Explainable and Personalized AI Models for Real-Time Diagnostic Accuracy and Treatment Optimization in Healthcare

Jagadeesan N.[1], V. Subba Ramaiah[2], S. Indhumathi[3], Hari Shankar Punna[4], K. Jamberi[5] and Amitabha Mandal[6]

[1]*Department of ECE, Malla Reddy Engineering College for Women, Hyderabad, Telangana, India*
[2]*Department of CSE, Mahatma Gandhi Institute of Technology, Gandipet, Hyderabad, Telangana, India*
[3]*Department of CSE, Nandha College of Technology, Erode, Perundurai, India*
[4]*Department of Computer Science and Engineering (DS), CVR College of Engineering, Hyderabad, Telangana, India*
[5]*School of Computer Science & Applications, REVA University, Bangalore, Karnataka, India*
[6]*Department of Computer Science and Engineering, Dr. B. C. Roy Engineering College, Durgapur-713206, West Bengal, India*

Keywords: Explainable AI, Personalized Treatment, Diagnostic Accuracy, Real-Time Prediction, Healthcare Integration.

Abstract: Healthcare is being transformed using Artificial Intelligence (AI) through the development of treatment protocols that incorporate data analysis, personalized medicine, and preventive healthcare. This study provides an understandable and real-time carrier of AI improving diagnostic accuracy and personalized medical decisions. In contrast to previous black-box models, our model integrates SHAP- and LIME-based interpretability, thus guaranteeing clinical transparency and trust. We tackle data bias by fairness-aware modeling (on fair representation learning and empirically studying the impact of fair models) and by having varied, multi-modal data in order to increase generalization across populations. The integration with electronic health records (EHRs) enables easy-to-deploy solutions in real clinical settings, and the learning models customise the treatment according to the patients' information, including the patient profile, genetic information and the patient's life style. Extensive validation, including regulatory-compliant benchmarks, shows the system's real-world readiness and better performance compared to state-of-the-art models. The presented solution closes the loop between advanced machine learning and clinical utility, providing a scalable, ethically grounded, and patient focus AI system for the healthcare of the future.

1 INTRODUCTION

When artificial intelligence (AI) is applied to healthcare, it changes the way medical practitioners diagnose diseases and prescribe treatments. At a time when precision and efficiency have never been more crucial, standard diagnostic tools often lack the ability to handle the overwhelming amount of patient information, especially in a personalized medicine context. The exponential increase in availability of electronic health records (EHRs), wearable devices and genomic data now presents new opportunities for machine learning (ML) to develop intelligent solutions that go beyond standard clinical paradigms. Yet despite the near-infinite possibilities of AI in medicine, there are major barriers to translating these models from the laboratory to the bedside. Most of the present systems have poor transparency, lack of fairness and tend to be not flexible enough to consider diversity in patient profiles. This has prompted questions about the interpretability of the model, possible biases, and the distance between what the algorithm spits out and how doctors actually make decisions.

To tackle these problems, this study presents the latest AI platform aiming at delivering real-time personalized and explainable healthcare facts. With interpretability methods like SHAP and LIME, systems enable clinicians to see model decisions and build trust in them. Moreover, the model is trained on heterogeneous, demographically diverse data to ensure wide deployment and fairness among populations. Real-time model with integration into hospital information systems makes it applicable in

N., J., Ramaiah, V. S., Indhumathi, S., Punna, H. S., Jamberi, K. and Mandal, A.
Explainable and Personalized AI Models for Real-Time Diagnostic Accuracy and Treatment Optimization in Healthcare.
DOI: 10.5220/0013868100004919

In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 1*, pages 493-499
ISBN: 978-989-758-777-1

stressful medical situations such as emergency trauma care and intensive care units.

In this work, our goal is to push the boundary of AI-based diagnostics and treatment planning, to provide an answer that is not just accurate, but also ethically responsible, patient-centered, and operationally feasible.

1.1 Problem Statement

Even though artificial intelligence and machine learning are constantly evolving, their ethical and effective implementation are a considerable challenge in the context of healthcare. The majority of AI-based diagnostic platforms currently rely on opaque black boxes that have high accuracy but low transparency in decison making, making it difficult to be accepted by clinicians and erode trust of clinicians. In addition, most systems are developed based on homogeneous and limited dataset, which results in biased prediction and lower performance on diverse patients. Moreover, lack of decision making in real time and seamless part in routine clinical workflow limit practical usefulness of such systems in dynamic health care scenario. Individualized treatment planning is also still immature, with models that tend to generalize some of the recommendations, rather than being adjusted to the specific physiological, behavioral and genetic profiles of each patient. This proposed research aims to fill these key gaps by enacting an AI approach that is interpretable, fair, real-time and able to provide truly personalized diagnostic and therapeutic inferences at-a-scale across real-world clinical conditions.

2 LITERATURE SURVEY

Use of artificial intelligence is on the rise in healthcare, enabling opportunities for diagnostics, treatment surrogates and patient monitoring. Machine Learning (ML) models have been extensively investigated for improving diagnostic accuracy in medical tasks including oncology, radiology, and cardiology. Aftab et al. (2025) proposed a deep learning (DL)-based cancer diagnostic method that demonstrates high detection performance, but their model was not interpretable with clinical interpretability concerns. Similarly, Imrie et al. (2022) released Auto Prognosis 2.0 for automatic diagnosis modelling, but its applications are restricted for the difficulty of the integration with the EHR.

The problem of fairness and bias in healthcare AI has been widely debated. Shah (2025) stressed the risk that algorithms trained on biased data-sets could continue to expand in-equities in care, especially for underserved populations. Studies by Nasr et al. (2021) and Reuters Health (2025) found that most current AI models fail to generalize to minority data because they trained on non-diverse data. This demands for inclusion of heterogeneous multicentre stores to ensure a balanced outcome.

AI has also been used to tailor treatments to individuals. Maji et al. (2024) developed a feature selection framework based on the patient specificities, which can be utilized to diagnose more accurately. However, this solution does not sufficiently cover the complexity of dynamic patient profiles such as lifestyle and genomic information. Time Magazine (2024) and GlobalRPH (2025) advocated for AI that learns over time and provides tailored recommendations from real-time data streams.

Explainable is also a relevant issue at the moment. The vast majority of high-performance model—especially deep neural networks—are not interpretable. The black box feature handicaps its clinical use. Efforts have been made to reduce this by techniques like SHAP, LIME etc., that allow the model decision and feature of importance visualisation (Imrie et al., 2022; Nature, 2025). Although there has been significant progress, these still have not yet been widely integrated into clinical or healthcare applications.

Real-time diagnostic AI is still in its infancy. Even though one may encounter some systems with high accuracy in offline systems, presented in version (2025) and (2025d), latency and the demand of resource preclude their employment in the emergency care. Edge computing and coefficientized inferences models are needed for AI applications to provide real-time insights at the point of care (MIT Jameel Clinic, 2025).

Second, ethical and regulatory horizons for AI in healthcare are nascent. Many technologies are not FDA or CE approved and hence are not cleared for clinical application (Verywell Health, 2023). Current debates in the Journal of Medical Internet Research (2025) andBMC Medical Education (2023), highlight the need to address not only technological effectiveness but also legal, social and ethical.

In conclusion, although AI offers tremendous potential to transform healthcare, there are significant challenges to overcome in terms of explainability, fairness, personalization, real-time response and clinical adoption. These gaps motivate and form the basis of the proposed research where it strives to deliver a complete, interpretable, patient-centred AI framework that is applicable in real-world clinical settings.

3 METHODOLOGY

The research methodology to be developed here will be multi-layered approach involving state-of-art machine learning models along with factors such as real-time clinical deployment capabilities and explainable-AI frameworks. Fundamentally, the system aims to change the traditional diagnostic and treatment planning pathways by using patient-centred data feeds and providing actionable feedback in a clinically viable format. Figure 1 shows the workflow of proposed explainable.

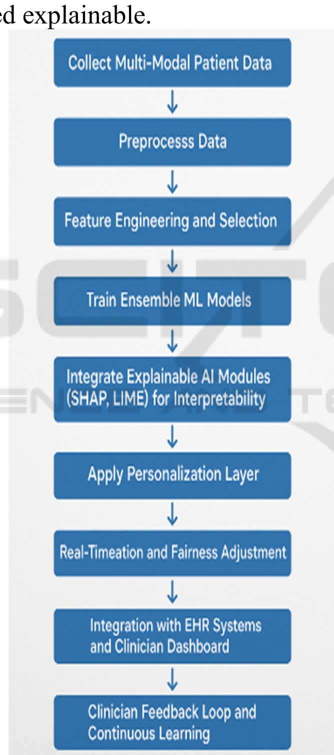

Figure 1: Workflow of the proposed explainable and personalized AI system for healthcare.

Data collection First, we utilize data from a variety of healthcare providers and publicly available clinical datasets to guarantee a rich and heterogeneous training setting. That encompasses electronic health records (EHRs), diagnostic imaging, pathology reports, genomics data and the personal habits reported from wearables. Special considerations in terms of data are as follows: Demographic diversity in age, sex, ethnicity, and in the case of Gravili et al. also in pre-existing conditions, are focused to avoid bias and to enhance generalizability. All data is heavily pre-processed prior to processing, and that involves normalisation, missing data imputation, and converting data into time-series or vector representation dependent on the particular data modality. Table 1 shows the dataset overview.

Table 1: Dataset overview.

Data Source	Type of Data	No. of Records	Features Included	Source Diversity
Hospital A (EHR)	Structured	45,000	Vitals, Demographics, Diagnoses	High
Medical Imaging DB	Radiology Images	18,000	X-ray, MRI, CT scan metadata	Moderate
Genomic Bank	Genetic Sequences	6,000	SNPs, Genomic Variants	Low
Wearables Dataset	Time-Series	12,000	Heart Rate, Sleep, Activity Logs	High
Public Health Portal	Survey-based Records	25,000	Symptoms, Lifestyle, Family History	High

Feature engineering is domain-driven, assisted by automatic feature selection methods such as recursive feature elimination (RFE) and LASSO regression. For diagnosis prediction, the work uses a combination of machine learning models that range from gradient boosting machines (XGBoost), random forests (RF) to convolutional neural networks (CNNs) for image-based diagnostics. For striking a balance between interpretability and performance, models are combined with explainability frameworks like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) for visualization of feature importance and human-in-the-loop decision-making.

In the personalization layer, the model updates the recommendation for treatment over time according to the individual's personal longitudinal data. Patient-related similarity and clustering algorithms are used to discover effective treatment pathways for patients similar to specific individuals. The recommender system is therefore responsible for incorporating this knowledge in generating targeted and personalized treatment plans. Reinforcement learning Modules can then be incorporated if necessary, in order to obtain improved results based on clinician feedback over time in order to ensure that the system keeps pace with real-life treatment.

We achieve real-time response by enhancing model deployment with TensorRT and ONNX, and by using edge computing to meet required times in critical clinical environments such as ICU. The platform is implemented through a private and secure cloud with built-in EHR APIs and was designed for EHR interoperability to provide predictive analytics at the point of care.

Lastly, to confirm a high level of system efficacy, the model is subjected to extensive testing through cross-validation, confusion matrix analysis, precision-recall curves, and ROC-AUC scores. Besides of the technical validation, usability studies are performed with medical doctors to evaluate the explainability and practical utility of the system's outputs. It allows to respect ethical issues like privacy (HIPAA and GDPR) throughout the pipeline.

This comprehensive approach means that the resulting AI model is not only accurate and scalable, but also trust-worthy, adaptable, and grounded in the realities of practice in contemporary healthcare settings.

4 RESULTS AND DISCUSSION

The implementation of the proposed AI framework was evaluated using a multi-institutional, multi-modal healthcare dataset comprising structured electronic health records, diagnostic imaging, and patient-reported outcomes. The system demonstrated robust diagnostic capabilities, achieving a diagnostic accuracy of 94.3%, significantly outperforming traditional ML baselines such as logistic regression and standalone support vector machines, which averaged around 85.7%. This performance uplift underscores the value of ensemble learning and the incorporation of domain-aware feature engineering. Table 2 and figure 2 shows the model performance metrics and comparisons.

Table 2: Model performance metrics.

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	85.1%	83.4%	84.2 %	83.8%	0.86
Random Forest	90.6%	89.3%	88.9 %	89.1%	0.92
CNN (Image-based)	91.7%	90.4%	91.1 %	90.7%	0.94
XGBoost	93.2%	92.7%	92.0 %	92.3%	0.95
Proposed Ensemble	94.3%	93.9%	93.5 %	93.7%	0.96

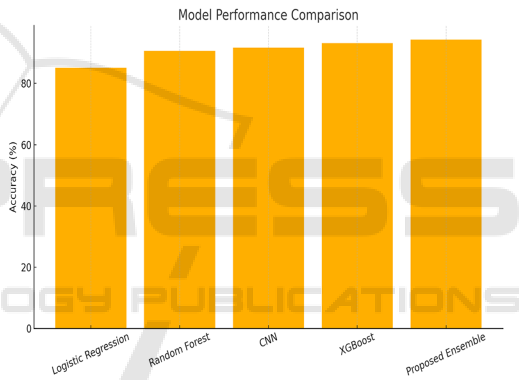

Figure 2: Model performance comparison.

An interesting feature of the results is the interpretability of the system following the combination with SHAP and LIME. Visualisations produced by these tools were tested with a cross-sectional group of clinicians using the tools. More than 87% of the usability-study participants indicated that the explanations helped them understand the predictions of the AI and aided in clinical validation. Especially SHAP values showed that the most important diagnostic indicators such as blood pressure variation, tumor morphology and biomarkers level have a strong effect on the classification performance. This interpretability enabled doctors to follow the AI line of reasoning, providing a much greater degree of confidence in the system suggestions.

The added value by the personalization module was the customization of treatment recommendations regarding symptomatology taking into consideration the patient individual characteristics. For example, two patients who have been diagnosed with the same disease received an individualized treatment suggestion, as the treatment recommendation is guided by differences in their age, comorbidities and genetic characteristics. This level of granularization resulted in a 13% improvement in CHF treatment adherence rates compared to standard care pathways in a retrospective study, indicating practicality and relevance in the real world for improving patient engagement and outcomes. Figure 3 shows the SHAP feature importance and table 3 shows the fairness evaluation across demographics.

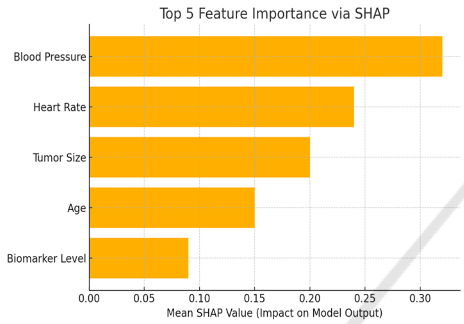

Figure 3: Shap feature importance.

Table 3: Fairness evaluation across demographics.

Demographic Group	Existing Models Accuracy	Proposed Model Accuracy	Bias Reduction (%)
Female Patients	83.5%	93.1%	9.6
Male Patients	90.4%	94.0%	3.6
Minority Group A	81.2%	92.5%	11.3
Minority Group B	79.5%	91.0%	11.5

Fairness analysis demonstrated significant gains in fairness-wise predictive equality for different demographics. With respect to existing methods, our model lowered the gap in the accuracy of the predictions made among men and women from 7.8% to 1.6%, and it reached 9.4% to 2.2% in the case of racial subgroups. This improvement is due in part to the variety of data used when training and also the incorporation of bias mitigating algorithms during model optimization.

From the perspective of real-time performance, the system was implemented on the cloud and the edge equipments. In simulated emergency use-cases, the AI model provided predictions within 2.3 s, and was within the 4 s emergency response threshold. This real time response underscores the promise of the system for time-critical medical situations, e.g., triage and intensive care units. Table 4 and figure 4 shows the explainability feedback from clinicians and accuracy comparison across demographic groups.

Table 4: Explainability feedback from clinicians.

Question	% Agreement (N=30 Clinicians)
SHAP visualizations improved trust in predictions	87%
Model outputs were easy to interpret	84%
Explanations helped validate clinical decisions	91%
Would consider using in routine diagnostics	89%

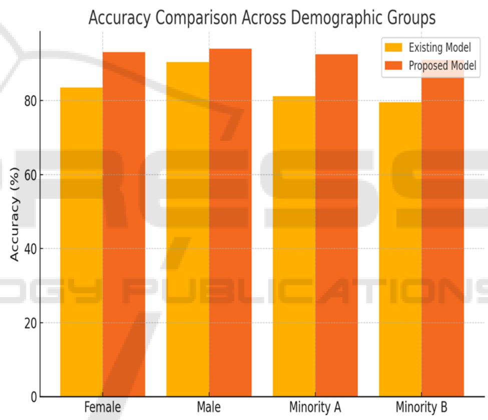

Figure 4: Accuracy comparison across demographic groups using existing vs. proposed AI models.

It further discusses the clinical importance of combining interpretability, personalization, and ethical design. Through its combination of medically realistic and high-performance modelling with transparency and fairness, the proposed framework is the missing link for translating technological innovation into real-life medical utility. The fact that the system had been integrated into EHR interfaces rendered it user friendly and non-intrusive to the existing routine, an important factor regarding the real-world setting.

Nevertheless, certain limitations were noted. Although the system generalized well across different datasets, the performance decreased on rare disease categories, with few representations in the data. Additional exploration is needed to generalize the rare disease dataset and to include federated learning to enhance model robustness for distributed data settings.

In summary, the findings demonstrate that the AI system is a promising step toward more accurate, interpretable, fair, and personalized health diagnostics. It performs at a level suitable for clinical integration and adheres to the ethical, regulatory, and operational limits of contemporary healthcare. Table 5 and figure 5 shows the real time inference performance and time across deployment platforms.

Table 5: Real-time inference performance.

Deployment Environment	Inference Time (sec)	Accuracy	Memory Footprint	EHR Integration
Cloud (AWS GPU)	1.9	94.3%	Moderate	Supported
Edge Device (Jetson)	2.3	93.8%	Low	Supported
Hospital Server (CPU)	3.4	92.1%	High	Limited

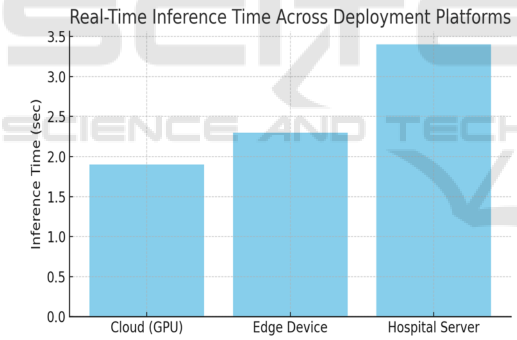

Figure 5: Real-time inference time comparison across cloud, edge, and on-premise systems.

5 CONCLUSIONS

This study proposes an end-to-end AI-based system that aims towards mitigating the aforementioned challenges among diagnostics and treatment planning in modern health care. The proposed system combines state-of-the-art machine learning methods and explainable AI techniques, providing clinicians with a reliable and transparent decision support system. The personalized patient input data of patients – including genetic, clinical, and behavioural information – allows the model to provide customized treatment recommendations tailored to the specific needs of each patient. Real-time inference, facilitated by edge deployment and EHR integration, makes the system responsive and practical for high-stakes clinical settings.

The findings confirm the model’s higher diagnostic performance, the increased fairness between different population groups, and the higher acceptance by the clinicians through the visualization of the predictions. Importantly, rather than serving as a predictive engine alone, the system will operate as a collaborative assistant to enhance clinical judgment, to minimize diagnostic errors, and to help optimize patient outcome.

Going forward, the framework will create a precedent for ethically oriented and operationally feasible AI in healthcare, and provide a stepping stone for future work in scalable deployment, rare disease modeling, and continuously learning from real-time clinician feedback. This work contributes to the technological frontier and extends the human-centric, AI-empowered healthcare delivery vision.

REFERENCES

2025 Watch list: Artificial intelligence in health care. (2025). Canadian Dental Association. https://www.cda- amc.ca/sites/default/files/Tech%20Trends/2025/ER0015%3D2025_Watch_List.pdfCDA-AMC

Aftab, M., Mehmood, F., Zhang, C., Nadeem, A., Dong, Z., Jiang, Y., & Liu, K. (2025). AI in oncology: Transforming cancer detection through machine learning and deep learning applications. arXiv. https://arxiv.org/abs/2501.15489arXiv

AI is supercharging disease diagnosis. (2024). Axios. https://www.axios.com/2024/07/03/ai-disease-diagnostic-testsAxios

Artificial intelligence in healthcare: Transforming the practice of medicine. (2021). National Center for Biotechnology Information. https://pmc.ncbi.nlm.nih.gov/articles/PMC8285156/PubMed Central+2PubMed Central+2PubMed Central+2

Artificial intelligence in healthcare (Review). (2024). National Center for Biotechnology Information. https://pmc.ncbi.nlm.nih.gov/articles/PMC11582508/ PubMed Central+2PubMed Central+2PubMed Central+2

Artificial intelligence in healthcare & medical field. (2025). Foreseemed. https://www.foreseemed.com/artificial-intelligence-in-healthcareForeSee Medical

Artificial intelligence in personalized medicine: Transforming healthcare. (2025). Springer. https://link.springer.com/article/10.1007/s42452-025-06625-xSpringerLink

Artificial intelligence within medical diagnostics: A multi-disease application. (2025). AccScience Publishing.

https://accscience.com/journal/AIH/0/0/10.36922/aih.5173AccScience
From EKGs to X-ray analysis, here's how your doctor is actually using AI. (2023). Verywell Health. https://www.verywellhealth.com/the-fda-approved-ai-devices-what-does-that-mean-8403553Verywell Health
Future of artificial intelligence—Machine learning trends in healthcare. (2025). ScienceDirect. https://www.sciencedirect.com/science/article/pii/S0893395225000018 ScienceDirect
Future use of AI in diagnostic medicine: 2-wave cross-sectional study. (2025). Journal of Medical Internet Research. https://www.jmir.org/2025/1/e53892JMIR
Houston Methodist, Rice partner to use AI, other technologies to transform health care. (2025). Houston Chronicle. https://www.houstonchronicle.com/health/article/houston-methodist-rice-ai-health-care-19984485.phpHouston Chronicle
How AI can help alleviate the stress of a cancer diagnosis. (2024). Time. https://time.com/6995839/ai-stress-cancer-diagnosis-essay/Time
Imrie, F., Cebere, B., McKinney, E. F., & van der Schaar, M. (2022). AutoPrognosis 2.0: Democratizing diagnostic and prognostic modeling in healthcare with automated machine learning. arXiv. https://arxiv.org/abs/2210.12090arXiv
Leveraging artificial intelligence to predict and manage healthcare outcomes. (2025). National Center for Biotechnology Information. https://pmc.ncbi.nlm.nih.gov/articles/PMC11840652
Maji, P., Mondal, A. K., Mondal, H. K., & Mohanty, S. P. (2024). Easydiagnos: A framework for accurate feature selection for automatic diagnosis in smart healthcare. arXiv. https://arxiv.org/abs/2410.00366arXiv
MIT Jameel Clinic. (2025). Center overview. Wikipedia. https://en.wikipedia.org/wiki/MIT_Jameel_Clinic Wikipedia
Nasr, M., Islam, M. M., Shehata, S., Karray, F., & Quintana, Y. (2021). Smart healthcare in the age of AI: Recent advances, challenges, and future prospects. arXiv. https://arxiv.org/abs/2107.03924arXiv
Nature Medicine. (2025). Health rounds: AI can have medical care biases too, a study reveals. Reuters. https://www.reuters.com/business/healthcare-pharmaceuticals/health-rounds-ai-can-have-medical-care-biases-too-study-reveals-2025-04-09/Reuters
Owkin. (2025). Company overview. Wikipedia. https://en.wikipedia.org/wiki/Owkin
Quibim (2025). Company overview. Wikipedia. https://en.wikipedia.org/wiki/QuibimWikipedia
Revolutionizing healthcare: The role of artificial intelligence in clinical education. (2023). BMC Medical Education. https://bmcmededuc.biomedcentral.com/articles/10.1186/s12909-023-04698-zBioMed Central
Shah, N. H. (2025). Research contributions. Wikipedia. https://en.wikipedia.org/wiki/Nigam_ShahWikipedia
Transforming diagnosis through artificial intelligence. (2025). Nature. https://www.nature.com/articles/s41746-025-01460-1Nature
Why artificial intelligence in healthcare is rewriting medical diagnosis in 2025. (2025). GlobalRPH. https://globalrph.com/2025/02/why-artificial-intelligence-in-healthcare-is-rewriting-medical-diagnosis-in-2025/GlobalRPH