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A review on ischemic heart disease prediction frameworks using machine learning

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ABSTRACT

Ischemic heart disease (IHD) is a leading cause of mortality worldwide, calling for advanced predictive models for timely intervention. Current literature reviews on machine learning (ML)-based IHD prediction frameworks often focus on predictive accuracy but lack depth in areas like dataset diversity, model interpretability, and privacy considerations. Existing IHD prediction frameworks face limitations, including reliance on small, homogenous datasets, limited critical analysis, and issues with model transparency, reducing their clinical utility. This review addresses these gaps through a systematic, comparative analysis of popular ML models, such as random forest (RF) and support vector machines (SVM), noting their strengths and limitations. Key contributions include a qualitative examination of prevalent tools, datasets, and evaluation metrics, identification of gaps in dataset diversity and interpretability; and recommendations for improving model transparency and data privacy. Major findings reveal a trend toward ensemble models for accuracy but highlight the need for explainable artificial intelligence (AI) to support clinical decisions. Future directions include using federated learning to enhance data privacy, integrating unstructured data for comprehensive prediction, and advancing explainable AI to build trust among healthcare providers. By addressing these areas, this review aims to guide future research toward developing robust, transparent ML frameworks that can be more effectively deployed in clinical settings.

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1. INTRODUCTION

Ischemic heart disease (IHD) is a leading cause of mortality worldwide among cardiovascular diseases (CVD), responsible for approximately 9 million deaths annually [1]. Heart diseases can go unnoticed until a heart attack occurs, which may then cause symptoms such as discomfort in the chest, a burning sensation like heartburn, digestive upset, difficulty breathing, a racing or irregular heartbeat, and swelling in areas like the feet, ankles, or abdomen [2]. Early detection and prediction of IHD are crucial to effectively address the needs of individuals at risk for cardiovascular illnesses. Detecting or predicting IHD early presents a significant challenge in healthcare [2]. Traditional IHD prediction methods, such as the Framingham risk score (FRS), logistic regression (LR) models, and Cox proportional hazards models, contributed significantly by establishing risk factor-based prediction, allowing early prevention strategies. However, they have limited accuracy, are prone to errors, are costly, resource intensive, and depend heavily on clinical assessments and invasive procedures and all this can delay early intervention, increasing mortality risk [3]. Researchers have explored various machine learning (ML) diagnostic methods to enhance IHD prediction and prognosis accuracy, addressing the weaknesses of traditional approaches but there still exist significant shortcomings with persistent gaps and unresolved issues.

Table 1 presents an overview of some of the previously published literature reviews on IHD diagnosis using ML approaches comparable to our proposed review. The major findings indicate that supervised ML algorithms effectively support IHD clinical decisions, with various models demonstrating potential as decision aids due to differing prediction accuracies. Internet of thing (IoT) integration enhances prediction accuracy in CVD contexts, while feature selection is critical for optimizing ML models. Convolutional neural networks (CNNs) have shown particularly high accuracy in heart disease prediction. The limitations of these literature reviews include insufficient emphasis on IHD prediction. There is also an overall lack of comprehensive analysis of the gaps, datasets, tools, evaluation metrics, and performance with graphical presentations.

Table 1. Comparison of literature reviews on ML-based IHD prediction frameworks

Author	Objective	Models	Dataset source	Contributions	Limitations and gaps
Hani and Ahmad [2]	A systematic review of ML algorithms for IHD prediction specifically.	naïve Bayes, artificial neural network (ANN), decision trees	Datasets from ScienceDirect, PubMed, CINAHL, IEEE Xplore	Supervised ML algorithms found effective in aiding IHD clinical decisions.	No comprehensive analysis of gaps, datasets, tools, evaluation metrics, performance
Baral *et al.* [4]	Reviews ML models for cardiovascular disease prediction.	Support vector machine (SVM), ANN, decision trees, random forest (RF)	Clinical datasets with patient demographics and diagnostic tests	Different ML models have shown varying prediction accuracies, suggesting potential as clinical decision aids.	Limited discussion on IHD, lacks analysis of gaps, datasets, tools, evaluation metrics, and performance.
Rao and Muneeswari [5]	A review of ML applications for heart disease prediction via IoT	XGBoost, SVM, AdaBoost, RF, LR	UCI heart disease dataset, Cleveland dataset, and hospital data	Highlights IoT integration on improving prediction accuracies for CVD.	Lacks details on IHD-specific predictors and practical implementation insights.
Naser *et al.* [6]	A comprehensive review of ML in cardiovascular disease prediction.	XGBoost, SVM, RF, CNN, logistic regression	Multiple databases, including PubMed, ScienceDirect	ML models improve prediction accuracy, with calls for feature selection importance.	Does not emphasize IHD, no graphical analysis of limitations, models, tools, or objectives.
Ahsan and Siddique [7]	Reviews ML approaches and challenges in CVD diagnosis.	naïve Bayes, decision trees, CNN, J48	Scopus dataset covering multiple studies on heart disease	CNN shows high accuracy in heart disease.	No analysis of gaps, datasets, tools, evaluation metrics, or performance, and no focus on IHD prediction.
Proposed (This review)	Comprehensive, Comparative, Qualitative, Systematic, and graphical analytical review of ML-based IHD predictions.	naïve Bayes, ANN, decision trees, SVM, RF, XGBoost, AdaBoost, CNN J48, and k-nearest neighbour.	IEEE Xplore, ScienceDirect, Scopus, Pubmed, Kaggle, Cleveland, Statlog, UCI Cleveland, and hospital data.	Comparative analysis of ML models, qualitative analysis of key trends and gaps, most adopted tools and metrics, guidance for future research	Exclude non-English studies which may limit global insights into IHD prediction, focus on structured data overlook valuable unstructured sources for prediction.

With the existence of unsolved issues in previous literature reviews, there is a need for a comprehensive, comparative, and analytical review of IHD prediction frameworks. This research will aim to address the shortcomings of earlier literature reviews by performing a comprehensive literature review with critical analysis, discussions, comparisons, and interpretations, then deducing trends, patterns, and insights and graphically summarizing the key findings together with finding ramifications and stating the research handiness in future. Furthermore, as the paper focuses on ML techniques, comparative analysis of the models, gaps, objectives, tools, datasets, contributions, and performance of various ML techniques are summarized in tabular form. Finally, the article offers some potential future research directions in ML-based IHD prediction. The following are the contributions of this research work:

i) Comprehensive comparative analysis of ML models, this review thoroughly compares popular ML models, such as RF, SVM, and CNN, assessing their strengths, limitations, and clinical applicability, and guiding researchers in selecting suitable models for IHD prediction.
ii) Qualitative analysis of key trends and gaps, the paper identifies recurring gaps, like limited dataset diversity, interpretability challenges, and privacy issues, while highlighting research objectives such as

improving prediction accuracy and providing a roadmap for addressing critical IHD prediction challenges.

iii) Identification of most adopted tools and metrics, this review documents commonly used tools (e.g., Python libraries and Weka) and evaluation metrics (e.g., F1-score and sensitivity), offering guidance on effective resources and metrics, promoting consistency and comparability across ML IHD studies.

iv) Guidance for future research directions, the paper suggests integrating explainable AI techniques for transparency and federated learning for data privacy, enhancing model reliability, interpretability, and ethical applicability, thereby advancing the clinical relevance of ML models in IHD prediction.

The paper is structured as follows: the methodology section provides a detailed account of the model selection and evaluation processes, with a strong emphasis on interpretability, data preprocessing, and ethical data handling practices. The results section presents a comparative analysis of ML models, underscoring their accuracy, interpretability, and relevance for clinical settings. The discussion then explores the broader implications of these findings, addresses privacy and ethical considerations, and suggests potential future directions for ML-based IHD prediction.

2. RESEARCH METHOD

This review adopts a systematic literature review (SLR) methodology adopted in [1], [2] to ensure a comprehensive, unbiased analysis of existing ML frameworks applied to IHD prediction. The systematic approach incorporates both established review practices and recent advancements in ML research to address the research questions and gaps identified in the introduction section, guiding the reader logically into the results section. The SLR's preferred reporting items for systematic reviews and meta-analyses (PRISMA) approach as shown in Figure 1 was chosen due to its structured, replicable nature, allowing for a consistent assessment across multiple studies and enabling a clear synthesis of trends, insights, and patterns in ML applications for IHD. PRISMA ensures transparency, reproducibility, and rigorous reporting of findings. The inclusion of visual summaries like pie charts supports this justification, offering a clear and evidence-based foundation for understanding ML's potential in predicting IHD and guiding future research in this domain.

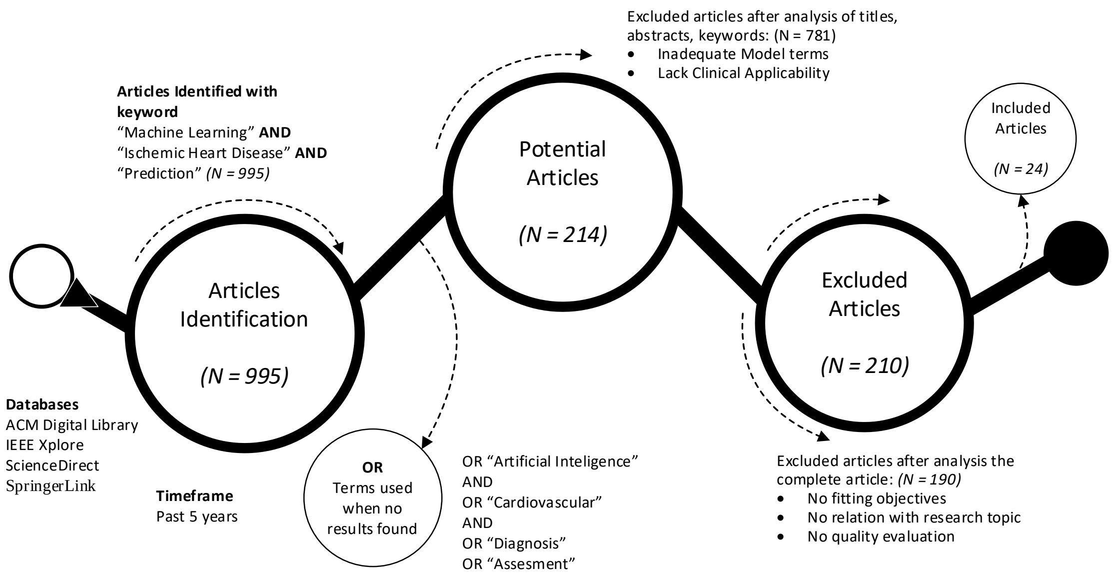

Figure 1. PRISMA flow diagram of SLR

Figure 1 shows the proposed PRISMA flow diagram for the SLR. The SLR for IHD prediction using ML involved multiple structured steps. First, a comprehensive literature search targeted studies from the last five years across reputable academic databases such as IEEE Xplore, ScienceDirect, SpringerLink, Association of Computing Machinery (ACM) digital library, and Web of Science. Keywords like "machine learning," "heart disease," "ischemic," "cardiovascular," and "prediction" were used in various combinations, resulting in 995 initial articles. Next, inclusion and exclusion criteria were applied to maintain relevance and accuracy. Articles were included if they focused on ML techniques for IHD prediction and addressed performance metrics such as accuracy, precision, and recall. Articles unrelated to ML, IHD, or lacking predictive modeling focus or model evaluation metrics, were excluded. This process narrowed down the pool to 214 potential articles. Data extraction followed, gathering essential information on authors, publication year, ML models, research objectives, evaluation metrics, limitations, datasets, and tools, which reduced the articles further to 24 and this data was then tabulated. Finally, data analysis and visualization were performed. Quantitative analysis, including pie charts, highlighted trends in ML models, datasets, and performance metrics, while qualitative analysis identified gaps, such as limited dataset diversity and interpretability challenges. This structured approach ensured transparency and replicability, providing a clear roadmap for future research in ML applications for IHD prediction.

3. RELATED WORKS ON ML-BASED IHD PREDICTION

Table 2 provides a concise yet comprehensive overview of 10 of the final selection of 24 articles organized into a table format to enable structured analysis later. Data extraction involved gathering key details such as author names, publication year, ML models, research objectives, evaluation metrics, limitations, datasets, and tools. This data was systematically selected using the PRISMA method, filtering articles based on relevance, quality, and focus on IHD prediction.

Table 2. Comparative tabulation of related works on ML-based IHD prediction

S.N	Authors	ML model	Research objectives	Evaluation metrics and performance	Gaps/limitations	Dataset and tools
1.	Nagavelli *et al.* [3]	XGBoost	Test decision tree algorithms for heart disease diagnosis.	Accuracy (95.9), precision (97.1), recall (94.67), F1-measure (95.35)	Limited datasets standard metrics and need to consider more metrics	Datasets: Cleveland and Statlog. Tools: un-named web application
2.	Shehzadi *et al.* [8]	RF	Develop a highly accurate model.	Accuracy (99), precision (100), recall (100), F1-measure (100)	Need to consider different input features for accuracy,	Datasets: Cleveland heart disease UCI. Tools: various libraries
3.	Maini *et al.* [9]	RF	Improve efficiency in predicting heart attack risks.	Accuracy (93.8), sensitivity (92.8), specificity (94.6)	Focus only on cost-effective prediction in rural India	Dataset: 1670 medical records. Tools: Python libraries
4.	Hossen *et al.* [10]	LR	To develop a computer-aided diagnostic system	Accuracy (92), precision (92), recall (92), F-measure (92)	Limited dataset, affected by lifestyle and environmental factors	Datasets: UCI Cleveland. Tools: not specified
5.	Hasanova *et al.* [11]	K-nearest neighbour	Proposed algorithms for efficient detection.	Accuracy (88.7), precision (91), recall (88), F1-score (85)	High operational costs, increased transactions, and poor accuracy	Datasets: Cleveland heart disease UCI repository. Tools: not specified
6.	Hassan *et al.* [12]	RF	Identify key features, for IHD predictability	Accuracy (96.28), specificity (96.28), sensitivity (95.37)	Limited datasets and limited evaluation metrics.	Datasets: UCI repository. Tools: not specified
7.	Sayadi *et al.* [13]	LR	Proposes a new model for early CAD diagnosis.	Accuracy (95.45), sensitivity (95.91), F1 score (96.90)	Inadequate datasets	Datasets: Z-Alizadeh Sani. Tools: Keras
8.	Muhammad *et al.* [14]	K-nearest neighbors	Enhancing prognosis accuracy for IHD	Accuracy (92), recall (91), precision (92.5), F1-score (92), AUC (90)	Small, imbalanced dataset and no comparison with traditional models	Datasets: Kaggle, UCI repository. Tools: Seaborn Matplotlib
9.	Khdair and Dasari. [15]	SVM	Compare ML techniques for accurate disease prediction.	Accuracy (73.8), precision (67.9), recall (46.3), F1-measure (55), specificity (88.4)	Only 13 user inputs for prediction, inadequate datasets, and very poor performance.	South African Heart Datasets: Disease dataset. Tools: Jupyter Notebook, Python libraries,
10.	Bakar *et al.* [16]	RF	Ischemic prediction with random forest	Accuracy (90), sensitivity (76.5), specificity (83.8), F-score (75.37)	Need for more complex and combined model	Behavioural risk factor surveillance system (BRFSS), no tools.

4. RESULTS AND DISCUSSIONS

This section will incorporate insights from Table 1 which shows a review of other literature reviews compared with the proposed; and Table 2 which shows related works on ML-based IHD predictions, covering key patterns, comparisons, critical discussions, or interpretations across different ML models for IHD prediction. The implications for future research will also be presented, containing insights into the ramifications of findings and what will come in handy in the future.

4.1. Critical analysis and trends

Table 1 provides a comparison of previous literature reviews on ML frameworks applied to IHD prediction, highlighting both emerging trends and significant gaps across studies. The critical analysis here is that, while many reviews emphasize the predictive accuracy of models such as RF, XGBoost, and CNN, there is a disproportionate focus on performance metrics like accuracy and precision over practical aspects like interpretability and real-world applicability. This overemphasis on predictive metrics can hinder clinical adoption, as practitioners require models that are both accurate and transparent. Most reviews rely on standard datasets, such as Cleveland and UCI, which, though valuable for initial evaluations, lack demographic diversity and limit model generalizability. This limitation raises concern about the relevance of these models in diverse clinical populations, particularly when addressing region-specific health patterns. Furthermore, few reviews discuss the complexities of integrating ML models into clinical workflows, which is essential for practical implementation. The critical analysis here is that the absence of IHD-specific predictors and a lack of focus on model interpretability reduce the practical utility of these reviews. Future literature reviews should adopt a broader perspective, examining models not only for their accuracy but also for their transparency, dataset diversity, and integration feasibility within healthcare environments.

Table 2 presents a detailed comparison of individual studies focusing on specific ML models for IHD prediction, examining objectives, datasets, evaluation metrics, and limitations. The critical analysis here is that, while ensemble models like RF and XGBoost achieve high performance (accuracy, precision, and recall), their “black box” nature limits interpretability, a vital factor for clinical settings. Clinicians need to understand model decision-making to make informed patient-centered decisions, and this lack of transparency poses a barrier to adoption, despite high accuracy metrics. The table also reveals a heavy reliance on datasets such as Cleveland and Statlog, which restricts the models' applicability across diverse populations. Limited data diversity means that models may not effectively capture the multifactorial nature of IHD in different demographic groups, which could lead to biases in predictions. Additionally, the studies in Table 2 often overlook the operational challenges associated with deploying these models in clinical settings, such as computational demands, compatibility with electronic health records, and the need for continuous model updates. The critical analysis here is that, although there is a growing trend toward comprehensive evaluation metrics (e.g., F1-score, AUC, and sensitivity), these alone do not address the fundamental issues of model generalizability and interpretability. Future studies should prioritize diverse datasets, address model transparency, and consider practical implementation aspects to create ML models that are more applicable and beneficial in real-world healthcare settings.

4.2. A summary of major findings

The key findings will be organized into the most adopted modes, significant gaps, evaluation of metrics preference, and privacy concerns. Most adopted model: i) RF emerged as the most widely adopted model for IHD prediction due to its high accuracy, achieving rates up to 99%. However, it is limited by a lack of interpretability, essential for clinical adoption; ii) Significant gap: the limited diversity in datasets, such as the frequent use of Cleveland and UCI heart disease datasets, restricts model generalizability. This highlights a need for diverse datasets to improve prediction accuracy across populations; iii) Evaluation metric preferences: F1-score and accuracy are the most used metrics for IHD prediction, as they effectively balance precision and recall, crucial in medical diagnosis. However, over-reliance on these metrics may overlook practical aspects like interpretability; and iv) Privacy concerns: data privacy remains a pressing issue, especially when integrating patient data from multiple sources. Techniques like federated learning are recommended to enhance data security while maintaining model accuracy and adaptability.

4.3. Ramifications of findings and future implications

The findings highlight that while ensemble models like RF and XGBoost excel in accuracy for IHD prediction, their limited interpretability remains a barrier to clinical adoption. The reliance on homogeneous datasets reduces model generalizability, underscoring the need for diverse, representative data. Future research should focus on the integration of explainable AI (XAI) techniques, such as Shapley additive explanations (SHAP) values and local interpretable model-agnostic explanations (LIME), to improve model transparency and foster clinician trust. Additionally, expanding to unstructured data sources, such as clinical notes, could provide a richer foundation for IHD prediction. Addressing these areas could lead to more reliable, applicable, and ethically sound ML models in healthcare.

4.4. Detailed interpretations of Table 2

4.4.1. The most adopted machine learning models from literature

Figure 2 shows the most adopted ML models for IHD prediction, with RF leading at 36.4%. This popularity is due to its high accuracy, robustness, and ability to handle large datasets and complex feature interactions effectively. SVM (22.7%) and XGBoost (13.6%) follow, valued for their precision and strong performance with structured data. LR and other models like multilayer perceptron and naïve Bayes each hold smaller shares, reflecting diverse approaches but highlighting RF's prominence in IHD prediction applications.

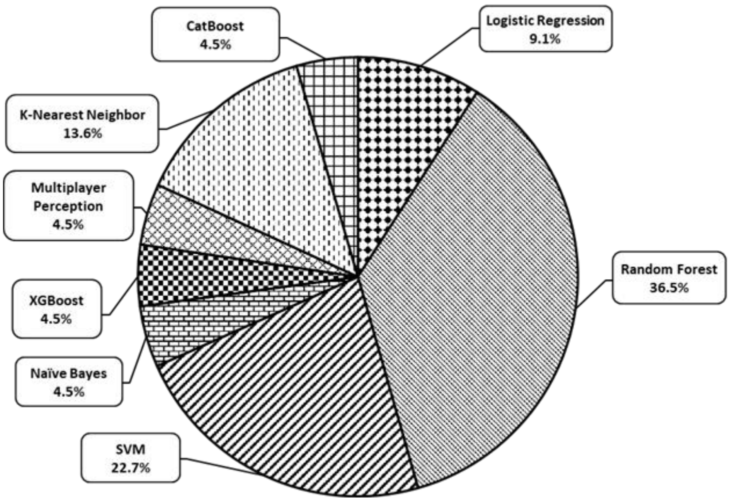

Figure 2. Most adopted ML model from literature for IHD prediction

4.4.2. The most prevalent objectives from current approaches

Figure 3 shows that the most prevalent research objectives in IHD prediction are focused on applying ML algorithms and model development, each representing 22%. These objectives highlight the priority given to advancing algorithmic approaches and creating effective prediction models. Other important objectives include feature analysis, clinical applications, and algorithm evaluation, each constituting 14%. These categories demonstrate a balanced emphasis on understanding model features, evaluating algorithm performance, and applying findings in clinical contexts. Methodology review and improving prognosis accuracy account for 7%, underscoring their emerging relevance within the field.

4.4.3. The most adopted machine learning datasets from the literature

Figure 4 illustrates that the Cleveland heart disease UCI repository, accounting for 33%, is the most frequently adopted dataset in IHD prediction due to its detailed clinical information, aiding robust model training. Kaggle and Electrocardiogram datasets, each at 15%, are also popular, offering diverse features for varied ML applications. Other sources contribute smaller portions, highlighting a reliance on established datasets and a potential need for broader data diversity to enhance model generalizability.

4.4.4. The most adopted machine learning model evaluation metrics from the literature

Figure 5 shows that the F1-score, at 17%, is the most widely adopted evaluation metric for IHD prediction, highlighting its utility in balancing precision and recall. Accuracy and precision each follow closely at 16%, with sensitivity and recall at 13%, showcasing the importance of predictive reliability in healthcare contexts. Specificity, area-under-the-curve (AUC), and regression each have smaller shares, with specificity and AUC emphasizing diagnostic power. This distribution suggests a focus on metrics that balance different prediction aspects, which is crucial in developing models that clinicians can trust for accurate and dependable diagnosis.

4.4.5. The most prevalent limitations of the current approaches

Figure 6 identifies data privacy issues as the most significant limitation in IHD prediction research, accounting for 20% of concerns. Scalability and interoperability issues each follow at 15%, indicating the challenges of implementing models across systems and patient datasets. Security concerns and cost management, each at 10%, highlight the importance of secure and cost-effective solutions. The “other” category constitutes 30%, encompassing various additional limitations, showing that multiple factors hinder IHD prediction model adoption. These findings underscore the need to address privacy, scalability, and interoperability to enhance the practical use of ML models in clinical settings.

4.4.6. Most adopted machine learning tools from literature

Figure 7 shows the most adopted ML tools for IHD prediction, with Python libraries leading at 25%. Python’s popularity stems from its versatile libraries and visualization capabilities, essential for effective data handling and model building. Weka follows with 19%, valued for its suite of ML algorithms. Tools like NVIVO 10, Flask, Jupyter Notebook, and MATLAB each hold smaller shares, offering specialized functionalities. This distribution reflects a strong preference for Python-based tools, highlighting their flexibility, computational power, and ease of use, making them ideal for IHD prediction research and development.

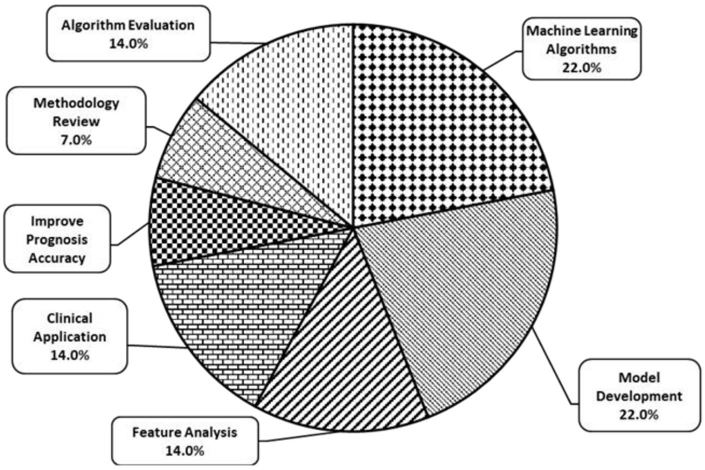

Figure 3. Most adopted research objectives from the literature for IHD prediction

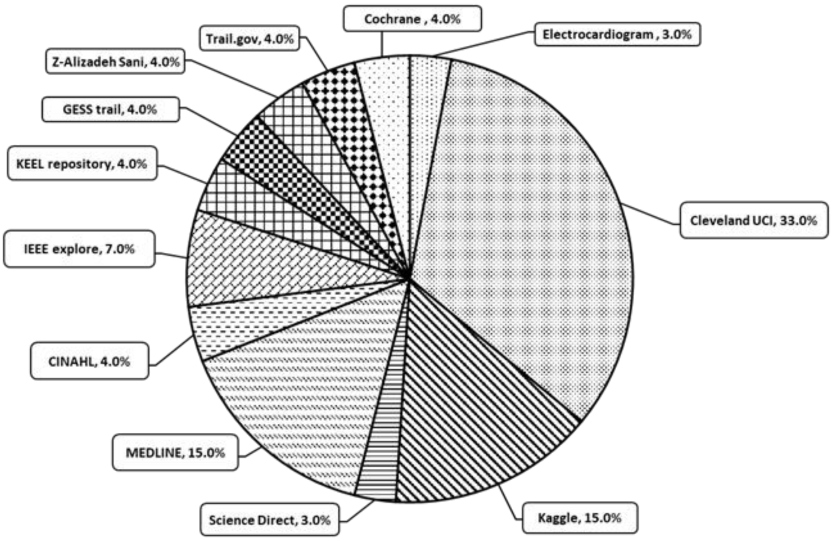

Figure 4. Most adopted ML datasets from literature for IHD prediction

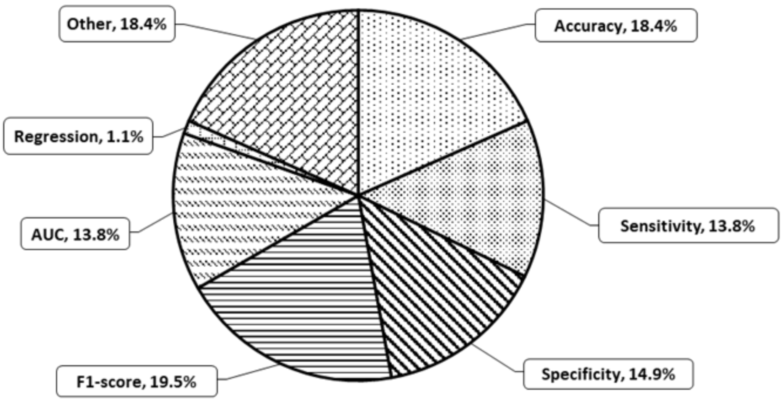

Figure 5. Most adopted ML metrics from literature for IHD prediction

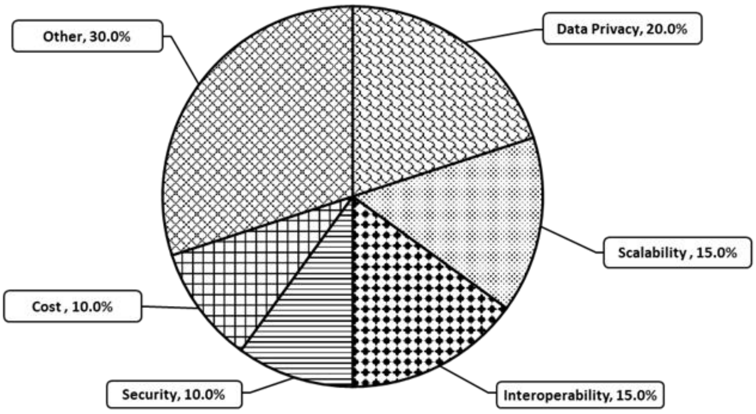

Figure 6. Most prevalent limitations with current approaches for IHD prediction

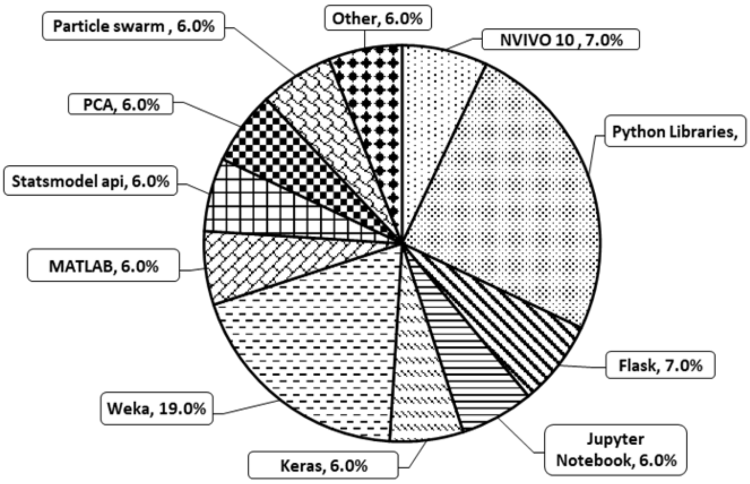

Figure 7. Most adopted ML tools from the literature for IHD prediction

4.4.7. Related works performance

Figure 8 shows the prediction accuracy performance of various ML models used in IHD prediction frameworks. The performance metrics of related works and their values are clearly presented in Table 1 under the "ML evaluation metrics and performance" column. This section will present the literature performance results and give a critical performance analysis to deduce any trends or patterns that emerge. The highest accuracy reported in Figure 8 is by Ali *et al*. [17] at 100%, followed by Taylor *et al.* [18] at 98.83%, and Hassan *et al*. [12] at 96.28%. Most frameworks demonstrate accuracy above 90%, indicating strong model reliability. Kumar and Kumar [19] show the lowest accuracy at 73.8%. The trend suggests that recent models consistently achieve high accuracy, highlighting advancements in ML techniques for medical predictions. Other frameworks [20]–[22] are shown in Figure 8.

Figure 9 shows the sensitivity performance of various ML models used in IHD prediction frameworks. The highest sensitivity is reported by Shehzadi *et al*. [8] and Ali *et al*. [17], both achieving 100%. This indicates these models' strong ability to correctly identify true positive cases of heart disease. Maini *et al*. [9], Hassan *et al*. [12], and Sayadi *et al*. [13] also demonstrate high sensitivity, exceeding 90%. Bakar *et al*. [16] and Muhammad *et al*. [14] show slightly lower sensitivity at 83.8%, indicating room for improvement in capturing true positives.

Figure 10 illustrates the specificity performance of different ML models used for predicting IHD. Khdair and Dasari [15] show the highest specificity at 96.28%, indicating a strong ability to correctly identify true negatives. Maini *et al*. [9] and Sayadi *et al.* [13] follow with specificities of 94.6% and 91.66%, respectively. Bakar *et al*. [16] and Muhammad *et al*. [14] report a specificity of 83.8%. These results reflect that while the models are generally good at identifying those without disease, there is variability in their performance.

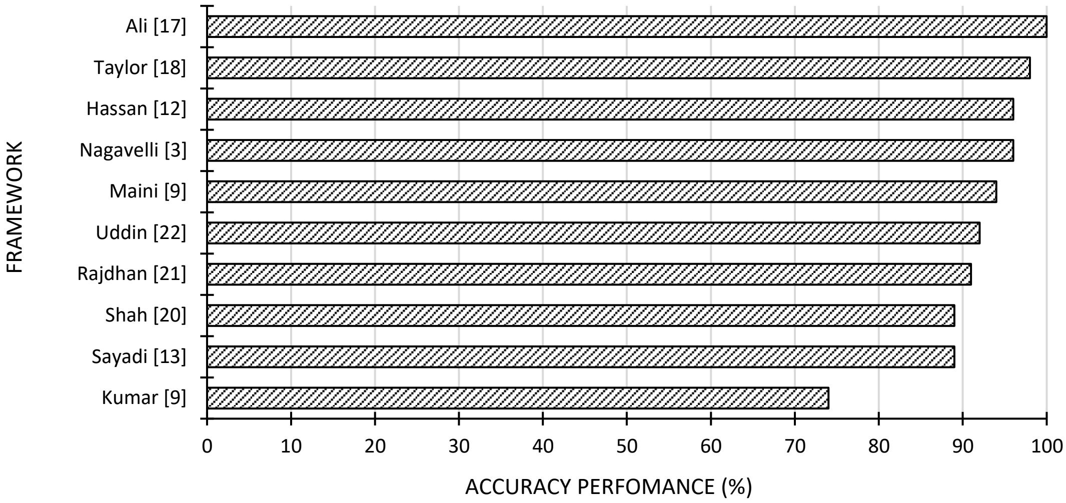

Figure 8. Performance analysis of related works based on accuracy metric

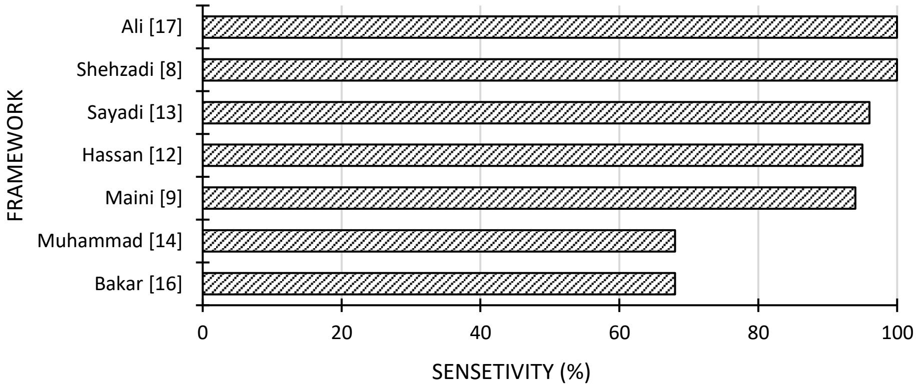

Figure 9. Performance analysis of related works based on the sensitivity performance metric

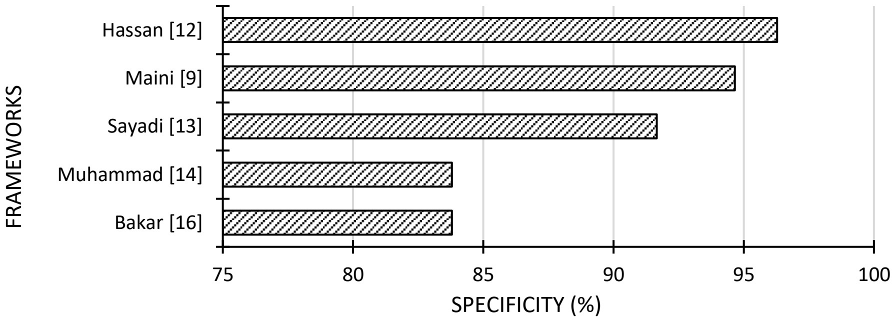

Figure 10. Performance analysis of related works based on specificity performance metric

Figure 11 presents the F1-score performance of various ML models used in IHD prediction. Shehzadi *et al*. [8] lead with an F1-score of 100%, showing excellent balance between precision and recall. The lower end of the spectrum includes Khdair and Dasari [15], Bakar *et al.* [16], Kumar and Kumar [19], Mittas *et al.* [23], and Bhatt *et al.* [24], indicating these models may struggle with balancing precision and recall effectively. Other high performers include Sayadi *et al.* [13] and Chandrasekhar and Peddakrishna [25], both above 95%. Models like Hossen *et al*. [10] and Muhammad *et al*. [14] achieve F1-scores around 85%.

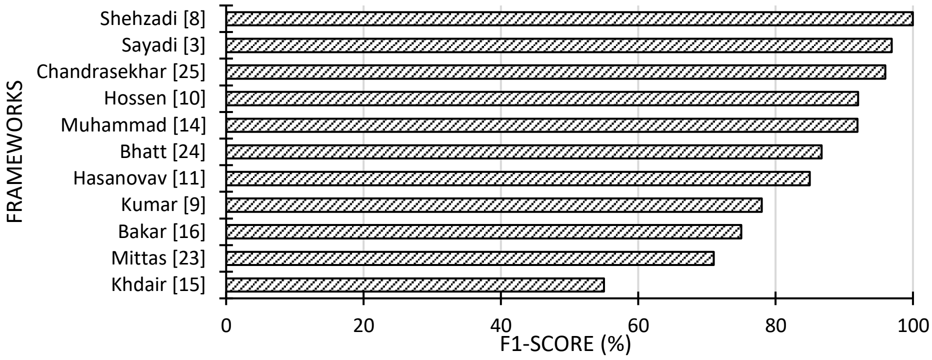

Figure 11. Performance analysis of related works based on F1-score performance metric

5. CONCLUSION

This review presented the critical role of ML models in predicting IHD, which remains one of the leading causes of death globally. Despite the abundance of studies focused on ML-based IHD prediction, existing literature reviews often fail to perform critical and in-depth analytics of gaps, objectives, models, performance, tools adopted, dataset diversity, interpretability, and clinical applicability. Current IHD prediction frameworks also exhibit gaps, including small and imbalanced datasets, limited focus on feature selection, and challenges with model transparency, which hinder their practical implementation. This review contributes to the field by systematically analyzing ML models such as RF and SVM, and comparing their strengths, limitations, and performance in clinical applications. Key contributions include identifying widely adopted tools and evaluation metrics, assessing gaps in current methodologies, and providing guidance on ethical considerations and model transparency. The major findings suggest a trend toward ensemble models for high accuracy; however, there is a need for diverse datasets and interpretable frameworks to facilitate clinical adoption. Future research should focus on enhancing privacy through federated learning, expanding data sources to include unstructured data for a richer analysis, and integrating explainable AI tools like SHAP and LIME to increase transparency. The future recommendation enables the development of more reliable, adaptable, and ethically sound ML models that can be integrated into healthcare for early IHD prediction, ultimately improving public health outcomes.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Chandapiwa Mokgethi	✓		✓	✓			✓			✓	✓			
Aone Maege	✓						✓			✓	✓			
Venu Madhav Kuthadi	✓					✓				✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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