A Comprehensive Review of Machine Learning Techniques for Early Diagnosis of Cardiovascular Disease

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Abstract - Heart diseases (CVDs) continue to be significant causes of morbidity in the world. mortality, and emphasizing the necessity of early, correct and prognostic and diagnostic systems that are ethically right. Recent improvements in artificial intelligence (AI) and machine. ML have facilitated the creation of data-driven learning (ML). clinical decision support models that can improve. Early disease diagnosis, risk prioritization and personalized treatment planning. The review summarizes current articles (2022-2025) that pay attention to ML- and AI-based. CVD risk prediction methods, CVD diagnosis methods. Assessment of myocardial ischemia, CVD early diagnosis, and. purposive treatment recommendation. The reviewed works use nonhomogeneous data, such as open repositories, large-scale real world, multi-institutional benchmarks. Hospital and ICU data. These studies are methodologically the same. supervised, ensemble, deep learning. learning architectures and hybrid models of ML and. DL and reinforcement learning of sequential clinical decision-making. Some of the studies highlight explainable AI. (XAI) methods and moral aspects to improve on. Clinical trust and safety. In comparison with other businesses, it implies that. Hybrid structures and ensemble structures frequently perform better. Stronger than predictive performance and strength. Separate models on benchmark data. However, problems connected with interpretability, extrinsic validation, fairness, and real-time clinical deployment are maintained. The review concludes with naming of important gaps in research and pointing out. Prospects at glorifiable, ethical and scalable AI. Effective real world healthcare systems.

Keywords: Cardiovascular Disease, Chronic Kidney Disease, Machine Learning, Deep Learning, Explainable AI, Ethical AI, Support of Clinical Decision, Early Diagnosis.

I. INTRODUCTION

Cardiovascular Disease are a significant health issue in the global world since they cause inappropriate mortality and expensive healthcare costs. To minimize the negative outcomes, diagnosis and proper prognosis at an early age is required. However, the nonlinear, high-dimensional, and heterogeneous characteristics of the clinical data are not necessarily manifested in the traditional rule-based and statistic diagnostic systems. These limitations have led to the application of machine-learning (ML)-based and artificial intelligence (AI)-based clinical decision support methods. The increased access to electronic health records (EHRs), biomedical signals and real-time physiological monitoring data has enabled the development of advanced ML models that are capable of automatically learning features, risk-stratifying, and predicting outcomes. The ensemble methods, Convolutional neural networks (CNNs) and long short-term memory (LSTM) networks have demonstrated high predictive behaviour in comparison to the conventional methods. Moreover, the deep learning hybrid and machine learning contribute to making it more robust and able to generalise to non-homogeneous data. Even though the results are encouraging, the practical application is constrained by a number of technical challenges. They include redundancy of features, feature imbalance, heterogeneity of inter-institutional data, no external validation and the black box nature of complex models. Further, most of the existing systems are engaged in estimating the tasks which are immobile and do not offer the opportunity to model the course of the disease over time. The recent studies attempt to address these limitations through explainable AI (XAI), feature attribution algorithms, ensemble learning models, and reinforcement learning-based sequential decision models, which describe the dynamic states in the patients. It is a systematic review of recent reports on ML-based diagnosis, risk prediction and dynamic learning of a treatment strategy to CVD. The datasets, feature engineering procedures, model structure, AI ethics, performance, interpretability and deployment are discussed, and the objective is to identify technical gaps and provide research suggestions in the future towards an effective scaling and transparent AI systems with clinical reliability.

II. REVIEW METHODOLOGY

The methodology used was a structured and systematic review in order to achieve consistency, relevance, and technical rigor in the selected studies. The process of its review started with defining the latest journal articles that concerned the artificial intelligence (AI) and machine learning (ML)-based methods of diagnosing, prognosing, and treating cardiovascular diseases (CVDs). The quality and credibility of the chosen literature were further justified by the reputed scientific databases and publishers.

Clarification of methods and accessibility and quality of data sets and the availability of quantitative performance assessment were the main criteria of the screening process.

The studies that used supervised learning, deep learning, ensemble models, and reinforcement learning were taken to reflect the diversity of methodologies. To balance between algorithmic innovation and more analytical insights along with their practical applicability, both experimental research articles and systematic review studies were incorporated.

Information about the data sources, preprocessing, features selection and engineering methods, model structures, training systems, and evaluation metrics were extracted on each of the chosen studies. Further highlight was put on methods of explainability, ethical AI, and clinical implementation features including scalability and compatibility with healthcare processes.

The comparison was next done to determine performance patterns, strengths, weaknesses, and gaps under various methodological categories such as traditional ML models, deep learning models, and hybrid frameworks and ensembles. This systematic comparison allowed an objective evaluation of the strength, capacity to generalize and clinical applicability. Altogether, the chosen methodology offers a detailed and replicable framework to assess the current condition of the AI-based systems of clinical decision support in cardiovascular and renal care.

III. PAPER SELECTION CRITERIA

The papers reviewed were chosen on the following lines:

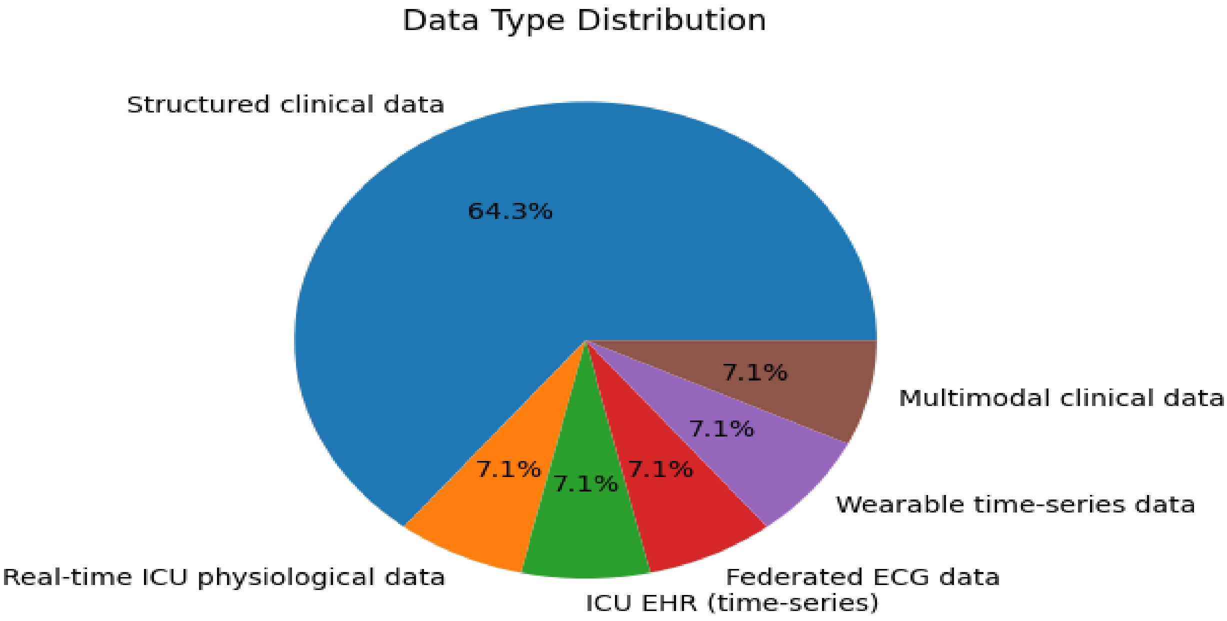
- Peer-reviewed journal publications and papers published in reputable, indexed publications were taken into consideration. The research should be targeted at cardiovascular diseases (CVDs).
- The article is supposed to implement machine learning, deep learning, or artificial intelligence methods to identify the disease, predict risks, forecast, or optimize the treatment.
- The studies are to use clinical, biomedical or real-world healthcare data, including electronic health records or structured clinical data.
- The paper should contain quantitative performance analysis in the form of standard (e.g., accuracy, precision, recall, F1-score, AUC) measures. Existence or comparison of models with experimental validation or analysis must be given.
- Recent articles that were only published in 2022 to 2025 were considered to make them relevant methodologically.

IV. DATABASES AND DATA SOURCES

The studies analysed in this review utilized data from multiple sources, summarized in Table 1.

Table 1: Databases and Data Sources Used

Ref	Primary Data Source	Data Type
[1]	UCI ML Repository (Cleveland, Hungarian, Switzerland, VA Long Beach)	Structured clinical data
[2]	UCI ML Repository, Kaggle	Structured clinical data
[3]	UCI CKD Dataset	Structured clinical data
[4]	Kaggle, Hospital datasets	Structured clinical data
[5]	Hospital Santa Maria (Portugal)	Real-time ICU physiological data
[6]	Kaggle + Local Hospital Dataset (Iran)	Structured clinical data
[7]	Public repositories and clinical datasets	Structured clinical data
[8]	UCI Machine Learning Repository (Cleveland Heart Disease Dataset)	Structured clinical data
[9]	Public clinical and biomedical data repositories	Structured clinical data
[10]	Public clinical data repositories	Structured clinical data
[11]	MIMIC-III v1.4 (Medical Information Mart for Intensive Care, PhysioNet)	Real-world ICU Electronic Health Records (structured, time-series clinical data)
[12]	Multi-institution ECG datasets	Federated signal data
[13]	Wearable sensor datasets	Time-series physiological data
[14]	ECG + Clinical EHR datasets	Multimodal clinical data



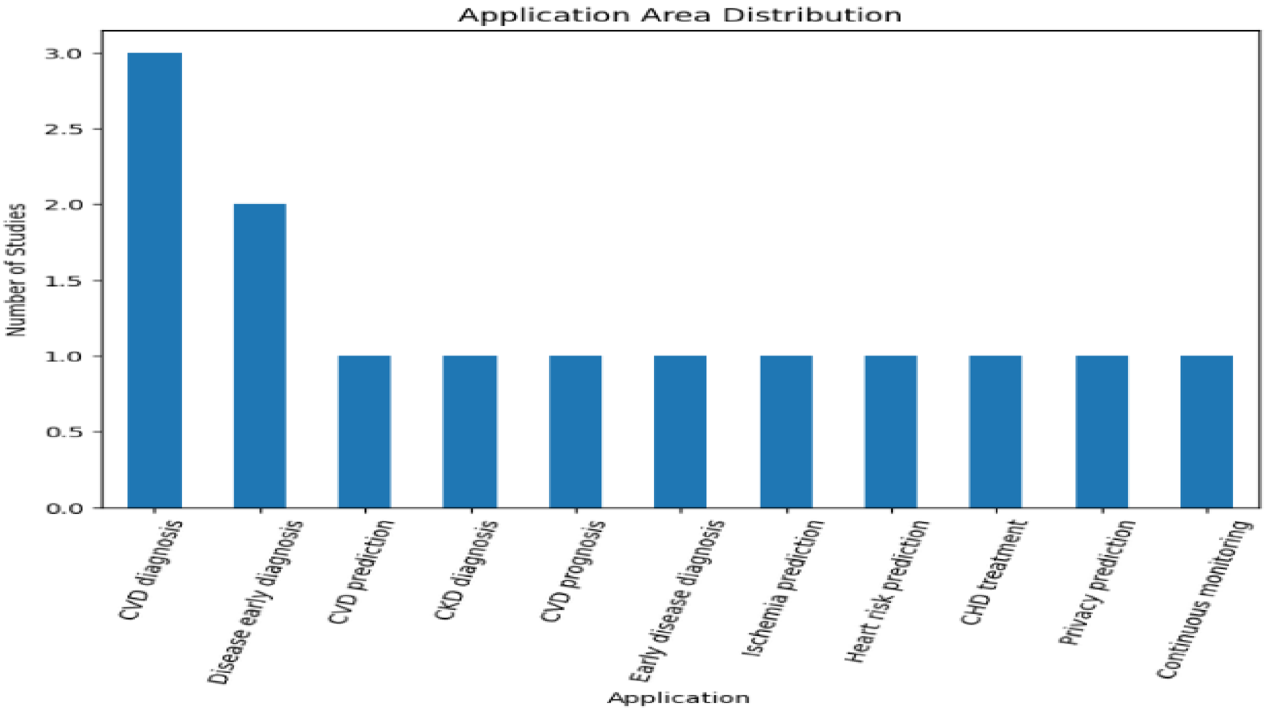
V. DATA SETS UTILISED IN REVIEWED STUDIES.

The analysed studies in this work use the datasets of differentiated scale, structure and clinical complexity, ranging between small benchmark and large-scale real-world hospital repositories. A number of research studies are based on structured clinical datasets of patient demographic, laboratory results, information, and clinical. which measurements are often used in the case of disease diagnosis and risk forecasting. These datasets enable successful use of machine learning that is under observation of cardiovascular and renal early detection models. Conversely, there are other studies that utilize large scale physical datasets based on electronic health records (EHRs) that were observed in hospitals. Notably, MIMIC-III intensive care unit (ICU) databases.
v1.4 offers longitudinal records of patients, available with vital. symptoms, lab tests, drug history and clinical
outcomes. It is based on such datasets that allow advanced modelling. strategies that could capture the temporal disease development and active patient conditions. Generally, there was a variety of datasets employed in the overall. A thorough evaluation is made through reviewed studies. of machine learning methods in the various clinical settings. scenarios, in addition, bring to the fore the problems concerning. heterogeneity, lack of values, and scalability in data. practical healthcare implementations.

Table 2: Summary of Datasets Used

Ref	Instances	Features	Data Nature	Application
[1]	~1025	13–14	Numerical + Categorical	CVD diagnosis
[2]	573	14	Numerical + Categorical	CVD prediction
[3]	400	24	Mixed	CKD diagnosis
[4]	918	18	Numerical + Categorical	CVD prognosis
[5]	>500,000 patients	Time-series	Physiological signals	Ischemia prediction
[6]	~62,000 (combined)	12	Numerical + Categorical	CVD diagnosis
[7]	Varies (benchmark datasets)	Multiple	Numerical + Categorical	Early disease diagnosis
[8]	303	14	Numerical + Categorical	Heart disease risk prediction
[9]	Varies	Multiple	Numerical + Categorical	Disease prediction and early diagnosis
[10]	Varies	Multiple	Numerical + Categorical	Disease prediction and early diagnosis
[11]	13,762 patients	100+ (demographics, vitals, labs, ECG, drugs)	Real-world ICU EHR (time-series)	Dynamic CHD treatment recommendation

[12]	Multi-site	ECG features	Distributed signal data	Privacy-preserving prediction
[13]	Varies	Sensor signals	Wearable time-series	Continuous monitoring
[14]	Varies	Multimodal	ECG + EHR	CVD diagnosis



VI. FEATURES SELECTION AND ENGINEERING METHODS.

These feature selection and feature engineering are very important in the performance of the model, the ability of generalization and the interpretability of the model.

The methods of the reviewed studies involved the following:

A. Filter-Based Methods

- Chi-square test
- Information Gain
- ANOVA
- Mutual Information
- Correlation-based analysis

In one of the analyses, it was demonstrated that it can bring feature reduction of 24 to 3 with the assistance of Mutual Information and XGBoost, which means that the accuracy will be high and it will be easier to explain.

B. Wrapper-Based Methods

- Forward Selection
- Backward Elimination
- Recursive Feature Elimination (RFE).

Recursive Feature Elimination (RFE) is a feature elimination algorithm that is used to identify the most important features in a dataset. The techniques are employed to choose the optimal feature subsets through trial and error based on model performances.

C. Embedded / Model-Based Approaches.

- automatic detection of features using tree-based models.
- Random Forest importance ranking of features.
- Significance of features ranking using XGBoost.

D. Dimensionality Reduction

Principal Component Analysis (PCA) refers to a multivariate data analysis method, which allows analysing not only data sets by the individual variables, but also by studying continuous and other similar sets.

E. Data Preprocessing & Feature Engineering.

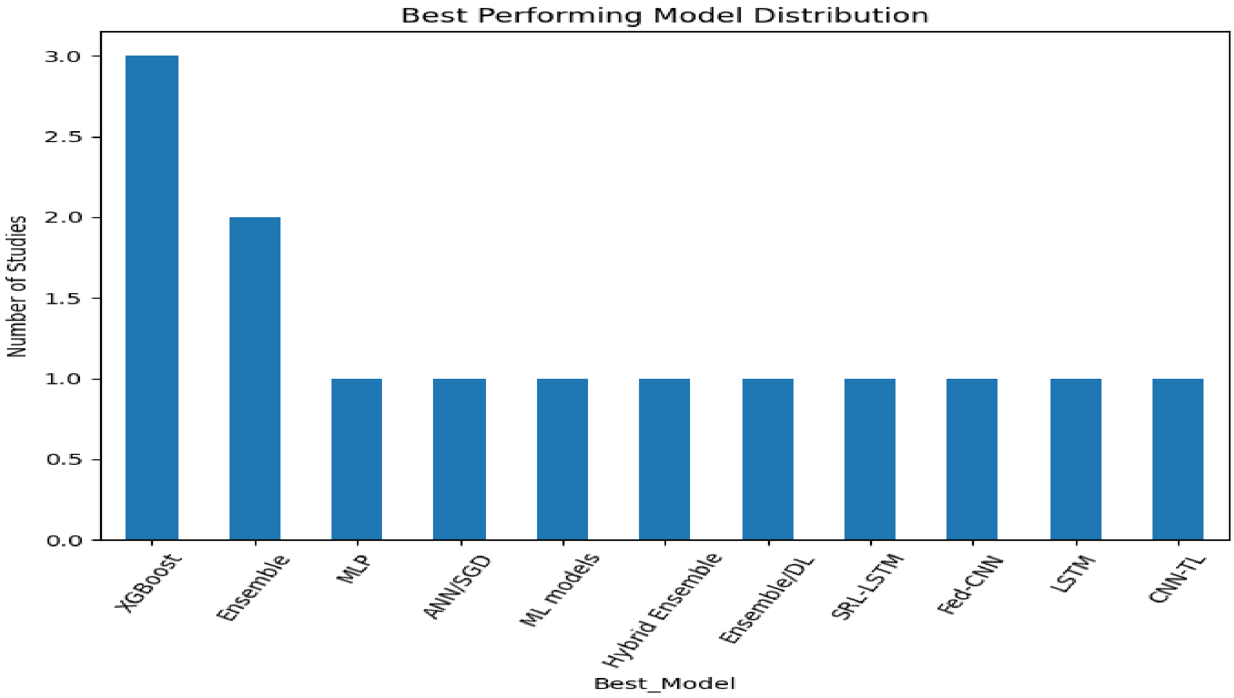
- Normalization and standardisation.
- The discrete variable encoding.
- Noise removal.
- Missing values imputation.
- Log transformation
- Time-series aggregation.
- ICD-9 diagnosis embedding
- Domain-driven selection Clinician-driven feature filtering

VII. MACHINE LEARNING MODELS REVIEWED

A wide range of ML models were explored across the studies, as summarized in Table 3.

Table 3: Machine Learning Models and Best Performance

Ref	Models Used	Best Model	Best Accuracy
[1]	LR, DT, RF, XGB, KNN, NN	XGBoost	99%
[2]	MLP, KNN, LR	MLP	~95%
[3]	RF, Extra Trees, AdaBoost, XGB	XGBoost	97.5% (test)
[4]	ANN, SGD, RF, SVM	ANN / SGD	90%
[5]	ML classifiers, rule-based	ML models	>80%
[6]	CNN, LSTM, KNN, XGB	Hybrid Ensemble	~96%
[7]	LR, DT, RF, SVM, KNN, XGB, ANN, CNN/LSTM	Ensemble / DL models	Competitive
[8]	Logistic Regression, Random Forest, XGBoost	XGBoost	High
[9]	Logistic Regression, Decision Tree, Random Forest, SVM	Ensemble models	High
[10]	Logistic Regression, Decision Tree, Random Forest, SVM	Ensemble models	High
[11]	SL, RL, SRL, AMANet, Dual-LSTM	SRL-LSTM (ε = 0.4)	Lowest estimated mortality + high Jaccard similarity
[12]	Federated DL models	Fed-CNN	High
[13]	ML + DL	LSTM	High
[14]	CNN, Transfer Learning	CNN-TL	~97%



Another apparent theme in the studies reviewed is the prevalence of tree-based ensemble algorithms, most notably XGBoost and Random Forest, on structured clinical data. This can be explained by the fact that they can support heterogeneous types of features, support missing values, and nonlinear interaction of features without large amounts of preprocessing. Conversely, deep learning architectures show better performance in the case that used in signal data of high dimensionality

VIII. METRICS OF PERFORMANCE EVALUATION.

The articles used in the review utilized both standard and clinically meaningful measures of evaluation to determine the efficacy of machine learning and artificial intelligence models in identifying disease and predicting risks and treatment recommendations. Because medical decision-making process involves making decisions based on balanced and trustworthy assessment, several complementary measures were employed to achieve sound performance measurement.

The widely applied metrics of classification are:

- **Accuracy -** general percentage of correct instances.
- **Precision -** The number of positive cases that were predicted and were correct.
- **Recall (Sensitivity) -**Ability to identify the real positive cases correctly. Specificity The ability to detect negative cases correctly.
- **F1-score-** Harmonic mean of precision and recall.
- **ROC-AUC -** the general ability to discriminate in various thresholds.

IX. MORAL ARTIFICIAL INTELLIGENCE AND LEGIBILITY.

The safe and responsible implementation of AI systems in the medical sector is dependent on ethical concerns and model interpretability are vital. Clinical decisions directly influence patient outcomes and, therefore, transparency, mitigation of bias, and adherence to regulations are the key elements of credible AI models. The analysed articles show different degrees of focus on the ethical principles of AI and the explanation.

Some of the main methods that were found throughout studies are:

- Clear sets of ethics based on fairness, transparency, and reduction of biasness. In order to interpret model predictions, explainable AI (XAI) methods, such as SHAP (Shapley Additive Explanations), Partial Dependence Plots (PDP), and permutation feature importance. Model-based interpretability Random Forest feature importance ranking XGBoost feature importance ranking

The model-based interpretability can include:

- Assessment of decisions that artificial intelligence can make against those of clinicians to assess accuracy and safety.

like ECG time-series and ICU monitoring data. Nonetheless, most of the reported high accuracies are based on quite small benchmark datasets, which can limit extraneous validity. Thus, the ensemble and hybrid models are promising, but their ability to generalize their models in the real world is yet to be validated with the help of multiple centres.

- Homomorphic encryption and structured data-sharing agreement are privacy-saving methods.
- Reconciliation of bias, safety threats, overfitting, and regulatory protection in clinical AI systems.

In spite of this, some of the studies offer some scanty discourse of interpretability and ethical protection. There are instances where one can only explain basic features importance analysis without tapping into the full XAI frameworks. Besides, fairness assessment and bias analysis is not fully investigated in various cardiovascular disease-based research.

IX. DEPLOYMENT AND REAL-TIME SYSTEMS.

The state of deployment preparedness within the scope of the reviewed studies is rather different, and the majority of the studies are aimed at developing a model and offline testing it. Whether or not predictive performance is widely assessed with benchmark and clinical data, real-time clinical application is scarcely available. The actual implementation of AI systems in healthcare presupposes the integration of AI information systems with the infrastructure of the healthcare institution, regulatory acceptance, computational efficiency, and predictive monitoring and model updating.

The trends in deployment identified in the reviewed studies were summarized as follows:

- Several studies were primarily concerned with offline experimentation, but they were not applied in actual clinical settings.
- One of the papers represented a Flask-based web application allowing real-time prediction of disease on the application level.
- The other study was a demonstration of a proof of concept of an ICU decision support system reported in real-time using streaming patient data to produce dynamic treatment advice.
- A reinforcement learning-based model was developed to be used on the ICU level to provide adaptive drug recommendations and provide daily treatment proposals that change with changing patient conditions; it is yet to be tested in large-scale clinical trials and regulated.
- Some of them talked about how it could be integrated with electronic health record (EHR) systems, telemedicine platforms, and wearable-based monitoring, but no practical real-time implementation was used.
- Most of the suggested models are not integrated with the clinical workflows and are tested only under the controlled offline settings.

IX. COMPARATIVE ANALYSIS OF REVIEWED STUDIES

Table 4: Comparative Analysis

Aspect	Key Observation
Best diagnostic accuracy	The hybrid ensemble models are competitive and high-accuracy models in a number of benchmark datasets.
Best traditional ML performance	XGBoost demonstrates better performance between standalone ML models.
Most suitable deep learning method	CNN-LSTM models are useful to learn more complicated feature interactions.
Best generalization capacity	Multi-dataset validation in displays better robustness and generalization.
Best explainability	Characteristic feature importance methods promote interpretability.
Best real-time applicability	ICU-based decision support system allows forecasting ischemia at the early stage.
Considerations of AI ethics	Fairness, mitigation of bias, and reliability are partially considered; no explicit ethical frameworks are present.
Deployment preparedness	Majority of studies are offline; demonstrates real-time capability, but is deployment-prepared but not clinically integrated.
Significant weakness	Minor validation on external elements and absence of explainability in hybrid deep learning models.
General Comparative Insight	Ensemble and boosting-based models show better performance and generalization on structured clinical datasets, which is found to be in line with results in previous research, but real-time clinical validation is constrained.
Overall Analysis	The data on the real-world ICU EHR is amenable to real-world evaluation, and hybrid supervised + reinforcement learning models are more effective than standalone models, with interpretability based on feature importance and close consistency with clinician decisions being crucial to safety and necessitating disease-specific model tuning to be scalable.
Data Type	Most studies rely on structured clinical datasets; recent works incorporate ECG, ICU, and wearable data
Models	Ensemble and hybrid ML–DL models consistently outperform single classifiers
Interpretability	Explainable AI (SHAP, feature importance) improves clinical trust
Ethical AI	Few studies explicitly address fairness and bias
Scalability	Federated and multimodal models show promise but lack real-world validation

X. RESEARCH GAPS IDENTIFIED

Although there has been great progress in AIs- and ML-related diagnostic and prognosis models of cardiovascular diseases and renal diseases, several gaps exist in the research. Although, numerous studies exhibit high predictive accuracy at a controlled experimental setup, shortcomings about validation, interpretability, fairness and real-world implementation are barriers to clinical translation.

The research gaps that have been observed in the reviewed studies are:

- Poor external and multi-center validation which limits extrapolation to different populations of patients and healthcare facilities. The fact that deep learning and hybrid ensemble models are not explainable well enough, especially in the case of high-performing neural network architectures.
- Less fairness and bias analysis, and little demographic inequality or algorithmic bias analysis.
- Limited real time, longitudinal validation data and particularly in live clinical settings.
- Underuse of wearable, IoT, and continuous monitoring information in the proactive management of the disease.
- Lack of future clinical trial, restrictive evidence of safety and efficacy in practice.

- Absence of clinical text data integration i.e. physician notes and hospital discharge summaries.
- Analysis during the limited dosage-level or treatment optimization in reinforcement learning-based frameworks.
- There are no standardized regulatory and deployment validation procedures.

XI. FUTURE RESEARCH DIRECTIONS

It is suggested that the future research should be guided by the following directions:

- Incorporation of Explainable AI (XAI) into deep learning models, especially into highly performing hybrid and ensemble ML-DL models to improve clinical trust and transparency.
- Upgrading of clinically interpretable deep learning models in early disease diagnosis and risk management.
- Performing multi-center/ cross-population validation studies to enhance external validity and strength across numerous healthcare contexts.
- Installation of real-time clinical decision-making systems with real-time ICU data, wearable technology, and IoT platforms of health monitoring.
- Investigation on hybrid and ensemble learning models which integrate a combination of statistical and deep learning models with reinforcement learning to achieve better predictive stability.
- Unstructured clinical data integration using Natural Language Processing (NLP) to insert physician notes and discharge summaries.
- Development of drug-dose optimization and adaptive treatment prescription systems.
- Federation and privacy- safeguarding learning systems.
- Creation of ethical AI auditing structures that are compliant with healthcare policies to guarantee justice, reduce bias, accountability, and patient safety.
- Development in the direction of multi-disease predictive modelling, which will allow assessing risk in all comorbid conditions.

XII. CONCLUSION

This review gives a full overview of recent diagnostics, prognostic, and treatment support systems based on artificial intelligence and machine learning in cardiovascular diseases and chronic kidney disease. The results suggest that classic machine learning models, especially the ensemble models, including XGBoost and Random Forest, set a high minimum bar with structured clinical data. Deep learning structures are also more predictive as they can model complex nonlinear relationships and frameworks that combine machine learning and deep learning architectures show enhanced robustness and generalization on experimental assessments on a variety of datasets. Besides, reinforcement learning-based methods combined with sequence models like LSTM demonstrate the potential to recommend dynamic treatment, strike a balance between outcome maximization and clinician-congruent decision behaviour. Regardless of these developments, there are several shortcomings. Several high-performing models are black-box systems that are not easily interpreted, limiting the level of trust and regulatory acceptance by the clinician. Ethical issues associated with prejudice, fairness, and transparency are not always resolved and external multi-center validation is inadequate. Moreover, most systems are tested in offline experimental settings, and there are few real-time implementations and clinical workflow systems.

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