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Artificial intelligence approaches for cardiovascular disease prediction: a systematic review

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ABSTRACT

Cardiovascular disease (CVD) remains a top global cause of mortality, highlighting the critical need for precise prediction models to improve patient outcomes and optimize healthcare resource allocation. Accurate prediction of CVD is paramount for early diagnosis and reducing mortality rates. Achieving efficient CVD detection and prediction requires a deep understanding of health history and the underlying causes of heart disease. Harnessing the power of data analytics proves advantageous in leveraging vast datasets to make informed predictions, aiding healthcare clinics in disease prognosis. By consistently maintaining comprehensive patient-related data, healthcare providers can anticipate the emergence of potential diseases. Our study conducts a meticulous comparative analysis of CVD prediction methods, focusing on various artificial intelligence (AI) algorithms, particularly classification and predictive algorithms. Scrutinizing approximately sixty papers on cardiovascular disease through the prism of AI techniques, this study carefully assesses the selected literature, uncovering gaps in existing research. The outcomes of this study are expected to empower medical practitioners in proactively predicting potential heart threats and facilitating the implementation of preventive measures.

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1. INTRODUCTION

Cardiovascular disease (CVD) is the leading cause of death worldwide, responsible for approximately 17.9 million deaths annually. Early detection and accurate prediction of CVD are critical in reducing mortality rates and improving patient outcomes. However, predicting CVD remains a complex challenge due to the multifaceted nature of risk factors and the necessity for personalized approaches to care. Advancements in technology and data analysis techniques have created opportunities to enhance the prediction and management of CVD, yet significant gaps remain in the integration and application of these advancements in clinical practice [1], [2]. Recent developments in machine learning (ML) and artificial intelligence (AI), particularly deep learning (DL), have revolutionized the field of medical imaging. These technologies enable the automated detection and diagnosis of CVD-related anomalies in images such as X-rays, computer tomography (CT) scans, and magnetic resonance imaging (MRIs) with increasing precision [3]. Furthermore, DL models are adept at processing complex data patterns, making them particularly useful in cardiology for detecting subtle signals in imaging data or ECG readings, which are indicative of a patient's cardiovascular health [4]. Unlike traditional statistical methods, ML and AI models can manage and analyze vast and complex datasets, offering more nuanced insights into individual risk profiles and potential preventative strategies. Numerous studies have demonstrated the potential of ML and AI in predicting CVD with varying success. For example, several studies have shown the benefits of integrating different data types, such as clinical data, genetic information, and real-time monitoring from wearable devices, to improve predictive accuracy. However, most current research primarily focuses on single data types without a holistic integration approach [5]. This limitation restricts the predictive accuracy and generalizability of these models in diverse patient populations. Despite the advancements in ML and AI applications for CVD prediction, significant gaps remain. Current models often lack the ability to integrate multiple forms of data, limiting their effectiveness in providing comprehensive risk assessments. Additionally, many ML models used in CVD prediction are complex and lack interpretability, which hinders their application in clinical settings where transparent and explainable decision-making is essential [6]. These challenges highlight the pressing need for innovative healthcare system designs tailored specifically to address these gaps, as emphasized in recent studies. This systematic literature review (SLR) aims to address these gaps by synthesizing existing research on ML and AI applications in CVD prediction, focusing on studies that integrate multiple data types to enhance predictive performance. By systematically analyzing these studies, we seek to identify the most effective models and techniques and highlight areas where further research is needed. This review contributes to the field by providing a comprehensive overview of current CVD prediction models, assessing their capabilities, limitations, and potential for future development. The paper is organized as follows: section 2 details the methodology employed for conducting this systematic literature review, including the criteria for study selection, data extraction, and synthesis. Section 3 presents the results, offering a detailed analysis of the findings from the reviewed studies, focusing on the strengths and weaknesses of various ML and AI models in predicting CVD. Section 4 discusses the implications of these findings for clinical practice and outlines potential directions for future research. Finally, section 5 concludes the paper by summarizing the key insights and providing recommendations for advancing CVD prediction research using integrative ML and AI approaches.

2. METHOD

This systematic literature review (SLR) was conducted to evaluate the application of AI techniques for CVD prediction. The review process followed a structured protocol to ensure rigor, transparency, and reproducibility. The methodology consisted of three main phases: review planning, review conducting, and review reporting.

2.1. Review planning

1) Defining the research questions:

The research questions were formulated using the PICOC framework to address gaps identified in the Introduction:

- Population (P): studies involving the use of AI for CVD prediction.
- Intervention (I): AI methods, including machine learning and DL techniques.
- Comparison (C): various AI methods and traditional statistical methods.
- Outcomes (O): accuracy and effectiveness of AI models in predicting CVD.
- Context (C): clinical settings and datasets used for AI model development and validation.

2) Specifying research databases:

A comprehensive search was conducted in three major databases: IEEE Xplore, Scopus, and ResearchGate. These databases were selected for their extensive coverage of high-impact studies in medicine, engineering, and computer science.

3) Developing a search string for article extraction:

The search strategy included a combination of key terms related to AI and CVD prediction, such as "CVD," "AI methods," "ML," "DL," "heart disease prediction," and "predictive modeling." Boolean operators (AND, OR) were used to refine the search queries.

4) Inclusion criteria:

- Studies published between 2020 and 2024 in peer-reviewed journals.
- Articles utilizing AI techniques for CVD prediction with quantitative outcomes.
- Studies written in English.

5) Exclusion criteria:

- Review articles, editorials, and non-peer-reviewed articles.
- Studies not focused on AI methods or not related to CVD.
- Articles without empirical data on AI model performance.

2.2. Conducting review
1) Primary and secondary search:
– Primary search: the initial search across the three databases identified a total of 1,178 records (IEEE: 162, Scopus: 675, ResearchGate: 341). After removing 436 duplicates, 742 records were screened by titles and abstracts.
– Secondary search: additional relevant studies were identified by reviewing the references of the selected articles during the full-text review stage.
2) Study selection process:

The study selection process followed the PRISMA guidelines, as depicted in Figure 1. A total of 1,178 articles were initially identified through searches in three databases: IEEE Xplore (162 articles), Scopus (675 articles), and ResearchGate (341 articles). After removing 436 duplicate articles, 742 records remained for title and abstract screening. Following this screening, 603 articles were excluded for not meeting the inclusion criteria specified in Table 1 (Appendix), leaving 139 articles for full-text review. Of these, 33 articles were excluded due to lack of full-text availability despite reasonable efforts to obtain them. The remaining 106 articles were assessed for eligibility, with 47 being excluded for not adequately addressing the research questions or lacking clear findings. Ultimately, 60 studies were included in the final synthesis.

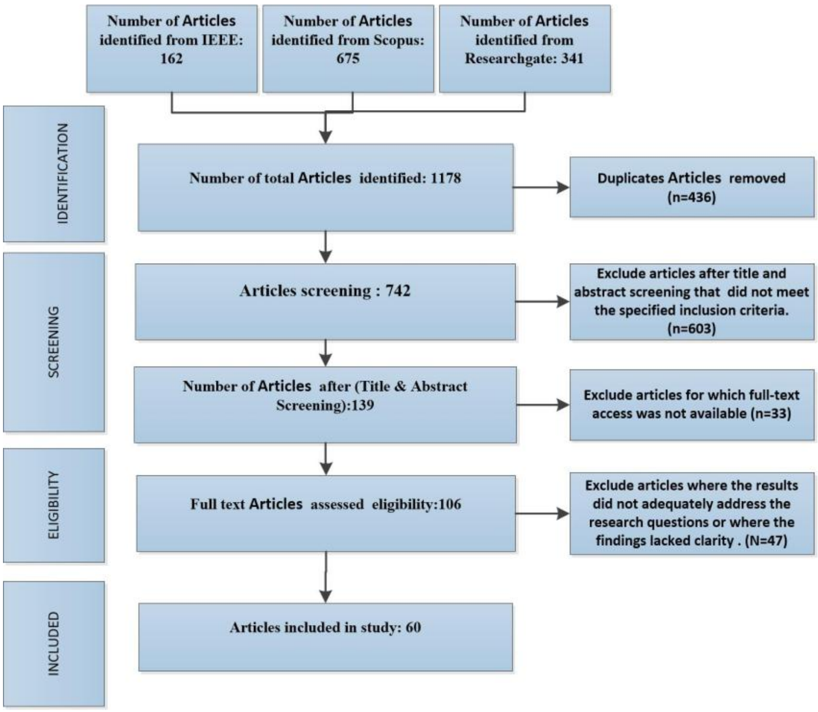

Figure 1. PRISMA flowchart

3) Data extraction and synthesis:

A standardized data extraction form was used to capture key information from each included study. The extracted data included study id, publication year, author name, research technique, and associated constraints. Figure 2 present the percentage of research papers from each research database. From these studies, various AI techniques, datasets, and outcomes were analyzed to extract significant trends and findings. This process identified key AI algorithms (e.g., random forest (RF), support vector machine (SVM), convolutional neural network (CNN), decision tree (DT), K-nearest neighbor (KNN), logistic regression (LR), and multilayer perceptron (MLP)), along with their respective performance metrics in predicting cardiovascular outcomes.

2.3. Review reporting

In the reporting phase, the quality assessment questions were utilized to evaluate the selected primary studies. The quality assessment criteria outlined in Phase 1 were applied to determine the rigor and validity of each study. The study quality rating ranged from 0 to 6, where a score of 6 indicated high quality and robust methodology, while a score of 0 reflected poor quality or insufficient methodological detail.

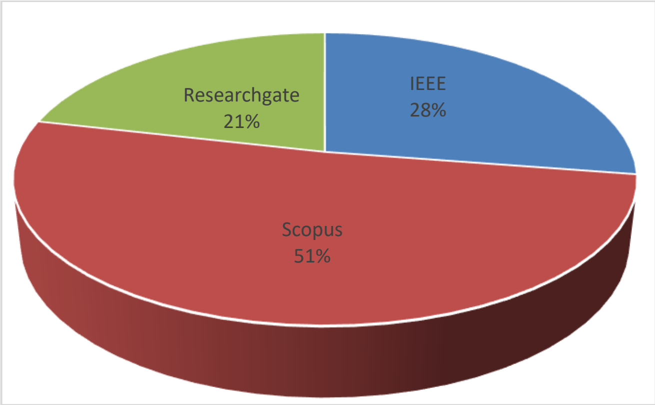

Figure 2 present the percentage of research papers from each research database

3. LITERATURE REVIEW

Over the past few years, numerous researchers have delved into the application of ML and DL techniques to enhance the precision of CVD prediction, aiming to classify AI methods and gauge their efficacy in CVD prognosis. We used standard evaluation instruments to scrutinize the studies for quality and presented the results through tables and figures. Additionally, our synthesis encompassed a narrative overview, emphasizing pivotal themes and trends within the contemporary research domain. This comprehensive approach enabled us to formulate conclusions regarding the current state of AI in CVD prediction and pinpoint areas where further investigation could fill existing research gaps.

3.1. Effectiveness of various machine learning algorithms for CVD prediction

Several studies have explored the effectiveness of various ML algorithms for CVD prediction using different datasets. Ware *et al.* [7] conducted a comparative study of various ML algorithms, such as LR, KNN, SVM, DT, and RF, for CVD prediction using the Cleveland dataset. They implemented data preprocessing techniques to handle missing data and eliminate noise from the dataset. Among the algorithms evaluated, SVM emerged as the top performer, achieving an impressive accuracy of 89.34% through their experimentation. Shekhar *et al.* [8] utilized several classification algorithms, including Naive Bayes (NB), RF, and LR. The experiments were conducted on the Cleveland dataset, with 80% of the data allocated for training and the remainder for testing. Notably, the RF algorithm demonstrated superior performance, achieving an accuracy of 90.16%. Hemalatha and Poorani [9] conducted a comparison of SVM, DT, MLP, RF, and J48 algorithms for predicting CVD. Interestingly, the NB algorithm surpassed the others, achieving an accuracy of 90.33%. Ozhan and Kucukakcalı [10] employed the XGBoost (XGB) model to estimate the risk prediction of CVD. They utilized a 10-fold cross-validation (CV) technique to evaluate the performance of the classifier. Notably, the suggested model attained an accuracy of 89.4%. Yilmaz and Hilal [11] proposed a predictive model comprising SVM, LR, and RF algorithms for CVD prediction. The performance of these models was assessed using the heart disease dataset from IEEE DataPort. Hyperparameters of the machine learning algorithms were optimized through a 10-fold repeated cross-validation process. Notably, the random forest algorithm achieved an impressive accuracy rate of 92.9%. Joloudari *et al.* [12] utilized various data classification models, such as chi-squared automatic interaction detection, SVM, and RF, to predict coronary heart disease (CHD). They employed the Z-Alizadeh Sani dataset, from the UCI machine learning repository. In the study conducted by Zeng [13], DT, KNN, SVM, and XGB algorithms were utilized to forecast heart disease utilizing 11 clinical features. Among these models, the SVM algorithm demonstrated superior performance, attaining an accuracy of 88.8%.

3.2. Feature selection techniques for enhancing ml algorithms

Akyol and Atilla [14] undertook a study to compare gradient boosting machines, RF, and NB algorithms for detecting CVD. They utilized recursive feature elimination coupled with CV to identify the most discriminative features. The experiments were conducted on both the Statlog heart disease dataset and the SPECT dataset. Remarkably, in both datasets, the NB algorithm demonstrated the highest classification rate, achieving accuracies of 86.42% and 77.78%, respectively. Rahim *et al.* [15] tackled the issue of imbalanced data by employing an oversampling technique. Additionally, they utilized the mean value method for imputing missing data and employed a feature importance approach for feature selection, their results showcased strong support for the new ensemble model, demonstrating exceptional accuracy rates of up to 99.1 percent when feature selection was integrated. Khurana *et al.* [16] employed chi-square and information gain, resulting in varied improvements in prediction accuracy across different algorithms. Additionally, they employed five distinct feature selection techniques in their study. Their findings revealed that SVM outperformed other algorithms in terms of predictive performance. They achieved an impressive accuracy rate of 83.41 percent. These studies highlight the importance of robust feature selection methods in improving the predictive performance of ML models for CVD.

3.3. Ensemble learning models

These studies highlight the importance of ensemble learning in CVD prediction has demonstrated notable improvements in accuracy, making it a promising approach for developing reliable predictive models for CVD. Mohapatra *et al.* [17] employed a stacked ensemble learning (EL) model on the Cleveland heart disease dataset for predicting CVD. They utilized ten distinct classifiers as base learners and evaluated the classification performance of the proposed EL model against these base classifiers. The results revealed that the suggested model achieved an impressive accuracy of 92%. This study underscores the effectiveness of EL algorithms in enhancing classification performance. Das and Sinha [18] proposed a voting-based EL model for predicting CVD. Their experiments were conducted using the Statlog heart disease dataset. Remarkably, the suggested model achieved an accuracy of 90.74% when compared against KNN, SVM, NB, DT, LR, and artificial neural network (ANN) algorithms. This study demonstrated that EL models offer higher success rates compared to classical classifiers. Khan *et al.* [19]. developed a novel ensemble stacking classifier for diagnosing and predicting CVD and diabetes. The model demonstrated superior performance, achieving an accuracy of 88.71% for CVD, surpassing individual models such as DT (85.23%) and SVM (84.72%). Doppala *et al.* [20] employed an EL approach for CVD prediction. They utilized NB, RF, SVM, and XGB algorithms as base classifiers. The majority voting technique was employed as the EL approach, utilizing the Cleveland, IEEE Dataport, and Mendeley data center datasets, respectively. Their proposed EL method exhibited accuracy rates of 88.24%, 93.39%, and 96.75%. Notably, the suggested model achieved higher classification rates compared to classical classifiers.

3.4. Advanced techniques and systems

García-Ordás *et al.* [21] applied a CNN algorithm for predicting CVD. They employed a 10-fold CV approach to mitigate randomness in their experiments. Their proposed model outperformed conventional ML algorithms, achieving an impressive accuracy rate of 90.09%. A novel system, BioLearner, has been introduced to identify critical biomedical markers for predicting heart disease. Employing ML techniques like KNN, neural networks, and SVM, BioLearner achieves an impressive accuracy rate of 95% [22]. Abdel-Jaber *et al.* [23] recurrent neural networks (RNNs) are employed to analyze sequential or time-series data across diverse domains including natural language processing, speech recognition, meteorological data analysis, and predictive healthcare.

3.5. Internet of things and emerging technologies

The emergence of internet of things (IoT)-fog-cloud-based models for predictive analytics has gained prominence due to their advantageous features. Fog computing demonstrates efficiency in handling computational tasks related to healthcare data, sourced from various IoT devices like wearable sensors, alongside previously stored electronic clinical data in the cloud [24]. A smart IoT system designed to predict heart disease, utilizing kernel discriminant analysis and a customized self-adaptive Bayesian algorithm, achieves an accuracy rate of 90% [25]. Subahi *et al.* [25] proposed an intelligent IoT system designed for heart disease prediction, utilizing kernel discriminant analysis and an adapted self-adaptive Bayesian algorithm, achieving a 90% accuracy rate.

3.6. Electrocardiogram and wearable devices

Hinai *et al.* [26] conducted a study focused on the comprehensive analysis of resting electrocardiogram (ECG) signals using DL methods for the identification of structural cardiac abnormalities. Their review identified a total of 12 articles: 3 articles addressed the detection of left ventricular systolic dysfunction, 1 article focused on left ventricular hypertrophy, 6 articles addressed acute myocardial infarction, and 2 articles focused on stable ischemic heart disease. The evaluation metrics utilized in these studies included AUC (area under the curve) and accuracy. Chakrabarti *et al.* [27] discussed the diagnostic capabilities of wrist-worn devices in detecting various diseases, notably cardiovascular conditions. Additionally, they offered insights into the utilization of ML algorithms for analyzing wearable data. The study also highlighted the existing challenges pertaining to wearables and medical data analysis.

4. DISCUSSION

This systematic literature review analyzed 60 studies to evaluate the application of various AI techniques in predicting CVD. The review focused on identifying trends in AI methodology, performance outcomes, and gaps that require further exploration. The discussion here integrates key findings, contextualizes them within the broader field, and outlines implications for future research and clinical practice.

4.1. Interpretation based on key findings

The review revealed a wide range of AI methods utilized in CVD prediction, including traditional machine learning algorithms like DT, RF, NB, LR, ANN, KNN, and SVM, as well as advanced DL techniques such as CNNs and hybrid models. The majority of studies employed datasets from well-known repositories such as the UCI machine learning repository, hospital records, and other clinical databases. The accuracy of these models varied significantly, ranging from 70% to 100%, depending on the dataset size, feature selection techniques, and algorithmic complexity. Figure 3 illustrates the distribution of AI techniques used in the studies included in this review. The predominant use of individual classifiers (e.g., SVM, DT, and LR) suggests that researchers often focus on optimizing single-model performance. However, our findings also indicate a growing trend toward ensemble methods, which combine multiple model predictions to enhance accuracy and robustness—an approach that remains underutilized in the current literature.

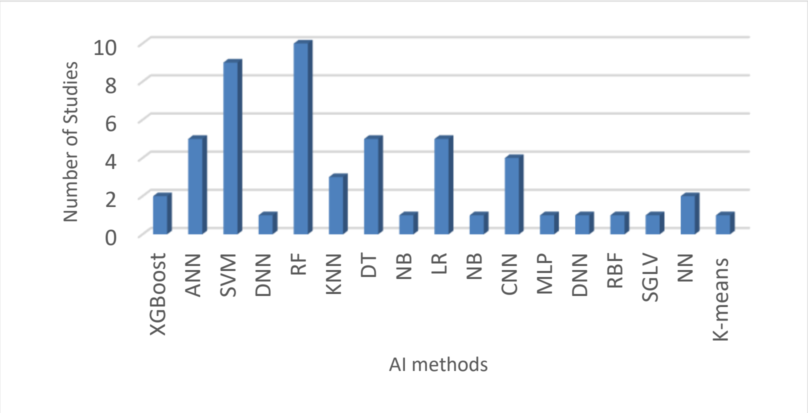

Figure 3. Illustrates the various techniques and methods used in the current research

4.2. Comparison with previous studies and study limitations

Compared to previous reviews, this study provides a more nuanced understanding of AI's role in CVD prediction. Our review highlights that SVM and RF algorithms remain popular due to their robustness and relatively high performance on medium-sized datasets. However, a significant gap identified across multiple studies is the lack of ensemble learning approaches. While ensemble techniques, such as RF combined with other classifiers, were shown to enhance predictive accuracy (as in the study by Asif *et al.* [41], which reported 98.15% accuracy), they remain underutilized. This gap presents an opportunity for future research to explore the benefits of integrating multiple AI models to improve prediction robustness and reliability. Additionally, many studies relied heavily on single, small datasets, such as the Cleveland dataset, which limits the generalizability of their findings. For instance, Sarra *et al.* [52] and Kolukula *et al.* [53] used datasets of approximately 300 records, which may not provide a comprehensive representation of diverse patient populations. This reliance on small datasets and lack of diverse data sources restricts the ability of these models to generalize across different demographic and clinical settings.

4.3. Implications for research

The findings from this review highlight several implications for both research and clinical practice. Firstly, the high accuracy achieved by some DL models, such as CNNs Amarbayasgalan *et al.* [35] and hybrid approaches combining neural networks with fuzzy inference systems (e.g., A. Nancy *et al.* [54], suggests a promising direction for developing more accurate and personalized CVD risk prediction tools. However, the review also underscores the need for larger, more diverse datasets to enhance model reliability and applicability in real-world settings. Studies like those by Patro *et al.* [31] and Ulah *et al.* [32] indicate that using small, homogeneous datasets limits the models' effectiveness in broader clinical applications. Therefore, future research should focus on integrating more comprehensive datasets and exploring data augmentation techniques to improve model training and validation processes. Furthermore, the significant reliance on single classifiers, as opposed to ensemble methods, suggests a potential area for improvement. Ensemble learning techniques, which combine predictions from multiple models, have been shown to enhance predictive accuracy and model robustness. Future studies should investigate the utility of these methods in CVD prediction.

4.4. Limitations and future research directions

This review has several limitations that should be considered when interpreting the findings. First, the exclusion of non-English studies may have resulted in the omission of relevant research, potentially introducing language bias. Additionally, the variability in study quality, particularly concerning dataset size and reporting transparency, poses challenges in directly comparing AI model performance. Many studies did not specify their feature selection processes or provide sufficient details on hyperparameter tuning, which could affect the reproducibility and generalizability of their findings

5. CONCLUSION

This systematic literature review conducted a comprehensive analysis of existing AI methodologies, comparing and evaluating them to identify the most accurate and efficient techniques for predicting CVD. The review examined approximately seventeen methods and algorithms across 60 studies, documenting their performance, accuracy, and the gaps in current research. The findings demonstrate that AI-based technologies have significant potential to revolutionize healthcare, particularly in enhancing the accuracy of disease prediction and the personalization of therapy recommendations. Among the algorithms analyzed, RF, SVM, CNN, and LR emerged as the most frequently utilized techniques. These methods, particularly CNNs and hybrid models that combine neural networks with fuzzy inference systems, have shown high accuracy, suggesting a promising direction for developing more precise and personalized CVD risk prediction tools. However, the study also revealed several critical gaps in the current research landscape. Many studies tended to focus on individual classifiers, which limited the potential for maximizing predictive accuracy. Additionally, hyperparameter optimization a key factor in enhancing model performance was often overlooked, potentially restricting the effectiveness of these predictive models. A significant limitation identified in the reviewed studies was the reliance on small, homogeneous datasets, which affects the generalizability and robustness of AI models in broader clinical applications. This limitation highlights the need for larger, more diverse datasets and the exploration of data augmentation techniques to improve model training and validation processes. Furthermore, the issue of imbalanced datasets leading to biased predictions for minority classes was a common challenge. This underscores the necessity of implementing techniques such as resampling, cost-sensitive learning, and ensemble methods to improve model balance and reliability. Looking forward, future research should focus on several key areas. First, there is a critical need to explore and develop explainable AI (XAI) techniques that make complex AI models more transparent and understandable to clinicians. This will be essential for gaining trust and ensuring the practical application of these models in clinical settings. Second, research should prioritize the collection and integration of diverse datasets, including multi-center and multi-modal data, to improve the robustness and generalizability of AI models. Finally, the potential of ensemble learning methods to address the limitations of individual classifiers should be further investigated, particularly in managing data imbalance and improving predictive accuracy. By focusing on these areas, the research community can develop AI tools that not only predict CVD with greater accuracy but also significantly improve patient outcomes through more personalized and equitable healthcare solutions.

APPENDIX

Table 1. Displays the dataset utilized for developing an AI model to predict CVD disease

Authors	Dataset	Techniques used	Accuracy	Limitations/gaps
Ayeshmi and Peiris [28]	Cleveland	XGBoost algorithm	94%	Dataset with a small sample size
Mohammad *et al.* [29]	Hospital Medical records	ANN	73.6%	Focusing on cases of admission to the hospital for heart failure within one year indeed narrows down the dataset to a specific outcome, potentially resulting in cases with more similar features to each other.
Nayak [30]	Hungarian, Cleveland, Switzerland	ANN	89.75%	There is a lack of combination with other machine learning classifications to form a hybrid model.

Table 1. Displays the dataset utilized for developing an AI model to predict CVD disease *(Continue)*

Authors	Dataset	Techniques used	Accuracy	Limitations/gaps
Patro *et al.* [31]	Heart attack prediction from Kaggle	SVM	92%	It is necessary to execute the model on various classifiers for analysis.
Ware *et al.* [7]	Hungarian dataset Switzerland dataset Cleveland dataset	SVM RF KNN DT NB LR	87.61 84.11 71.73 70.04 83.92 79.62	There is a lack of combination with other machine learning classifications to form a hybrid model.
Ulah *et al.* [32]	Cleveland dataset ((UCI, 2016)	SVM	97.90%	It is necessary to execute the model on various classifiers for analysis.
Ulah *et al.* [32]	Cleveland dataset (UCI, 2016)	SVM	97.90%	It is necessary to execute the model on various classifiers for analysis.
Tiwari *et al.* [33]	dataset from IEEE Data	RF, XGBoost	92.34%	We need to further investigate the proposed framework for handling large datasets.
Modak *et al.* [34]	Cleveland, Hungarian, Switzerland, and Statlog	Infnite feature selection and DNN	87.70%	We need to further investigate the proposed framework for handling large datasets.
Amarbayasgalan *et al.* [35]	Korean National Health dataset	DNN	89%	The limitation mentioned indicates that the proposed method lacks the functionality to address missing values in the dataset, which could potentially impact the accuracy and reliability of the model results.
Poojitha and Mahaveerakannan [36]	Data set with 184 samples	RF SVM	90.16% 81.97%	The model does not rely on heuristic techniques, and there is redundancy in the data.
Mulyani *et al.* [37]	Dataset from Kaggle, comprising 1025 records and 14 features.	CNN SVM DT KNN LR RF	100% 94% 86% 86% 82% 82%	We need to further investigate the proposed framework for handling large datasets.
Yilmaz and Hilal [11]	Dataset from the Data Port database	LR RF SVM	86% 92% 89%	All classification techniques rely on a single small dataset, with no specification provided for feature selection methods.
Yilmaz and Hilal [11]	Dataset from Kaggle.	MLP RBF	91% 79%	The dataset sizes are small, lacking feature selection
Doppala *et al.* [20]	Cleveland dataset consists of 303. Dataset consists of 1190 Dataset consisting of 1000 subjects	Proposed model Proposed model Proposed model	88.24 93.39 96.75	The technique employs a single, small dataset and does not undergo a feature selection process.
García-Ordás *et al.* [21]	Dataset consists of 918 cases with 11 features per case	neural networks	90.9%	A single small dataset was chosen without specifying the time duration for prediction in a hybrid model with other algorithms.
Lakshmi and Arjun [38]	Dataset contains 700 records of case data and 11 characteristics	RF	80.4%	A hybrid model incorporating other machine learning algorithms was not utilized, and a small dataset was employed without employing techniques to enhance accuracy.
Alkurdi [39]	Dataset contains 303	RF	97%	There is a lack of combination with other machine learning classifications to form a hybrid model.
Rustam *et al.* [40]	Dataset contains 918 observations and 11 attributes	SGLV	92%	A single small dataset was chosen without specifying the time duration for prediction in a hybrid model with other algorithms.
Asif *et al.* [41]	Three datasets from Kaggle	Extra Tree Algorithm	98.15%	The focus was on a particular subset of ensemble learning techniques. Moreover, the dataset employed was constrained in terms of its size.
Sureja *et al.* [42]	Tow dataset one includes 303 and second 299 records	SVM	98.75%	We need to further investigate the proposed framework for handling large datasets.
Prusty *et al.* [43]	Dataset contains 303	LR	90.7%	We need to further investigate the proposed framework for handling large datasets.
Yousefi [44]	Dataset of 294 people	DT	83%	All classification techniques rely on a single small dataset.
Rasheed *et al.* [45]	Datasets from Kaggle	RF	99.98%	Lack of detailed information about the dataset size and characteristics
Kavitha and Kaulgud [46]	Dataset from UCI contains 1025 patients	K-means clustering method.	96.4%	There is a lack of combination with other machine learning classifications to form a hybrid model.

Table 1. Displays the dataset utilized for developing an AI model to predict CVD disease *(Continue)*

Authors	Dataset	Techniques used	Accuracy	Limitations/gaps
Ullah *et al.* [47]	Dataset from UCI	CNN	84.6%	Quantum computers need a significant quantity of qubits to effectively withstand errors.
Abdulsalam *et al.* [48]	Cleveland consists of 303	SVC QSVC ANN	85.24% 88.52% 85.24%	All classification techniques rely on a single small dataset, with no specification provided for feature selection methods.
Kumar *et al.* [49]	Cleveland consists of 303	Quantum RF	89%	A hybrid model incorporating other machine learning algorithms was not utilized, and a small dataset was employed without employing techniques to enhance accuracy.
Tandon *et al.* [50]	Dataset consists of 87 patients	CNN	90%	The model does not rely on heuristic techniques, and there is redundancy in the data.
Sarra *et al.* [51]	Cleveland has 303 records	Bi-LSTM model	99.3%	The technique employs a single, small dataset and does not undergo a feature selection process.
Sarra *et al.* [52]	Cleveland has 303 records	ANN	93.44%	The model does not rely on heuristic techniques, and there is redundancy in the data.
Kolukula *et al.* [53]	Cleveland has 300 records	RF	98%	The model does not rely on heuristic techniques, and there is redundancy in the data.
Nancy *et al.* [54]	datasets from the Hungarian and Cleveland had 597 records.	Fuzzy inference system and gated recurrent unit	99.125%	This proposal uses small dataset, FIS may encounter scalability challenges, especially when operating with larger datasets, as the computational demands associated with processing fuzzy rules and membership functions can become prohibitive

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