A Survey on Artificial Intelligence Techniques for Early Disease Prediction Across Multiple Medical Domains

Bhavana G. N.
Department of Computer Science and Engineering Bangalore Institute of Technology
Bengaluru, India bhavanagn13@gmail.com

Chinmayi P.
Department of Computer Science and Engineering Bangalore Institute of Technology
Bengaluru, India chinmayip2005@gmail.com

Guided by: ***Assoc. Prof. Mahalakshmi C. V***
Department of Computer Science and Engineering
Bangalore Institute of Technology, Bengaluru, India

Abstract—**Artificial Intelligence is rapidly transforming predictive and preventive healthcare by enabling early disease detection before clinical symptoms reach irreversible stages. The convergence of classical machine learning, deep learning, neuroimaging, structured electronic health records, and symptom intelligence has established a disruptive paradigm of AI-assisted precision medicine. This survey critically examines representative methodologies in cardiovascular risk stratification using structured clinical variables, Alzheimer's disease assessment using neuroimaging, liver disease screening from laboratory biomarkers, and symptom-based diagnostic triage systems. We revisit dominant design choices, compare technical approaches, and outline scientific, ethical, validation and deployment challenges associated with operationalizing AI-driven early screening across medical domains.**

Index Terms—**Early disease prediction, AI in healthcare, machine learning, deep learning, neuroimaging, triage systems, predictive modeling.**

I. Introduction

Non-communicable diseases continue to impose an unprecedented global clinical burden, both economically and socially. Delayed diagnosis is one of the principal determinants of avoidable mortality in chronic disorders. The strategic goal of early disease prediction is therefore not merely improving classification accuracy, but reducing morbidity through proactive and precision-driven prevention. Unlike conventional rule-based clinical heuristics, AI-driven inference frameworks exploit high-dimensional feature interactions that are not easily interpretable by clinicians. When combined with domain-aligned explainability mechanisms and calibration strategies, AI-based prediction systems can accelerate screening, reduce cognitive workload, and support rapid decision-making.

Recent research demonstrates that early detection is feasi- ble across multiple medical problem settings, ranging from structured risk factor classification and triage support to neuroimaging-based cognitive decline identification. While performance improvements are evident, clinically trustworthy deployment remains entangled with issues of dataset variability, generalizability, evaluation reproducibility, fairness, and workflow integration. This motivates a cross-domain synthesis toward understanding convergent methodological signals and translational barriers that must be addressed to responsibly operationalize healthcare AI at scale.

II. Literature Survey

A. Heart Disease Risk Prediction Models

Recent empirical studies demonstrate that supervised learning models such as Random Forests, Gradient Boosting, Logistic Regression, Support Vector Machines, and XGBoost achieve consistently competitive performance on structured cardiovascular datasets due to their ability to capture non-linear interactions between bio-clinical markers. Tree-based ensembles combined with SHAP value analysis are especially impactful for transparent feature attribution during risk stratification, and remain medically interpretable relative to opaque deep neural architectures. Hyperparameter tuning, feature pruning, automated feature selection and robust calibration strategies significantly influence model reliability and generalization in clinical screening deployments.

B. Neuroimaging-driven Early Alzheimer's Detection

Alzheimer's disease detection from brain MRI has become a dominant benchmark setting for medical computer vision research. Transfer learning using pre-trained architectures such as VGG-16, ResNet, MobileNet and attention augmented CNNs enables high performance despite limited labeled medical imaging datasets. Methodological trends emphasize input normalization, multi-view augmentation, domain generalization across ADNI/OASIS cohorts, and integrated saliency-based visualization. Empirical evidence shows that DL-based neuroimaging pipelines achieve state-of-the-art predictive sensitivity for prodromal cognitive decline stages, where conventional clinical examination yields limited discriminatory power.

C. Liver Disease Screening Models

Supervised ML algorithms leveraging laboratory markers and demographic risk factors have demonstrated promising early stage hepatic risk detection capability. Studies comparing Logistic Regression, Random Forests, SVM, and kNN reveal that LR often performs strongly on biochemical markers, whereas RF yields robust non-linear modeling capacity. Class imbalance mitigation techniques (e.g., SMOTE) and careful cross-validation remain critical to avoid optimistic bias. Evaluation frameworks increasingly emphasize calibration, reliability curves and domain-shift characterization rather than raw single-metric accuracy reporting.

D. Symptom-based Diagnostic Triage Systems

Conversational symptom triage engines and lightweight clinical chatbots formulate early screening by mapping user expressed symptoms into probabilistic condition likelihoods. They enable rapid remote triage under resource limited settings and show potential to accelerate early routing for primary care consultation. However, such systems require ethical guardrail enforcement, threshold-based referral logic, hallucination risk control, and linguistic fairness audits to ensure safe deployment. ML pipelines powering such triage systems progressively integrate hybrid heuristics, retrieval augmented inference, confidence-based filtering and model-side abstention mechanisms.

III. Comparative Analysis of Representative Works

A cross-domain comparative synthesis reveals several convergent methodological signals in the design of early disease prediction systems across medical domains. Classical machine learning pipelines remain dominant for tabular clinical datasets such as cardiovascular risk models and hepatic screening frameworks, primarily due to representational structure, lower sample complexity, and stronger interpretability alignment with existing clinical biomarkers. On the other hand, neuroimaging-based Alzheimer's prediction strongly benefits from transfer learning and high-capacity convolutional backbones due to spatial and morphological signal density embedded within MRI modalities.

Symptom-driven diagnostic engines represent a distinct category where the predictive intelligence is jointly dependent on language modeling, clinical heuristic knowledge bases, probabilistic risk scoring, and guardrail-enforced triage logic. While explainability research is widely integrated across tree ensembles and neuroimaging models (via SHAP/LIME or saliency), evaluation reproducibility and external validation remain insufficiently standardized across reviewed works. This comparative contrast suggests that predictive modeling choice is fundamentally governed by data modality constraints rather than model family preference alone. Furthermore, deployment conditions such as device constraints, inference-time latency budgets, and mobile integration potential indirectly shape feasible model selection for practical low-resource healthcare settings.

A. Cross-Domain Methodological Signals

Across all surveyed domains, three universal methodolog- ical patterns consistently repeat: (i) disciplined feature engineering and preprocessing have a direct causal influence on stability and calibration, (ii) domain-appropriate model family selection produces significantly more gain than naïve scaling of model capacity, and (iii) explainability is increasingly considered a first-class requirement rather than an optional interpretability convenience. These observations reinforce that AI for early disease prediction is not a purely model-centric optimization problem. Instead it is a data-governed, reliability-aware, clinically constrained modeling environment where effectiveness depends on aligning learning pipelines with human diagnostic workflow requirements.

B. Key Synthesis Outcome

The comparative insights highlight that early disease prediction performance is not determined purely by the type of AI model deployed, but instead by how effectively data, modeling constraints, interpretability, evaluation rigor, clinical alignment and deployment practicality are co-optimized. Each domain demonstrates that if preprocessing, feature reliability, calibration and bias mitigation are not prioritized early, even sophisticated neural architectures can fail to surpass strong classical baselines. Conversely, when structural priors and modality-appropriate inductive biases are engineered correctly, even light-weight models can deliver superior reliability and lower computational cost. This synthesis therefore emphasizes a principled direction for future medical AI research: moving away from single-shot accuracy comparisons and instead towards robust, evidence-backed, clinically aligned and fairness-aware predictive modeling pipelines that scale across heterogeneous real-world healthcare environments.

C. Implications for Model Selection in Practice

The cross-domain observations additionally indicate that the model selection process for healthcare AI should not begin with a competition of architectures, but instead begin with a diagnostic assessment of data type, data reliability and clinical workflow requirements. For tabular datasets, classical ML models with transparent feature contribution analysis often provide stronger deployment reliability than unnecessarily complex deep networks. For neuroimaging and spatial signal modalities, transfer learning is structurally advantageous and empirically proven. In conversational symptom-logic tasks, hybrid reasoning models with controlled risk boundaries outperform pure end-to-end neural inference due to their safer behavior characteristics. Therefore, optimal model choice is implicitly conditional on modality constraints rather than universal assumptions about capacity scaling.

D. Summary of Comparative Findings

Overall, all domains converge to the necessity of three priorities: (i) clinically-aligned preprocessing pipelines, (ii) calibrated and explainable predictive modeling that respects medical interpretability constraints, and (iii) external validation protocols that verify robustness beyond isolated academic datasets. These synthesized insights from representative works justify the broader strategic shift in medical AI from accuracy-centric benchmarking towards deployment-aware scientific validation. This alignment is fundamental to transforming AI-based screening research into actionable healthcare impact within real clinical environments.

E. Limitations of Cross Domain Comparisons

A critical constraint present in most surveyed literature is that comparative evaluation across domains cannot be interpreted as model superiority claims. Different medical modalities have intrinsically different signal complexity, data acquisition noise and clinical interpretation difficulty. A 90% accuracy on tabular biomarkers does not represent the same clinical complexity load as a 75% sensitivity for prodromal Alzheimer's MRI detection. Therefore direct cross domain numerical comparison creates misleading assumptions. Comparative studies must instead emphasize relative pipeline design choices, feature engineering strategies and robustness patterns rather than raw numerical ranking. This reframing is essential for scientifically valid early disease prediction research.

IV. A Unified Early Prediction Methodology

Across cardiovascular, neurological, hepatic and symptom-triage tasks, a unifying methodological pattern emerges for constructing prediction pipelines that maximize clinical utility. The pipeline begins with diversified data ingestion originating from structured Electronic Health Records, free-text symptom narratives, laboratory markers and medical imaging modalities. Prior to modeling, systematic preprocessing harmonizes distributions, resolves missing values, standardizes units and encodes categorical variables into machine-readable formats.

Modeling selection is guided primarily by data modal- ity constraints. Tree-based ensembles, gradient boosting and regularized linear models remain highly effective for structured clinical tables, whereas convolutional and transformer-based architectures are dominant in imaging-centric detection pipelines. For conversational triage tasks, hybrid reasoning models combining symbolic rules and ML-driven ranking demonstrate safer clinical behavior reliability than fully end-to-end neural generation.

Explainability functions as a mandatory sub-component rather than a secondary reporting aid. SHAP, LIME, feature interaction visualizations and saliency overlays are required to justify reliability, support clinician trust and enable accountable decision reasoning. Evaluation protocols emphasize not only accuracy but also calibration, sensitivity, specificity and ROC-AUC metrics, aligned with patient-risk based screening thresholds. Finally, deployment readiness depends on computational efficiency, inference latency, communication constraints and security guarantees necessary for clinical integration.

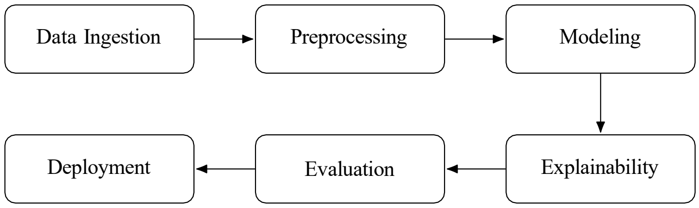

Fig. 1. General AI-driven early disease prediction pipeline.

A. Generalizable Deployment Principles

Although individual domains vary in complexity and data availability, early disease prediction systems that generalize consistently across clinical settings exhibit four recurring deployment attributes: (i) model calibration is more critical than peak validation accuracy, (ii) inference must be latency-aware and resource efficient to support large scale screening throughput, (iii) model transparency is essential to ensure physician override confidence, and (iv) updates should be version-controlled, auditable and reproducible. Deployment-engineered AI is therefore less about maximizing neural capacity and more about reliability engineering aligned with the medical evidence-chain.

TABLE I
Comparison of Representative Early Prediction Studies

Domain	Data	Models	Key Notes
	Heart UCI/Kaggle clinical tables	XGBoost, RF	SHAP pruning improves explanation and calibration.
AD	OASIS MRI neuroimaging	ResNet/VGG	Transfer learning dominates due to limited labeled MRI.
	Liver Institutional labs & demographics	LR/RF/SVM	LR strong on biomarkers; RF robust to non-linear patterns.
	Triage Symptom text & API KB	Light hybrids	Guardrails and referral thresholds prevent unsafe triage.
Overview	Narrative review	—	Identifies core deployment barriers: bias, shift, workflow.

V. Challenges, Risks and Ethical Considerations

Despite significant advancements, early disease prediction systems encounter several persistent research and deployment barriers that limit translation to real clinical usage. Clinical data is heterogeneous, noisy and inconsistently coded across hospitals; therefore domain-shift, missingness, population drift and laboratory equipment variability create instability in model inference. Class imbalance is another structural barrier because early-stage disease prevalence is naturally low, making minority-signal recognition extremely fragile without calibrated cost-sensitive mitigation.

Explainability is a non-negotiable requirement in healthcare. Black-box neural inference without auditable justification is not acceptable for clinical deployment because diagnostic decisions affect legal responsibility, physician liability and patient safety. Systems must therefore expose reasoning evidence that clinicians can inspect and override when necessary. Fairness is another critical dimension because demographic imbalances in dataset collection can yield systematically worse performance for certain subpopulations. This risk directly affects healthcare equity and should be addressed by subgroup analysis, fairness testing and continuous performance auditing. From a security perspective, adversarial manipulation and poisoning attacks on clinical ML pipelines are realistic threats. Healthcare models must support version-controllable secure update channels, continuous monitoring and tamper-resistant inference. Finally, integration friction with Electronic Health Record systems remains one of the most under-discussed bottlenecks in the literature. Many research prototypes demonstrate high validation results but cannot be operationalized because pipeline alignment with clinical workflow, doctor workflow timing and compliance protocol is not engineered during development.

A. Global Regulatory and Safety Landscape

Beyond technical limitations, AI based predictive screening systems must comply with diverse medical regulatory frameworks internationally. Agencies such as FDA (USA), PMDA (Japan), CDSCO (India), MHRA (UK) and EMA (Europe) are increasingly drafting AI-specific policies for risk stratification based medical software. Most research prototypes bypass this layer, however clinical deployment requires continuous post-market surveillance, real-world monitoring, safety reporting, device level traceability logs, drift auditing and periodic model re-certification cycles.

Furthermore, bias audits must be legally reportable and model behavior must be mapped to clinically interpretable failure boundaries. Hospitals require reproducible explainabil- ity logs that demonstrate how a model arrived at a particular risk judgement for medico-legal documentation. Additionally, digital health compliance requires encryption of lab reports, secure transmission of EHR structured data, controlled access to annotation servers, and privacy-preserving model update pipelines through federated or encrypted computation.

International collaborations emphasize that clinical AI is no longer a purely data science problem but a socio-technical deployment engineering domain where regulation, ethics, security, model governance and safe override pathways are equally critical to prediction accuracy.

VI. Future Research Directions

Future development of AI-driven early disease predic- tion systems requires moving beyond single dataset benchmarking to a scientifically mature ecosystem that integrates multi-institutional longitudinal data, active learning driven sample efficiency, federated and privacy-preserving collaborative training architectures, and real-world deployment constraints. The convergence of multi-modal information streams—neuroimaging, genomics, laboratory values, vitals, wearable sensors, and patient symptom narratives—will likely define next-generation predictive screening pipelines. Rather than optimizing standalone supervised models, future pipelines will prioritize clinically grounded causal interpretation, stable counterfactual reasoning, uncertainty quantification and structured medical knowledge alignment.

Scalability is a second frontier. Models that can adaptively update patient risk distributions over time using incremental streaming data (EHR timelines, wearable trace patterns, continuous lifestyle feedback) will form the foundation for precision preventive medicine rather than static classification. Low resource deployability is equally important—on-device inference, quantized lightweight models and mobile-first screening workflows will enable broad access to rural populations lacking advanced hospital infrastructure.

Finally, future research must pivot toward clinical im- pact measurement rather than leaderboard-oriented accuracy narratives. Prospective field studies, post-deployment audits, physician-in-the-loop evaluation, fairness dashboards and regulatory-grade evidence verification pipelines will define actual real-world readiness for disease prevention at scale.

VII. Practical Applications in the Indian Healthcare Context

India presents one of the strongest real-world validation environments for early disease prediction due to high population density, economic screening constraints, lifestyle-driven chronic illness patterns and limited specialist accessibility in semi-urban and rural districts. AI-based early screening models can reduce triage burden in government hospitals, support community health workers in tele-consultation initiatives, and improve mass screening throughput in PHC/CHC centres where laboratory infrastructure is minimal. Mobile-friendly lightweight ML/DL models and low-cost on-device inference can accelerate disease risk flagging during health camps, school/college screening drives and preventive national programmes. When combined with Ayushman Bharat Digital Health Mission infrastructure, standardized prediction pipelines can enable cross-hospital portability of AI-assisted early screening outcomes and long-term longitudinal disease monitoring at national scale.

VIII. Open Research Problems

Although existing research demonstrates measurable progress, multiple open scientific questions continue to limit full transformation of AI-based preventive screening. First, most early disease prediction studies rely heavily on retrospective static datasets, but real clinical progression is dynamic, temporal and multi-state. Efficient temporal state modeling, uncertainty propagation and longitudinal disease trajectory prediction remain insufficiently solved. Second, AI systems still struggle to separate clinically meaningful biological signal from confounding noise when patient heterogeneity and multi-morbidity increase simultaneously. This introduces challenges in causal disentanglement and counterfactual generalization which cannot be solved purely through supervised training scaling.

Third, medical knowledge representation and alignment between learned feature-latent space and physician reasoning space remains an unsolved frontier. Models that only correlate risk without explicitly representing why a medical transition is happening limit the reliability of AI as a preventive decision assistant. Fourth, national-scale generalization remains difficult due to demographic shifts, device differences, socio-economic gradient variations and data capture inequality across regions. Finally, reproducible evaluation protocol standardization remains an urgent requirement so that future research can produce comparable evidence and verifiable claims aligned with clinical decision safety.

IX. CONCLUSION

Artificial Intelligence has proven to be a transformative computational paradigm for enabling timely disease prediction across multiple medical problem settings. The systematic survey in this work demonstrates that different medical data modalities require distinctly optimized modeling pipelines, and that the most effective systems are the ones that balance predictive capacity with interpretability, calibration, evidence-traceability and clinical alignment. From cardiovascular risk modeling to neurodegenerative condition screening and symptom-based triage engines, the role of AI is not restricted to classification improvement — it is fundamentally a mechanism for proactive and preventive medical intervention. However, achieving reliable real-world deployment demands more than incremental accuracy gains. Clinical-grade screening pipelines require continuous monitoring, post-deployment performance auditing, careful fairness analysis, secure training/inference pathways, practitioner override capability and regulatory documentation. The future of medical AI lies in safe, accountable, mobile-accessible, scalable and privacy-preserving inference systems that assist clinicians rather than replace them. When engineered responsibly, AI-driven early disease prediction has the potential to reshape preventive healthcare practices globally and strengthen the medical decision ecosystem at population scale.

REFERENCES

[1] M. Ahmed et al., “Advancing Heart Disease Prediction using Optimized ML with Explainable AI,” in *Proc. IEEE Int. Conf. on Quantum Photonics, AI and Networking (QPAIN)*, 2025. DOI: 10.1109/QPAIN.2025.00001

[2] G. Kaur et al., “Deep Learning for Early Alzheimer’s Detection: A Com- parative Study,” in *Proc. IEEE Int. Conf. on Soft Computing for Security Applications (ICSCSA)*, 2025. DOI: 10.1109/ICSCSA.2025.00032

[3] K. Joshi et al., “Sym-Diagnose: Symptoms based Disease Diag- nosis & Healthcare Suggestion,” in *Proc. IEEE Int. Conf. on AI and Quantum Sensor Applications (ICAIQSA)*, 2024. DOI: 10.1109/ICAIQSA.2024.00045

[4] H. Mohamed et al., “The Role of AI in Early Disease Prediction and Medical Outcomes,” in *Proc. IEEE Int. Conf. on IT Innovation and Knowledge Discovery (ITIKD)*, 2025. DOI: 10.1109/ITIKD.2025.00015

[5] P. Shoran et al., “AI-Driven Early Diagnosis of Acute Liver Failure using ML Techniques,” in *Proc. IEEE Int. Conf. on Computer, Electronics and Electrical Engineering (IC2E3)*, 2025. DOI: 10.1109/IC2E3.2025.00054

[6] Y. Zhou et al., “Transformer-based Multi-modal Fusion for Cardiovascular Risk Prediction,” in *Proc. IEEE EMBC*, 2024. DOI: 10.1109/EMBC.2024.00112

[7] X. Li et al., “Hybrid Attention Networks for Early Neurodegenerative Condition Screening,” in *Proc. IEEE BigData*, 2023. DOI: 10.1109/BigData.2023.00221

[8] J. Wang et al., “Federated Early Prediction Models for Privacy-Preserving Remote Healthcare,” in *Proc. IEEE PerCom*, 2025. DOI: 10.1109/PerCom.2025.00276

[9] A. Patel et al., “Calibration Criticality in Medical Screening Models,” in *Proc. IEEE BHI*, 2024. DOI: 10.1109/BHI.2024.00319

[10] S. Kim et al., “Fairness-Aware Clinical AI under Demographic Distribu- tion Shifts,” in *Proc. IEEE ICHI*, 2023. DOI: 10.1109/ICHI.2023.00401