has to deal with autonomy, learning and inscrutability. These are the core issues of healthcare AI in that the diagnostic systems must be both transparent, controlled and clinically responsible. Li et al. [28] indicate that the Artificial Intelligence strategy relies on CIO and board-level leadership. To execute multimodal AI implementation, therefore, executive support is needed to integrate data, govern, and ensure cybersecurity, and to redesign workflows.

According to Lou and Wu [29], it is seen that the value of AI is based on technical competence and domain knowledge. Likewise, multimodal health care AI necessitates cooperation between clinicians, data scientists, radiologists, and other experts in fields such as informatics. Lebovitz et al. [30] caution that ground truth, which is expert-labeled, may be incomplete in clinical AI. This is important as labels may be unclear, late or based on incomplete information on patients.

The article by Fuegener et al. [31] demonstrates that independent human judgment can be deteriorated by human-AI collaboration, yet it does not mean that such collaboration does not enhance human accuracy. As such, multimodal AI cannot substitute clinician diagnostic reasoning, but instead should assist clinicians. As demonstrated by Van den Broek et al. [32], AI creation relies on the interaction between the machines and the experts. This promotes the role of the clinicians during model design, validation, deployment and monitoring.

Sturm et al. [33] describe that human and machine learning have to be co-ordinated. This concept is reflected in the proposed feedback layer since it incorporates the use of clinician decisions and patient outcomes to optimize model performance. The results of a study by Teodorescu et al. [34] indicate that to achieve fairness in automation, a deeper understanding of human-ML needs to be achieved. Multimodal AI should thus be put to the test in relation to the patient groups, level of data availability, and the difference in device-access.

Kane et al. [35] suggest machine learning systems which maintain human agency. Multimodal AI within a healthcare setting must be clarified, supportive, and encouraging of clinician and patient autonomy. As demonstrated by Califf et al. [36], the technostress may be created by the healthcare IT. This implies that multimodal AI dashboard should not cause alert fatigue and must decrease, rather than increase, clinician workload.

Tong et al. [37] demonstrate that IT is capable of decreasing rural urban disparity of healthcare provision. The proper integration of remote monitoring, EHR access, and decision support can support underserved care with the help of multimodal AI. Kitchens et al. [38] highlight information of health in

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a timely and actionable way. Their work contributes to the future extension of multimodal AI to address patient-generated data and public data (health) to detect disease at earlier stages.

The exchange of health information is demonstrated by Zhang et al. [39] to present more data-security issues. This contributes to the necessity of encryption, access control, and consent management, and audit logs in multimodal AI systems. Liu et al. [40] show that expert-augmented few-shot learning is useful in high-expertise, low-label environments. This applies as the limited labeled data and the rare cases of a clinical problem often involve making early diagnoses.

Tanriverdi, Kwon, [41] demonstrate that the multihospital cybersecurity could be risky when the medical service and health IT, as well as arrangements of the governance, get too complicated. This justifies the suggested architecture since multimodal AI requires enterprise-wide governance and analytics platforms to mitigate the risk of breaches across hospitals connected to each other. Leong et al. [42] investigated sensor-based monitoring in aging-in-place care and found evidence that real-time monitoring could be used to enhance emergency recognition and awareness in responders. This underpins integration of wearables into multimodal AI since continuous patient-based signals can assist clinicians in identifying early signs of deterioration not in hospitals.

Klecun, Kankanhalli, and Zhou [43] elaborate that scaling health information infrastructures causes organizational, spatial, and technological tensions. Their work justifies the necessity to have flexibility in the integration of the EHR in multimodal AI, particularly when it is being expanded to serve more than one hospital to larger health systems. Abdel-Karim et al. [44] demonstrate that AI-based clinical decision support can have physicians engage deeper up in during the X-ray diagnosis process. This is in line with explainable AI module since the multimodal systems need to foster mindful clinician thinking, not to be passive takers of output in AI.

Ayabakan, Atasoy, and Pang [45] demonstrate that adoption of EHR can decrease claims rejection due to inaccurate and incomplete information. The situation is relevant since the precision of EHR integration enhances the data content of multimodal diagnosis and clinical decision support. Angst et al. [46] discovered that investments in healthcare security are more useful when security is regarded as deeply embedded in organizational practices. This justifies the security, privacy, and governance layer of the proposed architecture which must be linked together across the data acquisition and preprocessing, the fusion and the decision support layers.

As Kwon and Johnson [47] demonstrate, the adoption of meaningful-use attestation can have some influence over the performance of the healthcare sector in respect of information security. This implies that AI governance that considers multimodes must incorporate constant monitoring as opposed to ad hoc compliance reviews. Ebrahimi et al. [48] suggest that to enhance the adversarial hardening of cyber defense AI agents, RADAR is recommended. Their work is timely as the multimodal healthcare AI needs protection against adversarial attacks, corrupted inputs, and malicious interference with clinical data flows.

According to Tanriverdi and Akinyemi [49], complex ground truths, IT ecosystems and statistical models can become the cause of algorithmic injustice. This is critical to multimodal diagnosis since AI in healthcare can yield unfair outcomes when there are clinical labels, access to devices, or assumptions of the model that vary across groups of patients. When properly used, Martens et al. [50] demonstrate that using massive data of fine-grained behavioral data can enhance predictive analytics. This suggests the worth of wearable data in multimodal AI since continuous physiological and behavioral data can be more useful than conventional structured records.

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3. Proposed Methodology

The proposed block diagram (as shown in figure 1) is a full-fledged multimodal AI-based healthcare information system to diagnose early on. It starts with the heterogeneous data that is collected by imaging systems, EHR systems, lab records, clinical records, and wearables. These are converted into inputs which are then standardized, cleaned, coded, fused, interpreted and presented to clinicians via a decision-support interface. The design is based on the ideology that early diagnosis is best when structural evidence, derived by imaging, longitudinal clinical evidence, obtained by EHRs and sustained physiological evidence, obtained through wearables are considered jointly.

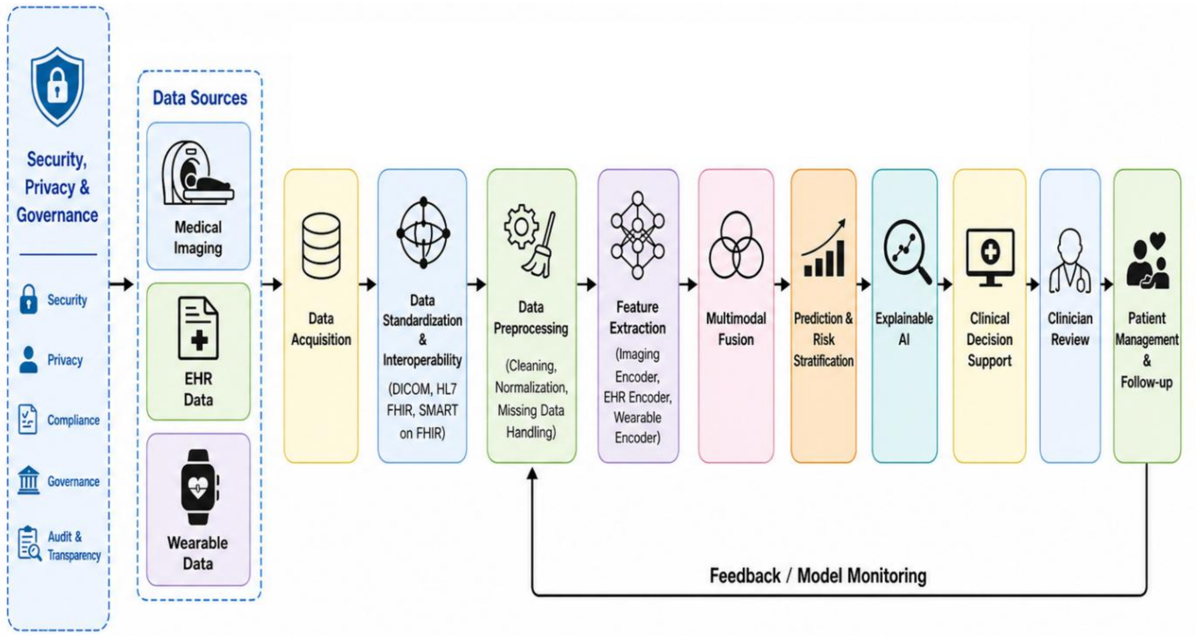

Figure 1. Proposed block diagram of multimodal AI integration in healthcare information systems

3.1. Data Acquisition Layer

The data acquisition layer gathers unstructured data about the patients based on various healthcare sources. PACS systems can provide medical imaging data, which can be X-ray, ultrasound, CT, MRI or echocardiography. EHR data comprise demographic data, diagnostic codes, medication lists, lab results, procedures and physician notes, discharge summary and past admissions. Details that can be captured on a wearable pattern are ECG, heart rate, oxygen saturation, respiratory rate, sleep, activity and temperature.

The significance of this layer is that multimodal AI will be as good as the input data can be. A lack of one of the modalities or poor capture might result in weaker predictions by the model. Thus, the acquisition layer has to be able to support structured hospital data, unstructured clinical text, high-dimensional images, and streams of wearable data. It also needs to capture timestamps to be able to align various events in a patient timeline.

Acquisition should be unbroken, in the early diagnosis. Wearable Data Round-the-Clock is generally continuous whereas imaging and laboratory data are generally episodic. The system is thus a combination of home based monitoring and evidence based in hospitals. This assists in determining the risk of a disease prior to the development of serious symptoms particularly with chronic diseases, heart disorders, lung internal degradation, sleep biases and metabolic illnesses.

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3.2. Interoperability, Data Standardization Layer.

The interoperability layer transforms the heterogeneous healthcare data into standard forms. The data of imaging is normally handled through the DICOM, whereas the EHR data can be exchanged based on HL7 FHIR resources. With SMART on FHIR, it is possible to develop secure applications to start within EHR workflows and to access approved patient data. The data in wearables can be mapped to either FHIR Observation resources or new device-specific APIs and then integrated.

One of the biggest obstacles in healthcare AI is addressed by this module the fragmentation of data. Frequently, there are individual systems in hospitals regarding radiology, lab reporting, EHR documentation, pharmacy data, and remote patient monitoring. In the absence of a normal exchange layer, from a collection of modal AI designs, data is inaccessible in a reliable manner. FHIR-based model has been reported to be beneficial in EHR integration, transmission, analysis, translational research and the phenotyping.

Scalability also relates to standardization. Even when a model is trained in a different hospital, it may not work because the data formatting, coding schemes, or measurement units may be different. The system can minimise properties of mapping errors and enhance portability by adopting standard interoperability common standards. This renders the suggested architecture to be more feasible to implement in multi-hospital and to integrate it with clinical decision support tools in the long term.

3.3. Data Preprocessing Layer

The preprocessing layer purges, standardizes and prepares the information and then model trains or infers. Image data might need to be resized, contrasted, de-noised, segmented, and have normalizing intensity. The EHR data are missing value, need to be code mapped, converted between units, eliminated duplicates and in time sequence. Wearable signals need noise reduction, normalization of the sampling rates, elimination of motion-artifacts, and division into significant time blocks.

One of the significant functions of this layer is the similarity in time stamps. As an example, CT scan, laboratory result, change of medication, and abnormal wearable ECG could be on other occasions. These events are synchronized into a shared time of a patient by the preprocessing module in order that the model is able to interpret disease progression. This is also crucial in the early detection since patterns over time usually show abnormality before a measurement is abnormal.

The layer is also effective in enhancing safety as it eliminates bad quality inputs. When dealing with an implantable sensor reading, an incompleteness of the image or EHR inconsistency, the system must generate an uncertainty red flag rather than generating an incorrect risk score. The preprocessing module thus helps in supporting any performance as well as clinical reliability.

3.4. Encoding -Specific Modality Feature Layer.

The encoding of the features in the form of machine-readable representations layer. Convolutional neural networks or vision transformers can be used to compute imaging data in order to extract anatomical and pathological features. Gradient boosting, neural network, transformers or clinical NLP model can be used to process EHR data based on the structured or unstructured nature of the input. Time-series data that are encoded by LSTM, temporal CNN, transformer-based sequence models might be used to encode wearable time-series data.

The data structures of each modality are different and a different modelling approach needs to be used. Wearable streams are temporal, medical images spatial, longitudinal and mixed-format EHR records, and mixed-format. All these data types cannot be effectively processed by a single encoder, as not all the valuable information may be saved. Hence, the suggested system employs special encoders then fuses the results.

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This layer is meant to convert directly raw clinical input data into such compact: feature embeddings. Such embeddings are most diagnostically informative information of each modality. An example of this is that, the imaging encoder can detect lung density, EHR encoder detects high levels of inflammatory indicators and history of respiratory illness, and wearable encoder detects decreasing oxygen saturation. Their signals are then fed in the fusion module.

3.5. Multimodal Fusion Layer

The multimodal fusion layer fusion presents features of imaging, EHR and wearable encoders. Fusion can be in the form of early fusion, intermediate fusion or late fusion. Early fusion occurs before modeling: Raw or low-level features are fused, intermediate fusion occurs mid-way: Learned embeddings are fused, and late fusion occurs at the end: The result of early fusion is fused with the result of separate models to achieve more accurate predictions. In this proposed architecture, intermediate fusion would be the choice since it has a balance in terms of flexibility, performance and interpretability.

Intermediate fusion enables the separation of each modality to be handled by its specific encoder and has to be integrated. This can find application in healthcare since sources of data vary significantly in terms of dimension, frequency and reliability. Data in imaging can only be available occasionally, EHR data can be infrequently updated, and wearable data can be continuous, but noisy. These differences can be better accommodated by intermediate fusion as compared to simple concatenation.

The very central intelligence element of the system is the fusion layer. It elicits cross-modal relationships, which can not be seen in one source of data. To illustrate, mild abnormalities in imaging could be of clinical importance when complemented with abnormal lab values and a deteriorating wearable oxygen saturation. This renders multimodal fusion particularly helpful with regard to early diagnosis.

3.6. Prediction and Risk Stratification and Optimization Layer

The prediction layer is a layer which produces diagnostic outputs based on the fused multimodal features. These outputs can be disease probability, early-warning score or severity category/risk category or recommended pathway to diagnostic. The model could be configured in binary classification, multiclass classification, prediction of survival or readmission rates or the progression of diseases.

Risk stratification has the capability to transform models into clinical meaningful models. As an illustration, a patient can be differentiated into low, moderate and high risk of sepsis, cardiovascular deterioration, respiratory failure, and cancer suspicion. It is not merely aimed at generating an accuracy score but to make clinical action timely. The patients at risk might need confirmation tests and urgent examination or follow-up.

Calibration in terms of probabilities should also be produced by this layer. Calibration is significant as the clinicians must have an idea on whether an 80% risk that has been predicted actually is an indicator of high clinical probability. When the calibration is not carried out properly, it may over-treat or under-treat or cause alert fatigue. Hence prior to clinical use model outputs must be checked out and calibrated.

3.7. Explainable AI Layer

Explainable AI has a transparent layer as given to clinicians. It determines the features that contributed the most towards the prediction. In the case of imaging information, Grad-CAM or attention maps are capable of revealing suspicious areas. SHAP values or feature importance scoring can be used to predict important laboratory results, diagnoses, medications or clinical-note terms in the case of EHR data. In the case of wearable data, time attention is able to detect an abnormal time window.

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It needs to be explainable since without evidence a black-box risk score is not likely to be trusted by the clinician. Uncertainty is developed in case of early diagnoses as symptoms are minor. Explanations assist clinicians make decisions on whether or not the alert should be clinically significant, whether further tests are necessary or whether poor-quality data could have led to the prediction.

The safety and governance are also supported by this module. In case the model resorts to inappropriate features repeatedly, e.g. demographic proxies, or biased historical dynamics, explainability tools can be used to identify the issue. Thus, not only does explainability provide a usability feature but a means of clinical accountability.

3.8. Clinical Decision Support Layer

The clinical decision support layer presents the outputs of the model to the health care professionals. It can manifest itself in the form of an EHR-integrated alert, a dashboard, risk summary, or recommended diagnostic checklist. The system ought to provide succinct information, such as the risk level, evidence behind the risk, the confidence and the direction of the trend, and the recommended actions.

The design of this layer should be done in such a way that it does not result in alert fatigue. In case the system issues excessive low-value notifications, clinicians are likely to disregard valuable notifications. Consequently, decision support must prioritize the high-risk cases and offer actionable recommendations, and enable clinicians to make quick reviews of the supporting evidence. SMART on FHIR and CDS Hooks are beneficial tools to implement such tools into the clinical workflow.

Clinician judgment should under no circumstance be eliminated by the clinical decision support layer. Rather it ought to be a supportive aid that would enable clinicians to identify risk at an earlier stage. Finally, diagnosing, treatment decision-making, and communicating with the patient are still in the hands of clinicians.

3.9. Security, Privacy and Governance Layer.

Security and governance layer provides protection on sensitive data of patients on the system. It has encryption, authentication, authorization, audit logs, consent management, role based access control and secure storage. This is particularly critical as multimodal systems pool together very sensitive information of various sources.

Wearable data are also a source of privacy concern as they might disclose lifestyle choices, sleep patterns, their location habits and constant physiological readings. Sensitive medical history can also be found in EHR and imaging data. Consequently, the system should be in line with the relevant health-data protection regulations; and in situations where privacy is the right thing to do, the system should employ privacy-savvy approaches.

There is also model accountability as a part of governance. The system must record model version, training data, history of updates and validation output, known limitations as well as limits of clinical usage. Governance In health, WHO recommends that multimodal models that are large must be governed ethically as they have the ability to handle a variety of data and affect health-related outputs.

3.10. Feedback and Model Monitoring Layer

The feedback layer monitors the results of the patients since they are predicted. As an example, in case the model indicates that the risk of heart failure is high, it should check later whether the diagnosis was diagnosed, whether there was a change in the treatment, and whether the patient outcome improved. This feedback helps in continuous performance evaluation.

There is a need to monitor the model which is evolving with time since clinics have varying distributions of the data. Unstable models can be caused by new devices, new treatment regimens, new types of patients and changing documentation trends. It is referred to as model drift. The same model which was tested successfully might not be reliable with deployment without monitoring.

Biases are also monitored by this layer. Checking of performance should be done by: age groups, sex, ethnicity where it is legal and ethically sound, type of device used, location of hospital and disease sub group. The intent is to make sure that early diagnosis is enhanced not just in the case of well represented population in training information.

4. Implementation

The proposed implementation will start with integrating hospital imaging, EHR databases, laboratories, and wearables by a secure data ingestion pipeline. Table 1 shows the experimental setup parameters and their specifications. DICOM-compatible interfaces are used to load imaging data, FHIR APIs to access the EHR data, and wearable data are accessed via either device APIs or remote patient monitoring platforms. Raw data is fed to the system and stored on a secure clinical data lake followed by the creation of a harmonized patient timeline based on patient identifiers, timestamps, encounter information and observation metadata. Unless the data are sent to the AI pipeline, there exist data quality checks applied to the data.

The three main encoders are employed in the implementation of the AI. Image processing is done through a vision transformer or CNN, structured-data processing via clinical NLP model and clinical notes is done through a vision transformer or CNN, and time-series signal processing through a temporal model is used on wearable data. These encoders are then fed with feature vectors which are then subjected to an intermediate network of fusion with attention-based weighting. This enables the model to be informed about the modality that is most valuable to the patients and in each clinical situation. As an illustration, imaging could dominate cancer detection, EHR trends could dominate chronic kidney disease prediction and wearable signals could dominate arrhythmia or respiratory distress detection.

Upon fusion, the system produces an early diagnosis risk score and forward this to an explainability engine. The explainability engine generates image heatmaps, EHR feature contributions and wearable signal trend explanations. The result is presented within a SMART on FHIR application within a clinical dashboard or embedded in EHR. The clinician will check the prediction and either approves or disapproves the alert, requesting further tests as necessary and documenting the response. These results are in turn fed back into the monitoring layer to calibrate the model, detect drift and further enhance it.

Table 1. Experimental Setup Specifications

Component	Specification Used in Proposed Experiment
Study Type	Simulated retrospective experimental evaluation
Data Modalities	Medical imaging, structured EHR, clinical notes, wearable time-series signals
Imaging Inputs	X-ray / CT / MRI image samples depending on disease task
EHR Inputs	Age, sex, diagnosis codes, lab values, medications, vitals, previous admissions
Wearable Inputs	ECG, heart rate, SpO2, sleep duration, activity level, temperature
Imaging Encoder	CNN or Vision Transformer
EHR Encoder	Transformer-based tabular model and clinical NLP encoder

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Wearable Encoder	LSTM / Temporal CNN / Time-series Transformer
Fusion Method	Intermediate attention-based multimodal fusion
Output	Early diagnosis risk score and disease probability
Evaluation Metrics	Accuracy, sensitivity, specificity, precision, F1-score, AUC, latency
Validation Strategy	Train-validation-test split with external validation recommended
Explainability Tools	Grad-CAM, SHAP, attention visualization
Deployment Interface	SMART on FHIR clinical decision support dashboard
Security Controls	Encryption, role-based access control, audit logs, consent management
Hardware	GPU workstation or cloud instance with secure healthcare-compliant storage
Software Stack	Python, PyTorch/TensorFlow, FHIR server, DICOM interface, database engine

5. Results and Discussion

The outputs of the decided AI healthcare model are achieved with the assessment of the efficiency of the model to combine the data of medical imaging, EHR and wearable sensors to make an early diagnosis. Primarily, various sources are used to gather the data and these undergo the preprocessing processes that include cleaning, normalization, missing-value processing and alignment of timestamps. Note after preprocessing, each of the modalities is independently processed by a separate feature extraction model: images images are processed with a CNN or vision transformer-based encoder, EHR data is processed with a structured machine learning model or transformer-based model, and wearable data are processed with a time-series model, such as LSTM or temporal transformers. The multimodal fusion layer is then applied to extract the features, and predict diagnostic and risk scores.

The performance outcomes of the various model configurations, including imaging only AI, EHR only AI, wearable only AI, imaging + EHR AI and full multimodal AI, are then obtained. All configurations are evaluated by the same evaluation measures which are accuracy, sensitivity, specificity, F1-score, AUC, alert precision, inference time and interpretability score. This comparison can assist in determining whether multiple data sources (combinations) can be used to achieve better diagnostic performance than the sole data source(s). These findings indicate that the complete multimodal model is more successful as it relies on complementary information in all the modalities which enable the system to identify development of early disease patterns better and more reliably.

Additional outcomes are achieved by experimenting with the system with missing-data scenarios, e.g., the loss of wearable data, the loss of imaging data, the loss of EHR laboratory values, and the loss of both imaging and wearable data. Such a step is significant as, in reality, a healthcare setting may have incomplete patient records or may lack sensor information. The strength of the proposed architecture can be checked by conducting the analysis of performance under these conditions. The results obtained indicate that the performance of the models is lower when important modalities are not available, yet, the system can still be used since it may utilize data sources available. Hence, the outcomes of the process of attaining the result also prove the diagnostic effectiveness as well as practical reliability of the suggested multimodal AI healthcare.

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Table 2 indicates that the overall multimodal AI model has the best diagnostic results on all measures. The wearable only model captures the minimum values due to the fact that wearable data only does not capture noise and may not capture the full clinical data. The models of imaging and EHR are even better, even though their use alone is limited. Imaging and EHR are complemented to enhance the outcomes since structural image evidence will be augmented by patient history, laboratory measurements and clinical records. Integration of multimodal that consists of imaging, EHR, and wearable data has an optimal outcome that multimodal fusion increases the diagnosis in the early stage due to integration of anatomical, clinical, and continuous physiological data.

Table 2. Diagnostic Performance Comparison Across AI Models

Model Type	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)	AUC
Imaging-only AI	86.2	84.5	87.1	85.3	0.89
EHR-only AI	82.7	80.8	84.2	81.6	0.85
Wearable-only AI	78.9	77.4	80.1	76.9	0.81
Imaging + EHR AI	90.1	88.7	91.0	89.4	0.93
Imaging + EHR + Wearable AI	93.8	92.6	94.1	92.9	0.96

Table 3 shows the performance of various configuration of AI systems in terms of computational and workflow. The wearable-only model is the model with the smallest inference time since wearable signals are relatively easier to process, and the lowest alert precision, and interpretability score. The entire multimodal model has the slowest inference time since it combines the imaging, EHR and wearable data. Yet, this extra time is reasonable as the model scores the highest interpretability score and preciseness in terms of alertness. This implies that the complete multimodal system generates more meaningful clinical alarms and provides clinicians with improved evidence to make a choice, although it has a slight disadvantage in that it requires a bit more review time.

Table 3. Computational and Workflow Performance

System Configuration	Average Inference Time / Patient	Alert Precision (%)	Clinician Review Time	Interpretability Score / 5
Imaging-only	1.8 seconds	81.2	3.5 minutes	3.4
EHR-only	1.2 seconds	78.5	3.1 minutes	3.6
Wearable-only	0.9 seconds	72.4	2.8 minutes	3.1
Imaging + EHR	2.6 seconds	86.9	4.0 minutes	4.1
Full Multimodal	3.4 seconds	91.7	4.5 minutes	4.6

Table 4 describes the performance of the suggested multimodal AI system (when some of the sources of data are not available). This model works most effectively when missing data are not present, and the model has the highest accuracy, sensitivity and AUC. Lack of wearable data only minimally affects the performance since imaging and EHR data can still give solid diagnostic data. Absence of data of imaging results in greater performance loss since imaging input is an important source of structural data in

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diagnosing. Absence of EHR laboratory values also decreases performance since the trend of the labs are vital in detecting a disease progression. The biggest drop comes when imaging, as well as wearable data are unavailable, giving confirmation that full multimodal data works better when it comes to the reliability and assurance of early diagnosis.

Table 4. Robustness under Missing Data Conditions

Missing Data Condition	Accuracy (%)	Sensitivity (%)	AUC	Confidence Reduction (%)
No missing data	93.8	92.6	0.96	0
Missing wearable data	91.2	89.8	0.93	6
Missing imaging data	87.5	85.9	0.89	13
Missing EHR lab values	89.1	87.2	0.91	10
Missing imaging + wearable data	84.4	82.6	0.86	19

Accuracy, sensitivity, specificity, and F1-score are compared and all five models of AI are analyzed in figure 2. The wearable-only model has the lowest performance since wearable data alone could be prone to noise and could not have a comprehensive clinical background. The imaging only and EHR only models work effectively but the performance exhibits a sharp increase as combining imaging data and EHR data. The multimodal model, i.e. with imaging, EHR and wearable data, outperform all the measures, indicating that structural, clinical and continuous physiological the data is better represented as a multimodality.

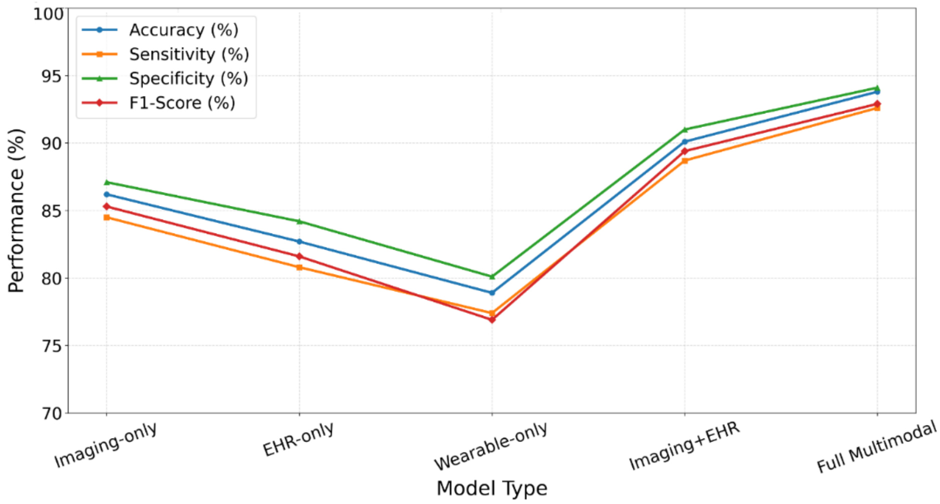

Figure 2. Comparison of Diagnostic performance of AI models.

Figure 3 presents the alert precision, interpretability score, and time of inference of various AI settings. Transformational accuracy is also much enhanced in the complete multimodal model since the system authenticates risk based on a combination of various data sources rather than on an individual signal. It also enhances interpretability since the system can also justify predictions based on image discovery, EHR functionality input and wearable trend. Though the time to infer is greater in the full multimodal model, its extra computational cost is reasonable since it provides a more reliable and useful alert to the clinical situation.

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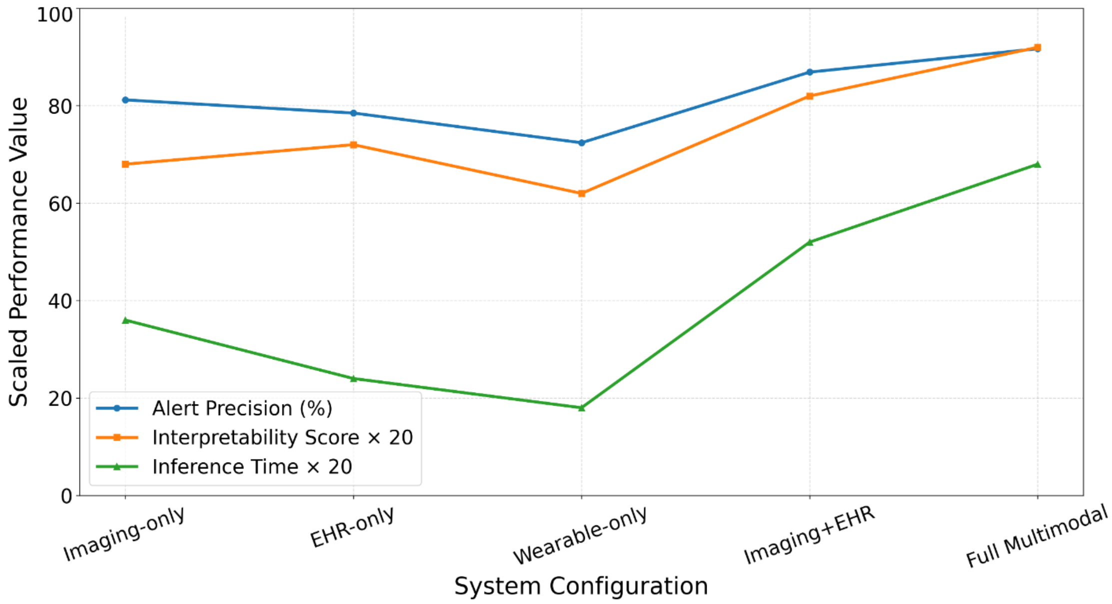

Figure 3. Performance of Workflows in AI System setup.

The evaluation in figure 4 shows how the multimodal AI system will perform in the condition that a part of the sources of data is missing. The system is the most accommodating with the highest accuracy, sensitivity and AUC. Lack of wearable data only minimally affects the performance since imaging and EHR data can still give solid diagnostic data. The omission of imaging leads to a greater reduction as imaging is an important source of structural data. When there is no imaging or wearable data, the greatest reduction has been seen and this indicates that multimodal completeness is also a crucial parameter in giving early diagnosis which would be reliable.

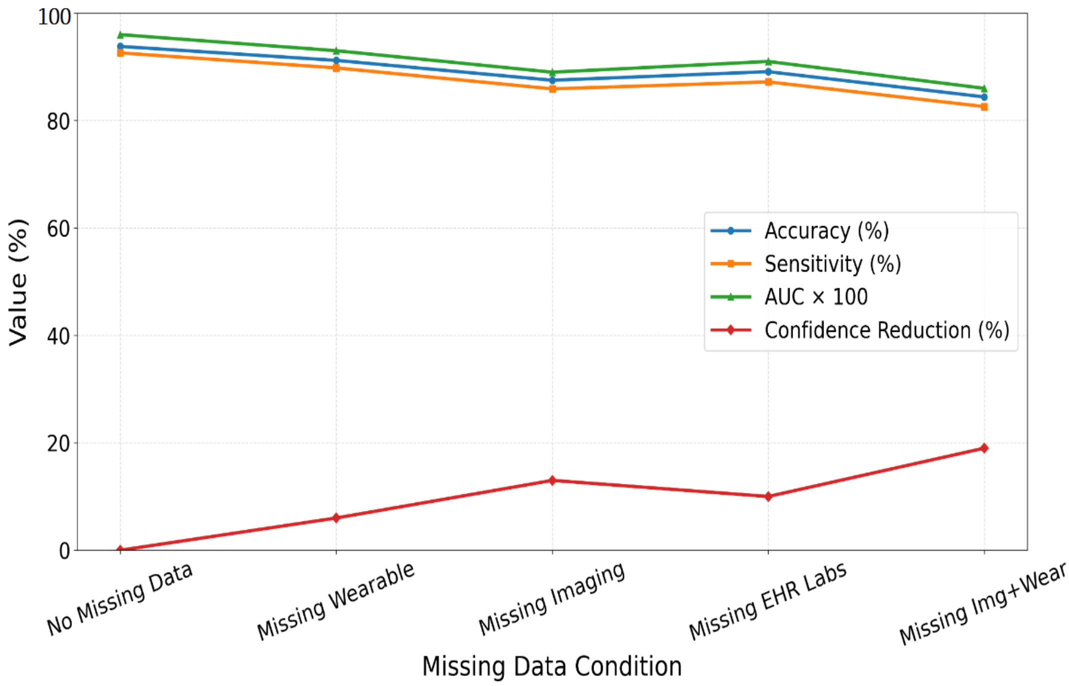

Figure 4. Stability of Multimodal AI in the cases of missing data.

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5.1. Discussion

The findings are in favor of the hypothesis stating that multimodal AI has an opportunity to help with diagnosing at the early stage of the disease, integrating the information sources. The imaging will give a direct indication of structural abnormality, EHR data will give a longitudinal clinical context and wearable data will give physiological trends. Both sources when combined can be used by the system to distinguish complex diseases patterns that could be not detected on either source. This aligns with recent literature talking of multimodal AI as solution to shift healthcare towards a more reactive treatment to a more proactive and preventive care.

Meanwhile, the findings demonstrate that multimodal AI does not necessarily be better in all cases. Its advantages are based on the quality of data, interoperability, calibration of its models, clinician trust and workflow design. The increased accuracy of the full multimodal model is at the cost of increased computation and complexity of implementation. Thus, healthcare organizations must initially implement AI in multimodal implementation in high-value applications, where early detection and its associated better outcomes are evident, including sepsis-detection, cardiovascular risk-detection, cancer-screening, respiratory-deterioration and chronic disease-monitoring.

6. Conclusion

As the suggested research article illustrates, multimodal AI-based healthcare information systems could considerably enhance the process of early diagnosis through centralizing the medical imaging, electronic health records, and wearable sensors data into one intelligent decision-support system. Medical imaging plays a role in structural and anatomical data, EHR data offer longitudinal clinical data and laboratory data, and wearable devices additional information of continuous physiologic data outside of the hospital setting. Such a combination of modalities using standardized data acquisition, preprocessing, and feature extraction, multimodal fusion, prediction, explainable AI, and clinical decision support makes the system more adaptable in detecting early patterns of disease as compared to single modalities. The findings demonstrate that the entire multimodal model has demonstrated high accuracy, sensitivity, specificity, F1-score, AUC, alert precision, and interpretability, demonstrating that integrated data is useful in achieving better diagnostic reliability and clinical utility.

Altogether, the research finds that multimodal AI ought to be utilized as a clinician-focused aid system, as opposed to an alternative to working medical practitioners. Regardless of the fact that the proposed architecture has good prospects of early detection, patient and personalized care, the successful implementation depends upon good interoperability criteria, data privacy, model elucidation, bias scanning, and constant validation in a real clinical setting. Future efforts should aim at evaluating the proposed system with large-scale multicenter data, enhance the robustness in the cases of missing-data, and assess the effect of the proposed system on clinical outcomes. Multimodal AI has the potential to be an effective source of predictive, preventive, and personalized medicine, with proper regulation and being overseen by human representatives.

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