A COMPREHENSIVE SYSTEMATIC REVIEW FOR CARDIOVASCULAR DISEASE USING MACHINE LEARNING TECHNIQUES

Islam D. S. Aabdalla[1] and Dr.D.Vasumathi[2]

[1]PhD. scholar of CSE JNTUH University
[2]Professor of CSE JNTUH University

ABSTRACT

The global upswing in cardiovascular disease (CVD) cases presents a critical challenge. While the ultimate goal remains elusive, improving CVD prediction accuracy is vital. Machine learning and deep learning are crucial for decoding complex health data, enhancing cardiac imaging, and predicting disease outcomes in clinical practice. This systematic literature review meticulously analyses CVD using machine learning techniques, with a particular emphasis on algorithms for classification and prediction. The meta-analysis covers 343 references from 2020 to November 2023, preceding a thorough examination of 65 selected references. Acknowledging current hurdles in CVD classification methods that impede practical use, this systematic literature review (SLR) is conducted.

The study provides valuable insights for researchers and healthcare professionals, facilitating the integration of clinical applications in machine learning settings related to CVD. It also aids in promptly identifying potential threats and implementing precautionary measures. The study also recognizes prevalent classical machine learning methods, emphasizing their clinically relevant diagnostic outcomes. Deliberating on current trends, algorithms, and potential areas for future research offers a comprehensive insight into the present state of affairs.

KEYWORDS

Machine learning, Classification,CVD, Deep learning, ECG, Disease classification.

1. INTRODUCTION

Cardiovascular diseases (CVD), encompassing coronary heart disease (CHD), cerebrovascular disorders, peripheral vascular ailments, rheumatism-induced heart disease, and congenital heart disease, pose a significant global threat, contributing to widespread mortality [1]. The anticipation of these illnesses presents a formidable challenge. While individuals may experience variations in their vascular pressure and heart rate, the average heart rate generally varies between 60 and 100 heartbeats per minute, and the average blood pressure is approximately 120/80. Any disruption to the average blood circulation in the heart can result in severe consequences, referred to as cardiovascular diseases [2]. According to reports from the World Health Organization (WHO), approximately 17.9 million deaths occur annually. They are attributed to heart-related complications, with over four-fifths of cardiovascular disease (CVD) deaths linked to heart attacks and strokes. Unhealthy lifestyle choices, such as poor dietary habits, insufficient physical activity, excessive alcohol consumption, and tobacco use, contribute to an elevated risk of heart-related complications. CVD is a severe global disorder, and specific medical conditions significantly increase the likelihood of acquiring cardiovascular conditions, particularly heart disease [3].Risk factors include hypertension, a family history of CVD, low levels of HDL (good)

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cholesterol, a high-fat diet, and elevated levels of LDL cholesterol. As individuals age, the probability of developing cardiac disease increases, making it a more common occurrence [4]. Early detection is crucial for saving lives, and identifying individuals at an elevated risk of CVD in its initial phases can prevent unexpected and premature deaths. There is a growing interest in employing ML methodologies for cardiovascular disease classification, offering potential improvements in accuracy and efficiency [2]. Typical attributes for assessing heart disease include age, gender, fasting blood pressure, chest pain classification, resting electrocardiogram, number of vessels highlighted by resting blood pressure, serum cholesterol, thalach, ST depression, pain loc, fasting glucose, exercise-induced angina (exang), smoking status, dietary habits, body weight, height, and obesity [5].CVD presents a significant challenge, and while achieving the ultimate goal remains tough, enhancing prediction accuracy is crucial. ML and DL are essential in decoding complex health data, improving cardiac imaging, and predicting disease outcomes. This review explores ML techniques for CVD, focusing on classification and prediction algorithms essential for early detection and effective treatment. ML algorithms find widespread cardiovascular disease classification applications, extracting valuable features from datasets[6]. and enhancing the accuracy and efficiency of medical identification. Incorporating ML into clinical practice poses difficulties, but it discerns complex relationships for precise predictions, adeptly handles diverse data types for improved accuracy in identifying at-risk individuals, and enables early intervention. ML-based classification aids clinicians with decision support systems, contributing to CVD management and diagnosis. Although ECG is used for CVD diagnosis, visually spotting irregularities requires significant time and effort[7].ML-based classification revolutionizes diagnostics and forecasting. The review analyzed PubMed, MEDLINE, and Web of Science datasets, addressing conflicts and evaluating criteria including clinical significance, patient considerations, algorithms, validation, clinical usefulness, and efficacy [8]. The analysis extensively examines ML-based CVD classification, emphasizing accurate classification for early detection and effective treatment [9]. It highlights benefits and addresses challenges in ML-based cardiovascular disease classification, holding significant potential for improving diagnosis, treatment, and patient outcomes[10].However, model performance uncertainty concerning bias, fairness, and intelligibility persists [11].

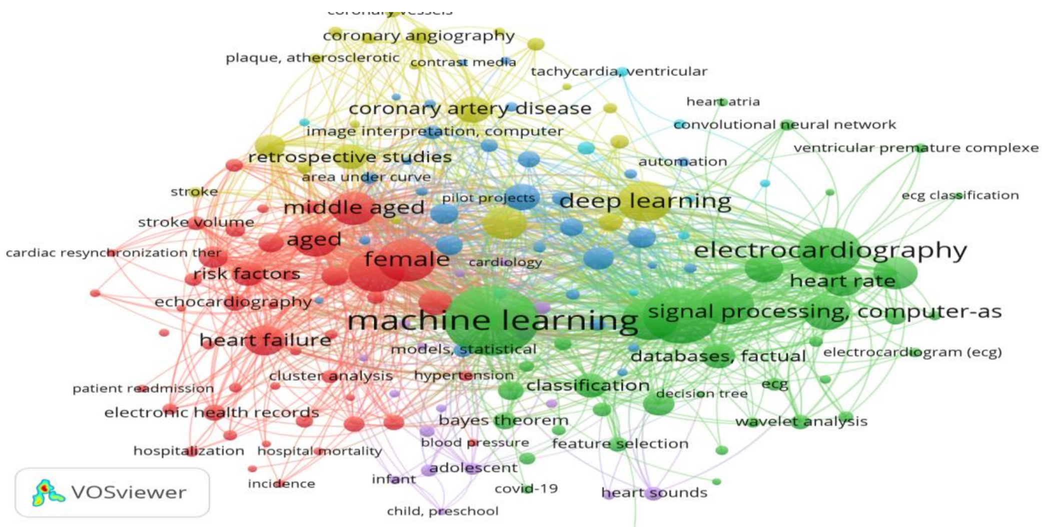

Figure 1. depicts the evaluation criteria utilized in current literature to assess CVD.

Figure 1 depicts prevalent CVD, backed by studies that emphasize heart arrhythmia and coronary artery disease as central clusters. Krittanawong et al.[38],employed decision trees and random forests for cardiovascular disease classification. Recognizing trends, methodologies, gaps, and ML-based heart disease classification opportunities is vital. The meta-analysis covers 343 references from 2020 to November 2023 after thoroughly examining 65 selected references. Identifying challenges in CVD classification methods hindering practical application, this systematic literature review (SLR) provides valuable insights for researchers and healthcare professionals. It aids ML integration in clinical CVD settings, facilitating threat identification and precautionary measures. The study acknowledges prevalent classical ML methods, emphasizing clinically relevant diagnostic outcomes. Deliberating on current trends, algorithms, and potential research areas offers a comprehensive view of the present state. The metadata analysis aims to address various aspects in the subsequent in-depth analysis papers:

1. Provide an integrated, synthesized overview of the existing knowledge on cardiovascular disease (CVD) classification techniques.
2. Highlight current methodological strategies and unique perspectives.
3. Describe research insights, identify existing gaps, and propose future research directions, illustrating the study's significance. Furthermore, it is to offer a comprehensive survey of the current landscape of ML applications in cardiovascular disease classification. By examining existing studies' methodologies, datasets, and performance metrics, this review strives to distill critical insights into the strengths and limitations of ML-based approaches.

Research Questions:

RQ1: What difficulties exist in cardiovascular disease (CVD) classification research?
RQ2: What are the commonly employed metrics for evaluating performance in CVD classification?
RQ3: What algorithms are utilized to classify cardiovascular disease (CVD)?

The subsequent sections of the document are structured as follows: Section 2 briefly summarizes the review methods, followed by the examination of clinical CVD in Section 3. The results and responses to the research questions are then presented and discussed in Section 4, 5 limitations concluding with the future work outlined in Section 6.

2. METHODOLOGY

A comprehensive analysis of the literature using systematic review entails creating inquiries and employing systematic, clear procedures to locate, choose, and critically assess pertinent research. The aim is to gather and assess data from the studies incorporated in the review [12]. This approach is chosen for its accurate and reliable synthesis of academic literature, recognized across various research fields. The systematic literature review (SLR) adheres to the Preferred Reporting Information for Systematic Reviews and Meta-Analysis (PRISMA) recommendations, ensuring clarity and transparency in the presentation of systematic literature reviews[7].Our systematic search encompassed vital databases, including PubMed, IEEE Xplore, and Scopus, employing a structured set of search terms related to machine learning and cardiovascular disease. The inclusion criteria span studies published between 2020 and 2023, concentrating on ML models designed for CVD diagnosis and risk assessment. Evaluating study quality and data extraction adhered to established guidelines for systematic reviews, ensuring a rigorous and systematic approach.

2.1. Data Collection

The studies included in this review were gathered from different Internet-based repositories, including Scopus, Web of Science, PubMed, Google Scholar, and arXiv, from biomedical journals, machine learning journals, and deep learning journals. Additionally, proceedings from various conferences were considered. The data collection process involved the following steps:

Identification of data identification:

Standard and specific databases relevant to this research were identified, encompassing biomedical journals, machine learning and deep learning journals, and conference proceedings.
The selection of keywords was based on the research questions, including cardiovascular disease, ECG, machine learning, classification, and algorithms. The search query used was "cardiovascular disease" OR "CVD" OR "ECG" OR "classification" OR "machine learning" OR "algorithms." The search criteria were designed to ensure both accuracy and recentness.

Screening and Determining Eligibility of Initial Data

They commenced the search with specified keywords and uncovered 343 articles. I independently evaluated the titles and abstracts using a standardized extraction form and resolved conflicts through discussion. Articles unrelated to machine learning or heart disease were omitted, including reviews and non-human studies. Following the title and abstract screening, 65 articles were thoroughly examined, all meeting the inclusion criteria. Figure 3 outlines the exclusion and inclusion processes employed in this study. Reasons for article exclusion during full-text screening encompassed a need for more imbalanced data analysis methods, a singular focus on models' performance without addressing potential limitations, the absence of peer-reviewed status, and inaccessibility to the full text.

Observations and Findings

Outcomes from analyzing metadata and observations are detailed below, stemming from content analysis of 65 publications and a metadata study of 343 papers screened for cardiovascular disease (CVD) classification relevance. Varied CVD patterns pose challenges for universal models due to inconsistent data quality, noise, and recording variations, impacting algorithm accuracy. The inclusion and exclusion criteria in Figure 2 guide the process, while Figure 3 shows papers on CVD classification from 2020 to 2023. The investigation into CVD has sparked interest, with authors proposing integrated methods (Table 4). Analyzing clinical data involves interpreting information from clinical sources to gain insights into cardiovascular health, including occurrence, risk factors, diagnosis, treatment, and outcomes. The overall strategy is shown in Figure 2.

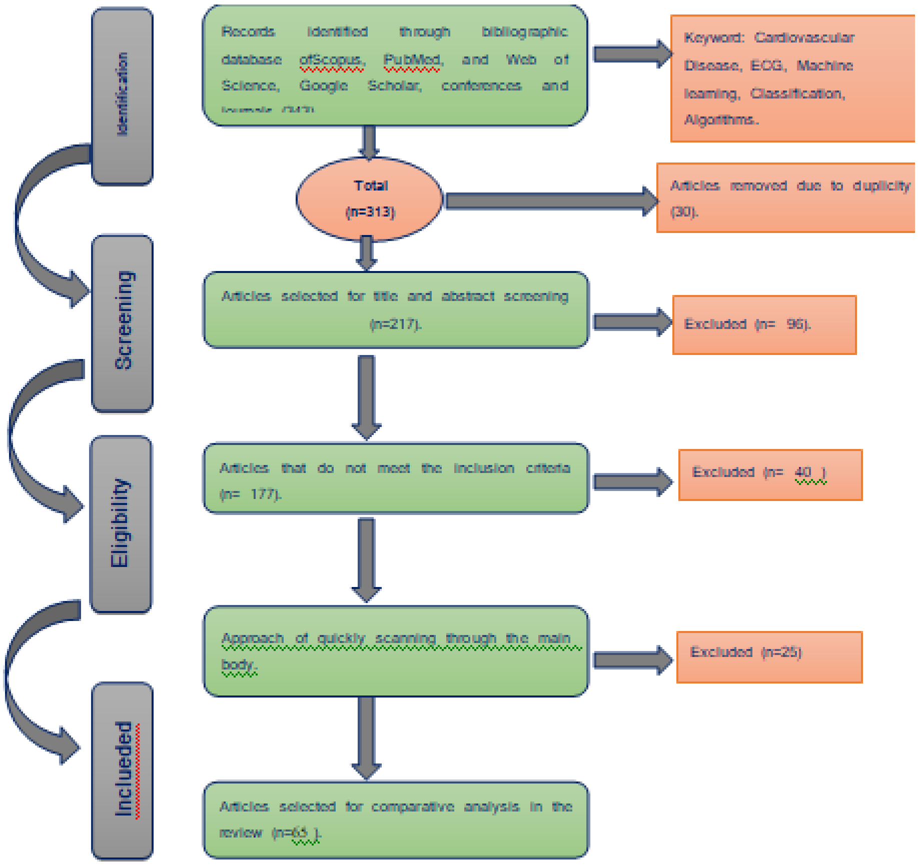

Figure 2. Depicts the schematic diagram employed in the review.

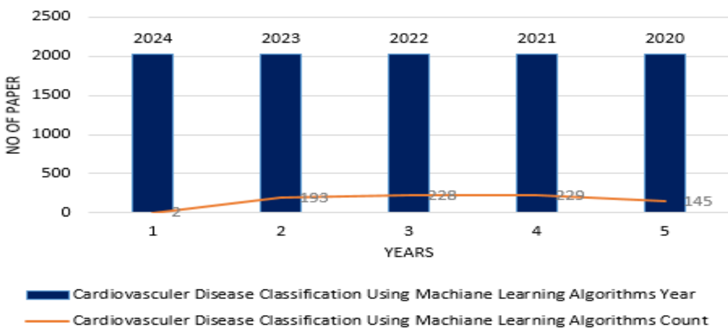

Figure 3. Quantity of published papers from 2020 to 2023 in CVD classification

Uses of Cardiovascular Imaging

AI, including machine and deep learning, revolutionizes CVD medicine, particularly cardiology imaging. Electrocardiography, crucial for early heart disease detection, is swift, painless, and widely used, revealing CVD lesion pressure gradients cost-effectively. Utilizing acoustic waves, echo is a safe method, employing 2D, standard Doppler ultrasonography, and 3D ultrasound to capture heart muscle images, examining the four chambers. A semantic classification model trained on left ventricle tracings now segments video frames without prior human tracings [4]. Narula et al. [11] demonstrated that algorithms with supervised learning, particularly when utilizing STE data, could more accurately distinguish between athlete heart disease and hypertrophic cardiomyopathy than traditional measurement systems. ML models in electrocardiography also hold promise for another application, specifically in heart valve disease [16]. Moghaddasi et al.[17]Introduced novel features for recognizing micropatterns in ECG images. The method suggested attains a specificity rate of 99.63% and a sensitivity rate of 99.38% for detecting the severity of MR.

Additionally, Playford et al. [18].Evaluated AI's ability to estimate aortic valve area using additional echocardiographic data, excluding the left ventricular outflow tract measurement requirements, achieving a performance level of 0.95 in recent development, Ouyang et al. [19].They developed EchoNet-Dynamic, an advanced video-based deep learning algorithm with over 0.92 accuracy. This 3D convolutional neural network precisely evaluates cardiac function by segmenting the left ventricle and estimating the ejection fraction from echo videos. It matches or surpasses the accuracy of human experts. I also introduced CADNet, a sophisticated framework for automated coronary artery calcification and shadow border detection in IVUS images. CADNet incorporates Convolutional Block Attention Modules (CBAM) and Atrous Spatial Pyramid Pooling (ASPP) in an encoder-decoder U-Net structure, effectively identifying vessel components in the presence of artifacts and complex lesions in IVUS images with up to 360° of calcification. Experimental results on 1097 IVUS images from 12 patients demonstrate CADNet efficacy, with mean intersection over union (mean IoU) at 0.7894, dice coefficient at 0.8763, precision at 0.8768, and recall at 0.8774. Compared to alternative techniques, CADNet excels in IVUS image segmentation accuracy, showcasing robust calcification and shadow border detection performance—a promising field advancement [20].AI reduces observer variability and ensures accurate diagnoses in electrocardiography by automating measurement and image segmentation of cardiac parameters, potentially revealing clinically meaningful insights [2].AI-based image quality classification is crucial for accurate diagnosis, particularly within the cardiovascular domain. An FDA-approved AI-powered echocardiographic device aids users in capturing high-quality images. However, cardiologist review and approval of acquired images remain essential for thorough patient assessment[21]. Electrocardiography evolution has increased parameters and examination complexity, requiring nonspecialists to rely on findings. Building effective AI models demands a significant amount of labeled echocardiographic data, and ongoing efforts focus on collecting such data[6].Deep learning models exhibit promise in accurately predicting ejection fraction, even when trained on mislabeled data, showcasing their ability to mimic human recognition successfully[22].

Magnetic Resonance Imaging (MRI)

Within heart MRI, the segmentation of ventricles emerges as a promising domain for applying ML methods. This approach streamlines the measurement of ventricular volumes, contributing to heightened precision and consistency in clinical evaluations [23].Avendi et al. [24]utilized deep learning algorithms trained on cardiac MRI data for the automatic classification and segmentation of the right ventricular chamber to improve algorithmic accuracy. Similarly, various automated NN has been effectively created for left ventricle classification, especially in cardiac cine MRI. Another noteworthy use of machine learning in cardiac MRI includes identifying chronic myocardial or sub acute scars [25]. Dawes et al. employed supervised ML to evaluate systolic cardiac motions in three dimensions, enabling the prediction of adverse outcomes in individuals with pulmonary diseases, such as early mortality or right heart failure. This prediction was independent of conventional risk factors. Further details on cardiac computed tomography were not provided in the text.

Machine learning (ML) image analysis is increasing in cardiac CT for diagnosing coronary artery disease and atherosclerosis. This involves techniques like coronary artery calcium scoring and fractional flow estimation in noninvasive coronary computed tomographic angiography. However, CCTA often overestimates stenosis severity compared to invasive angiography. Moreover, angiographic stenosis does not consistently correlate with the hemodynamic significance indicated by fractional flow reserve (FFR). Various ML models[26]enhance CCTA by accurately reclassifying non-aerodynamically significant stenosis.

Regarding coronary plaque characterization, ML models applied to automatic coronary artery calcium scoring help reduce false positives and minimize interobserver variability. Utilizing supervised machine learning, a CNN was used to directly detect and quantify coronary artery calcification (CAC), calculating the Agatston score directly from CT scans without prior segmentation. In cardiac CT, machine learning has applications in prognosis and myocardial infarction detection through texture analysis methods. The SMARTool Project introduces an innovative approach to managing CAD patients, encompassing diagnosis, prognosis, and treatment based on machine learning risk stratification and computational biomechanics. Machine learning analysis, utilizing historical and future-oriented data, including clinical details, humoral information, and CCTA imaging, aims to differentiate individuals at low risk from those at medium-to-high risk for CAD. The CAD diagnosis involves three-dimensional reconstruction of coronary arteries and noninvasive estimation of brilliance, with classification relying on intricate computational models for arterial plaque growth.

Uses of Cardiovascular Electrocardiography(ECG)

The prominence of cardiovascular diseases (CVD) as the benchmark has drawn the attention of numerous researchers to conduct studies[12]. Classification of cardiovascular disease refers to categorizing or grouping different types or classes of cardiovascular diseases based on specific criteria or characteristics [27]. ML or data analysis may involve developing models or algorithms to classify individuals into specific cardiovascular disease categories, often using features or patterns extracted from medical data such as ECG, imaging, or clinical records.

Numerous researchers have endeavored to delineate boundaries through various techniques. The extraction of features from electrocardiograms, proven crucial for detecting cardiovascular diseases, has garnered significant attention from the research community.

Nevertheless, due to the intrinsic challenges of ECG CVD, Diverse ECG patterns challenge universal classification models due to inconsistent data quality, noise, and recording variations across sources, impacting algorithm accuracy and reliability. Developing a comprehensive model for accurate CVD classification faces challenges, particularly with imbalanced datasets. There is still room for enhancement in this area of analysis. This classification process can aid in prognosis, diagnosis, and treatment planning for patients with heart conditions. Recently, there has been a growing inclination toward utilizing ML algorithms to classify cardiovascular disease[2]. These methods have demonstrated promising outcomes by enhancing diagnostic accuracy and efficiency and identifying individuals at high risk of developing CVD. However, it is crucial to acknowledge that incorporating machine learning algorithms into clinical practice comes with challenges. These challenges encompass the intricacies of feature extraction procedures and the requirement for domain expertise in crafting adequate inputs for the classifier[6].

Evaluating and validating machine learning (ML) approaches with extensive clinical datasets is crucial for ensuring their reliability and applicability across diverse cases. While ML methods hold promise in classifying and analyzing cardiovascular disease, further research and validation are essential for unlocking their benefits and seamlessly integrating them into clinical practices. A systematic literature review on CVD classification using ML techniques would contribute valuable insights to healthcare, offering an overview of current research and guiding future directions. Medical imaging, along with diagnostic electrocardiography, significantly benefits from ML integration. The ECG, crucial for detecting heart electrical abnormalities, undergoes streamlined anomaly identification through ML models, particularly in deep learning (DL). This reduces interpretation time and lessens reliance on individual variability. Noteworthy progress includes Hannum et al.'s 34-layer deep neural network successfully classifying 12 arrhythmia types, outperforming a dataset annotated by certified cardiologists. Ongoing automation efforts encompass diagnosis, prognosis, drug design, and testing, using abundant data from medical imaging and electronic medical records [28]. ML and DL in medicine aim to customize medical decisions, health practices, and therapies for individual patients[10].

Nevertheless, the existing status of AI in the medical domain is considered promising but needs more substantial data and evidence [12]. Concerns about bias, privacy, security, transparency, causality, transferability, informativeness, fairness, and confidence accompany machine learning in medicine. The direct impact of these systems on human health underscores the urgent need to comprehend the decision-making processes involved[29]. particularly in areas where disease diagnosis leads to life-changing outcomes[30]. Precision medicine, where experts seek nuanced information beyond binary predictions to support diagnoses [29].Represents another crucial area. Addressing these challenges requires clear explanations for how and why a model generates its outputs [30]. Thus, issues of explainability and related concepts like interpretability and transparency have gained significant attention in machine learning in medicine in recent years[31]. Despite substantial evidence supporting their utility, widespread adoption of machine learning-based systems in routine medical practice beyond specialized applications is likely only if these challenges are effectively tackled. A potential solution is having these systems offer satisfactory explanations for their decisions [8]. To achieve widespread adoption beyond specialized applications, machine-learning-based systems in routine medical practice require effective solutions to challenges. A potential remedy is for these systems to explain their decisions satisfactorily[31].

ResNet led MI detection at 99.99%, followed by CNN at 99.95%. Papers consistently reported accuracies above 97%, averaging over 93%, with CNN recording the lowest MI detection accuracy at 78%. This section details the highest, average, and lowest accuracies for each DL technique in MI localization. CNN achieved the highest accuracy at 99.87%. Limited research on LSTM for MI localization exists, with only one study each for AE and GRU models. AE and GRU models share identical maximum and average accuracies, though the minimum for AE remains unspecified. The remaining three models in MI localization exhibit accuracies below 65%.

Additionally, this section explores the maximum accuracy of DL techniques trained on diverse ECG datasets with different leads. Generally, networks trained on 12-lead ECG data from the PTB database outperformed those with fewer leads. Specifically, using 12-lead ECG data from the PTB database, ResNet achieved the highest accuracy at 99.99% in MI localization. Using only lead II ECG data yielded favorable outcomes in CRNN, CNN, and AE methods on the PTB database. However, it is essential to acknowledge that this result may be influenced by three studies achieving high performance solely in MI detection using lead II ECG data without achieving comparable results in MI localization. This paper examines various algorithms in CVD classification, reviewing studies based on utilized algorithms, databases, challenges, and evaluation metrics, providing a comprehensive explanation for each research question and corresponding discoveries. A systematic literature review (SLR) involves formulating questions and employing systematic and explicit procedures to discover and critically assess relevant research. The objective is to collect and assess data derived from the studies incorporated in the review[32]. This technique is favored for its accuracy and dependability in consolidating academic literature, gaining broad acceptance in CVD classification.

RQ1: What challenges exist in the domain of CVD classification?
In summary, the response to this inquiry is that challenges are present in CVD classification.

Incorporates different research challenges related to patient profile diversity, data quality inconsistency, and ECG recording variations. The complexity of cardiovascular conditions poses a hurdle to creating comprehensive classification models, and imbalanced datasets may lead to biased models. Additional challenges include ensuring the interpretability of model decisions, achieving generalization across diverse populations, and integrating models into clinical practice. Rigorous validation, addressing ethical concerns, and keeping up with technological advancements further contribute to the complexities in this research area. Table 2 outlines the drawbacks identified in each paper. The literature review emphasizes a recognized limitation in the current machine-learning approach for cardiovascular disease (CVD).

Sample of Data Set: Systems often advise small sample sizes for high accuracy. An investigation reveals that ML algorithms perform poorly with large sample sizes. Conversely, the same classifier excels with exclusive attributes in compact and efficient techniques, significantly impacting estimated accuracy.

Clinical Aspect: Some research needs to include monitoring, which leads to insufficient observation of clinical features, hindering patient data provision for informed treatment decisions.

Data-Clinical Correlation: Inconsistent findings with healthcare practices make interpretation challenging. Meta-analysis enhances study effectiveness by applying consistent techniques and addressing the limitations of ML approaches in handling insufficient and inconsistent clinical data.

Data Distribution: There are no standardized rules for data usage; joint random splitting is 80%:20% or 70%:30%. Limited data sizes for each CVD type affect the combined results.

Feature Selection: Many studies overlook the impact of feature selection on data splitting. A good approach improves ML model performance and reduces processing costs from inappropriate input data.

Hyper-parameter optimization: Existing research lacks parameter tuning, hindering system improvement. Anonymous hyper-parameter customization leads to substantial statistical diversity.

Algorithmic optimization approach: Researchers often present heuristic ML frameworks for predicting cardiovascular disease, improving accuracy at a minimal computational expense.

Ensemble Technique: Studies overlook ensemble methods for enhancing ML models in predicting cardiovascular diseases, combining findings into a single score. Researchers and practitioners increasingly favor DL algorithms over traditional ML for MLBHDD model development, with 27 out of 49 studies adopting DL-based approaches. For example, Awan et al. used MLP, achieving 48% sensitivity and 70% specificity for predicting CVD patient readmission within 30 days[34]. Li et al[13]. Introduced the craftNet DNN model, achieving 86.82% to 89.25% accuracy in recognizing handcrafted features for cardiovascular disease detection. Kala and Dixit[42]. Employed a 1D CNN model to detect early-stage heart disease, achieving 93% accuracy using data from 300 actual patients.The second most utilized algorithm is SVM, with Liu et al. employing it in the CAB approach and achieving 99.71% accuracy for arrhythmia patients[46]. Rath et al[18]. Proposed a model that combines GAN and LSTM, accurately detecting heart disease patients with up to 99.4% accuracy Shah et al[44]. Also tested SVM along with RF, Ordinal Regression, NB, and LR on the Cleveland dataset, where SVM exhibited the best performance with 95% accuracy.Other algorithms were also explored, including ensemble learning[38]and linear methods. This section aids scholars in identifying gaps in recent literature. Recognition of cardiovascular disease (CVD) is crucial due to its lifethreatening nature. Table 1 details the limitations of each research paper. Based on the literature review, the existing machine learning approach for CVD is characterized by one of the following constraints[33]. Deep learning models enhance risk stratification for cardiovascular diseases using electronic medical record data and medical images. However, assessing these models goes beyond statistical success measures, necessitating a framework for clinical utility evaluation[1]. These models should be accurate and transparent about limitations, ensuring understand ability for healthcare providers. The existing literature lacks powerful, interpretable models for medical practice, urging future efforts in these aspects for improved patient outcomes. Evaluating deep learning models in clinical practice requires scrutiny by healthcare providers to ascertain their clinical relevance [2]. Unlike widely observed trends in machine learning research, the paper stresses the importance of explainability and interpretability for deep learning models[10]. Other regression models, like the MAGIC score and the Seattle Heart Failure Model, quantify patient risk for cardiovascular diseases [6]. Deep learning models show potential for improving risk stratification for cardiovascular diseases, particularly in medical electronic health records and imaging. However, evaluating the clinical utility of these models takes time and effort, requiring accuracy, transparency, and interpretability for healthcare providers. Healthcare providers must critically assess deep learning models to determine their clinical usefulness and accurate application to specific patient demographics. The broader literature needs more powerful, explainable models for medical practice, necessitating future work to develop impactful models. Implementing deep learning models in clinical practice necessitates a comprehensive strategy, including assessing failure scenarios and explaining model learning. This paper explores the utilization of various datasets, including the unfiltered original dataset (DS2,1) and a database processed through wavelet de-noising (DS0,2;1), for comparison and experimentation. Cross-validation experiments are conducted to evaluate the system's robustness[5]. The outcome showcases the high accuracy of the proposed CNN model in detecting arrhythmia assessed across different heartbeats [2].Performance metrics such as accurate upbeat beats, false negative beats, and false positive beats are employed for evaluation[10].

Table 1: Summarizing Challenges and Future Directions in Cardiovascular Disease (CVD) Classification

Challenges	**Future Directions**
Diversity in patient profiles	Enhanced model adaptability to individual traits
Imbalanced datasets	Strategies for handling imbalances and biases
Variations in ECG recordings	Advancements in signal processing techniques
Inconsistent data quality	Implementation of standardized data protocols
Complexity of CVD conditions	Development of more nuanced classification models
Model interpretability	Research on transparent and interpretable models
Applicability across populations	Incorporation of diverse demographic factors
Integration into clinical practice	User-friendly interfaces and workflow integration
Rigorous validation	Continuous improvement in validation methodologies
Ethical considerations	Development of ethical guidelines for CVD models
Continuous technological progress	Adoption of state-of-the-art technologies

The challenges that could be tackled in future research within the CVD image analysis domain are condensed and presented in Table 1. These challenges include the complexity of feature extraction procedures and the need for domain expertise in creating suitable inputs for the classifier[6].As an illustration, Daraei and Hamidi introduced a myocardial infarction (MI). A prediction model based on machine learning, utilizing J48 algorithms, achieved an accuracy of 82.57%[11]. Bashir et al. employed machine learning approaches, including naive Bayes, decision trees based on the Gini index and information gain, and SVM, to create an ensemble model for predicting and analyzing heart patients, achieving an accuracy of 87.37%[34].In recent developments, deep learning (DL) has introduced an additional layer, emphasizing data-driven approaches for heart disease diagnosis with Accuracy approaching 100%. Dutta implemented a convolutional neural network for diagnosing coronary heart disease[28], and Li et al[27]. Introduced a deep neural network model named CraftNet. Despite the multiple hidden layers in deep learning models, understanding the specific contribution of each layer in the final prediction often poses challenges[35]. Additionally, a potential challenge is associated with the biased performance of machine learning algorithms toward the majority class.

RQ2: What are the commonly employed performance metrics in CVD classification?

Various metrics gauge classification task performance. In cardiovascular disease (CVD) classification, such as Accuracy, Accuracy assesses correctness, precision focuses on optimistic predictions, and recall echoes the model's ability to recall relevant instances. Specificity discerns the model's skill in identifying negative instances. F1 Score blends precision and recall for balanced performance. The ROC-AUC assesses the model's capability to distinguish between positive and negative cases; the Confusion Matrix furnishes details regarding true positives, true negatives, false positives, and false negatives. Matthews Correlation Crescendo (MCC) balances elements of the confusion matrix. Kappa Cadence gauges model alignment with expectations. The Precision-Recall the nuances of optimistic predictions. Researchers use these metaphorical notes for a thorough CVD classification model evaluation. They comprehensively evaluate the model's performance in detecting and classifying cardiovascular diseases [18] .

RQ3: What are the various CVD classification algorithms?

Machine learning is increasingly used to define subtypes and predict risks in cardiovascular diseases. Despite its growing application, using regularly employed ML models in cardiovascular disease management remains to be determined. ML offers a unique AI method, categorizing cardiac disease datasets with fewer features and higher performance indicators[1]. Moreover, physicians are assisted in predicting outcomes by identifying complex patterns[36]. ML plays a pivotal role in addressing challenges posed by the scale and complexity of medical data, aiming to recommend early detection and treatment of cardiac conditions[6]. For example, Hamidi and Daraei's ML-based model achieved 82.57% accuracy in early Myocardial Infarction (MI) prediction using J48 algorithms[11]. Bashir et al. employed various ML methods, creating an ensemble model for heart patient analysis with 87.37% accuracy[37]. Deep Learning (DL) achieves close to 100% accuracy in heart disease diagnosis, as seen in Dutta's CNN-based model for coronary heart disease[12], and Li et al.'s DNN model named CraftNet[27].and Li et al.'s DNN model named CraftNet[27]. However, discerning the specific contribution of each layer in DL models remains challenging[35]. This study used a UCI dataset with 76 columns, but only 14 encompassing heart disease attributes and risk factors were chosen for the experiment. Specific attributes or risk factors used are not mentioned. It compares ML algorithms for heart disease classification, evaluating metrics such as Accuracy, RMSE, MAE, precision, and recall[6]. Lacking details about the dataset's size or characteristics[2].It does not discuss potential biases or limitations of selected ML algorithms, and there is no consideration of demographic factors' impact on CVD prediction [6]. Generalizability to diverse populations or healthcare settings must be addressed[10]. The authors do not explore potential ethical or privacy concerns related to using medical data for machine learning prediction models[4]. This study proposes an ML model for CVD classification. Krittanawong et al. highlight the paper's key points[38]. This study assesses predictive efficacy for coronary artery disease, heart failure, stroke, and cardiac arrhythmias. Of 344 studies, 103 cohorts (3,377,318 individuals) met the criteria. Boosting algorithms predicted coronary artery disease (pooled AUC 0.88, 95% CI 0.84–0.91), and custom-built algorithms had a pooled AUC of 0.93 (95% CI 0.85–0.97). For stroke prediction, SVM algorithms had a pooled AUC of 0.92 (95% CI 0.81–0.97), boosting algorithms had a pooled AUC of 0.91 (95% CI 0.81–0.96), and CNN algorithms had a pooled AUC of 0.90 (95% CI 0.83–0.95). Insufficient studies hinder meta-analysis in heart failure and cardiac arrhythmias, suggesting no significant difference, though SVM may excel. The promising predictive ability of ML algorithms in cardiovascular diseases, especially SVM and boosting algorithms, includes heterogeneity among ML algorithms concerning multiple parameters, aiding clinicians in data interpretation and optimal algorithm implementation. In Table 2, the summary highlights the advantages and challenges associated with machine learning and traditional statistics in terms of explainability, flexibility, variable selection, identifying interactions, and handling different data sizes.

Table 2. A comparison between traditional statistics and machine learning in general terms[39]

	Machine Learning	**Traditional statistics**
Explainability	Due to the hidden layer's complexity, clinicians may struggle to interpret machine learning outcomes, especially in neural networks.	Clinicians easily comprehend odds ratios, hazard ratios, and confidence intervals generated by conventional statistical methods.
Flexibility .	Highly flexible due to no assumptions.	The necessary assumptions for various models limit their applications.
Variable selection	ML utilizes diverse data, including numerical data, reports, and imaging, to discern valuable variables from noise, especially in genomics, where predictors outnumber outcomes.	Statistical methods, like LASSO, use past calculations to distinguish genuine predictor variables from noise by regularising and selecting variables for model generation.
Identifying interactions	Unsupervised ML excels at discovering new predictor interactions compared to traditional methods.	Variables must be collectively chosen to identify interactions, which may not occur if the prevailing belief assumes none due to a lack of evidence.
Variables must be jointly chosen to identify Interplay it is unlikely if the prevailing belief assumes no interaction due to insufficient evidence.	Incorporating various data types into the calculation is more Plainthan traditional statistics.	It is not feasible to analyze multiple data types with traditional statistics.
Size of data sets .	ML excels with large datasets but could be more dependable with smaller ones.	Typically more dependable than ML with smaller datasets.

Ganga[40]Explored machine learning for cardiovascular disease prediction, emphasizing early detection. The authors highlight its potential for precise outcomes through insights from healthcare datasets. The study covers genetic algorithms, random forests, naïve Bayes ANN, SVM, particle swarm optimization, and ant colony optimization, achieving 99.65% maximum accuracy with the Cleveland dataset. Various classification techniques like NB, DT, SVM, RF, ANN, and ensemble learning are widely used. The study suggests that future research could integrate diverse optimization techniques with machine learning for improved predictive accuracy. R.K. Halder and Uddin, M.N [41]. Introduced an ensemble method-based multiplayer dynamic system (MLDS) for cardiovascular disease prediction using machine learning, achieving high accuracy (88.84% to 94.16%) across various train-test data ratios. Feature selection techniques like CAE, GRAE, and IGAE are employed, and classifiers, including RF, NB, and GB, are integrated into the model. The KNN algorithm is utilized when base classifiers fail. Data preprocessing involves converting gender values, handling missing data, and outlier removal using DBSCAN. The MLDS is evaluated on Kaggle and UCI datasets, outperforming five comparison models. However, the paper lacks discussions on limitations, generalizability, biases in datasets, computational resources, and model interpretability.

Machine Learning Techniques:

Arthur Samuel coined In 1959 'machine learning' was coined, defining it as a field where computers autonomously learn without explicit instructions[42]. It involves developing algorithms based on past data and experience, which is the essence of machine learning. In 1997, Tom Mitchell further characterized machine learning as a process where a computer program learns from experience E concerning tasks T and performance measure P, improving its performance in T as measured by P with experience[43]. As a subset of artificial intelligence, machine learning enables systems to learn from data, avoiding explicit programming. It employs various algorithms to enhance, interpret, and predict outcomes through continuous learning from data[44]. Data can be automated user training sets or other records obtained through interactions with the environment. In all scenarios, the effectiveness of a learner's prediction depends on the quality and size of the data. Figure 4 illustrates the results of a machine learning (ML) model trained and tested with additional data for prediction. A classification approach is a model providing predictions based on previously trained data[12]. Machine learning is pivotal in developing analytics models that are applied to accurate diagnoses, prescription medicines, pathological tests, early disease detection, and informed decision-making. Medical diagnosis, in particular, is crucial as it influences treatment. Therefore, the widespread use of machine learning techniques in healthcare, as outlined in[13]. Is vital for swift and accurate treatment decisions. Leveraging computer-based decision support systems plays a significant role in ensuring accurate diagnoses and cost-effective treatments.

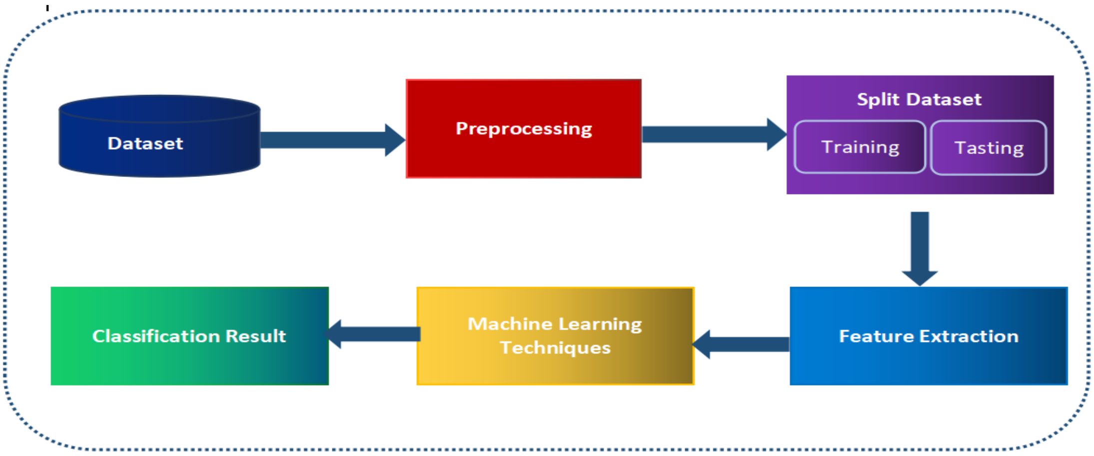

Figure 4. A general framework for cardiovascular disease classification.

Machine learning aims for increasingly positive outcomes through precise predictions. The classifications of machine learning techniques are detailed as follows:

Support Vector Machines (SVM): SVM serves as a supervised learning algorithm for classification tasks, identifying the optimal hyperplane that separates different classes within a feature space.

Random Forests: This ensemble learning method constructs numerous decision trees and integrates their outputs to enhance accuracy and mitigate overfitting.

K-Nearest Neighbour (k-NN): A straightforward and effective classification algorithm, k-NN assigns a data point it is class based on the majority class among its k-nearest neighbors.

Logistic Regression: Utilized for binary classification problems, logistic regression models the probability of a specific outcome.

Naive Bayes: A probabilistic algorithm, Naive Bayes calculates the probability of a data point belonging to a particular class based on its features.

Artificial neural networks, also known as multilayer perceptron (MLP), simulate complex non-linear functions inspired by biology and are essential tools in machine learning [27]. With hidden input, neural networks utilize the hidden layer to transform inputs into patterns controlled by the output layer, excelling at instructing computers to recognize intricate patterns [28]. In use since the 1940s, neural networks, especially with backpropagation, have gained significance in AI by allowing adjustments to hidden layers when outputs deviate from user expectations[44].

A decision tree a tree-like structure in predictive models, is widely used across various fields. It employs an algorithmic approach to partition data into different scenarios and is a practical strategy for supervised learning techniques applied in classification and regression[16]. The Decision Tree method starts by calculating attribute entropy, dividing the dataset based on predictors or variables, and repeating the process with the remaining features.

Random Forest is a well-known and effective machine learning technique proficient in classification and regression, excelling particularly in classification tasks
[20]. Bagging Aggregation, a machine learning algorithm, utilizes the bootstrap method to approximate values such as the mean from many data samples [21]. The average of mean values estimates the actual average value. Bagging follows a similar procedure but predominantly employs decision trees. It generates individual models for each sample by considering the number of data samples for training and providing predictions when needed. These predictions are averaged to evaluate the output value more effectively[22].

Ensemble Methods: Techniques like AdaBoost and Gradient Boosting amalgamate predictions from multiple weak learners to create a more robust classifier.

Neural Networks: Simple NN with one or more hidden layers can also be employed for CVD ECG classification, especially in cases where deep learning may not be necessary.

Deep Learning Techniques:
Gated Recurrent Units (GRU): GRU are a type of recurrent neural network similar to LSTM but with a simplified architecture. They are effective for sequence modeling.

Capsule Networks: Capsule networks aim to overcome gaps in traditional neural networks by better handling hierarchical relationships within data.

Generative Adversarial Networks (GAN): While GAN are primarily used for generating data, they can also be applied to anomaly detection and improve the robustness of classifiers.

Transfer Learning: Pte-trained models, such as those trained on ImageNet, can be fine-tuned for CVD ECG classification tasks. This is especially useful when dealing with limited datasets.

Self-Supervised Learning: This learning paradigm involves creating supervisory signals from the data, often by defining pretext tasks. It has shown promise in specific medical image analysis tasks.

Convolutional Neural Networks (CNN): Specifically designed for tasks involving images, CNN excel in ECG signal classification, automatically acquiring hierarchical features from raw data.

Long Short-Term Memory (LSTM): LSTM are a type of RNN designed to handle data sequences. They are effective in capturing temporal dependencies in time-series data like ECG signals.

Bidirectional LSTM (Bi-LSTM): Bi-LSTMs process sequences in both forward and backward directions, providing better context understanding and capturing long-term dependencies.

Deep Residual Networks (ResNet): ResNet architectures utilize residual learning to address the vanishing gradient problem in deep networks, making them suitable for intense neural networks. Attention mechanisms concentrate on particular segments of the input sequence, enabling the model to emphasize pertinent aspects while undertaking classification.

Autoencoders are used for unsupervised learning and feature extraction. They can be applied in preprocessing stages to enhance the representation of ECG signals before classification.

Graph Neural Networks (GNNs): GNNs are designed to work with graph-structured data. They can be applied when the relationships between different components in the ECG signal are crucial. Table 3 outlines the advantages and disadvantages of some deep learning models.

Table 3. Pros and cons of the six distinct deep learning approaches

Models	**Pros**	**Cons**
Convolutional Neural Network	Sharing weights reduces training parameters .	1. Valuable information is lost in the pooling layer. 2. Limited interpretability.
Long Short-Term Memory (LSTM)	1. Ideal for handling sequential signals. 2. Addresses vanishing gradient in temporal sequences	The LSTM model encounters complexity with prolonged training and prediction times.
Convolutional Recurrent Neural Network	It combines CNN and RNN to analyze ECG morphology and beat-to-beat variations in MI research.	Significant computational expense
ResNet	1. Deepening the network during training. 2. Addressing adverse effects of increased depth, like degradation. 3. Mitigating information loss compared to CNN, but training duration extends	The duration of training is extended.

GRU	Simplifying structure match to LSTM while maintaining effectiveness.	GRU performs less active on extensive datasets than LSTM.
AE	Conducting feature dimension reduction aids data visualization analysis.	Compression applies only to samples resembling the training data

Table 4. Evaluating Machine Learning Methods for Predicting Cardiovascular Disease.

Author	**Proposed Study**	**Dataset Used**	**Proposed Algorithm**	**Limitation/Gaps**	**Accuracy**
Chintan M. et al. [45]	Improvements to enhance classification accuracy.	70,000 patient records	RF, DT, MP, and XGBoost.	Single database dependency variable scope gaps.	87.28%
Jilbab et al. [46]	Use six standard tools and six machine learning algorithms for classifying cardiac disease.	UCI	LR, SVM, KNN, A NN, NBand, RF.	Small dataset, and the algorithms may not encompass all available techniques.	84.48%
Siddiket al. [47]	Predict HD using ML algorithms and improve prediction accuracy.		LR, DT, KNN, NB, SVM		91%
Sindhu[48]	CVD	UCI	RF, DT,SVM, KNN	Insufficient dataset.	85.71%
Nissa[49]	ML algorithms for CVD prediction and assess their performance..	1329 instances and 14 attributes .	ANN,RF,LR ,SVM,NB	Limited insights for heart disease diagnosis, incomplete details on sample size and dataset in machine learning evaluations.	97.29%
Uddin, M. N[41]	Ensemble method-based multilayer dynamic system	70,000 from Kaggle.	(RF), (NB), and Gradient Boosting	Lack of modelcomparison.	94.16%
Nisa, N. et al.[35]	Comparative analysis of techniques for predicting heart disease.	UCI	RF, SVM, DT,	The time complexity remains undetermined, and the framework is also unspecified.	99.35%
Patil,[5]	Developing a machine learning-based algorithm for risk prediction of CVD		NN,KNN,N B		98.71%

Hau Tran, et al.[51]	Early detection of CAD deep learning framework with TL and XGBoost of CAD.	1250 samples SPECT MPI	XGBoost	need for thorough evaluation and detailed dataset discussion.	81.5%
Sajja, T[52]	Proposed a CNN to classification the disease at an early stage	UCI	CNN	Enhancing Risk Factor Dataset Inclusivity.	94%
Ketuet al.[23]	predict HD using the pickled model in Flask's ML models.	UCI	DT, KNN,RF, LR, ANN.	Small dataset used.	100%

This study strongly recommends further enhancements by shifting the focus from theoretical frameworks and classification to practical datasets[11]. It suggests exploring improved forecasting techniques and developing innovative feature selection methods to deepen understanding essential elements and enhance precision in heart disease prediction. Deep learning, leveraging CVD data, has the potential to enhance comprehension of heart disease subgroups and automate ECG workflows. Encouraging research engagement and employing advanced representation learning methods on echocardiographic data requires standardized benchmarks due to the limited availability of publicly accessible datasets[63]. Applying machine learning and deep learning in cardiovascular fields presents extensive possibilities, enabling personalized care. Cardiology, especially in cardiac imaging, is transforming, and physicians must be prepared for these changes. Instead of resisting the integration of AI into cardiology, physicians should embrace it, acknowledging that their expert knowledge will remain essential. These techniques can be tailored or specialized based on the specific requirements of cardiovascular disease (CVD) ECG classification issues and the characteristics of available data, striking a balance between model complexity, interpretability, and computational resources[65]. With ML advancements, researchers utilize data-driven methods for diagnosing heart-related diseases through ECG signals. ML-based approaches provide early identification, enabling routine self-assessments with affordable sensors, unlike traditional tests that cause delayed diagnoses[10]. Analyzing heartbeat rhythms can detect heart disease early, categorizing beats into five types. Abnormal heartbeats, known as arrhythmia, were a focus in 13 out of 49 selected papers due to their severe consequences, contributing significantly to morbidity and mortality among cardiac patients [11].The recent discussion on advancements in modeling, imaging, and monitoring CVD with machine learning explores its application in analyzing, visualizing, and monitoring these diseases. The paper emphasizes machine learning's potential to address challenges like computational cost, limited resolution, and data analysis obstacles. It specifically focuses on applying deep learning methods to expedite flow modeling, improve resolution, reduce noise in blood flow imaging, and accurately detect cardiovascular diseases using wearable sensor data. The authors stress the need for collaboration among experts in computational fluid dynamics, blood flow imaging, cardiology, wearable sensors, and machine learning to leverage cardiovascular research[2]. further. Deep learning techniques and profound neural networks were utilized to accelerate flow modeling, enhance resolution, diminish noise, and reduce scanning time in blood flow imaging methods. Machine learning algorithms, including deep learning, were applied to accurately detect and classify cardiovascular diseases using data gathered from wearable sensors[10].Physics-informed neural networks were integrated to surrogate model the flow field with minimal or absent simulated data, reducing the necessary training samples. Geometric details of blood vessels, such as the aorta and coronary artery branches, were acquired through computed tomography angiography (CTA) scanning to construct training datasets for predicting flow dynamics using deep learning[4].It is crucial to foster collaboration among experts in computational fluid dynamics, blood flow imaging, cardiology, wearable sensors, and machine learning for further cardiovascular disease analysis and monitoring advancements. Increasingly utilizing machine learning techniques and intense learning can significantly enhance cardiovascular monitoring, care, and management. Continuous research and development are imperative to decrease the computational cost and time required for CFD simulations using deep learning methods, making them more applicable for clinical applications. Efforts should also improve the resolution and quality of images obtained from 4D-flow MRI by applying deep learning techniques to reduce noise and scanning time.Additionally, it is advisable to explore further applications of machine learning for early detection and risk stratification of cardiovascular diseases using data from wearable sensors[66]. Precision medicine elevates care through early disease risk prediction and personalized treatments, leveraging advanced diagnostics and genomic medicine. AI and ML play pivotal roles by providing insights and enabling predictive models for physicians through high-throughput data [2]. ML algorithms, like decision trees and random forests, are applied in real-time healthcare monitoring, therapeutic decision support, and disease prediction[6]. They assist cardiologists in predicting cardiovascular risk, detecting cardiac events, and extracting phenotypic information from the EHR for rare diseases and cancer phenotyping. Specific ML algorithms, e.g., linear regression, naive Bayes, and KNN, find use in computational analyses, clinical decision support, and drug response anticipation[10]. Despite the potential, challenges include insufficient accuracy for widespread medical use, limitations in understanding gene function, and unaddressed ethical and privacy concerns in precision and genomic medicine. The future holds promise for ML in precision and genomic medicine, but overcoming obstacles like the research-to-clinic divide and addressing limitations are crucial for realizing its full potential[6]

3. RESULTS

In the study's initial goal of identifying heart disease-related literature addressing imbalanced datasets, it was observed that all 65 articles utilized imbalanced datasets, either from actual or open sources. Although not all studies recognize different data as a challenge, recent literature increasingly acknowledges its impact on model performance. Authors employ various strategies to address imbalanced data; some utilize data-level solutions[68], while others prefer algorithm-level solutions [69] for lower time complexity. Standard data-level solutions include the widespread application of SMOTE, and a few studies adopt other methods like under-sampling. DL-based methods are prevalent among algorithm-level solutions, utilizing GAN to augment ECG data and enhance classification accuracy. Cost-sensitive approaches are also considered. Daraei and Hamidi utilized the Metacost classifier with varying cost ratios, achieving a sensitivity of 86.67%, an F1-score of 80%, and an accuracy of 82.67% with a cost ratio of 1:200. Gan et al. proposed AdaC-TANBN, integrating TANBN with a cost-sensitive classification algorithm, showcasing the effectiveness of cost-sensitive approaches in handling class imbalances with the Cleveland dataset. While arrhythmia is extensively studied in machine-learning-based heart disease diagnosis, cardiac arrest remains a significant concern in intensive care units. Screening encounters challenges due to low sensitivity and high false alarm rates, suggesting a need for researchers to broaden their focus to encompass all heart diseases, not solely arrhythmia. ML models primarily utilize Cleveland data and MIT-BIH arrhythmia, with limited attention given to real-world data.

Clinical decision support systems encounter instability, necessitating continuous model adjustment based on new patient data. ML algorithms, including SVM, KNN, ANN, CNN, and GAN, are employed, with CNN and GAN garnering attention for their robust performance. Imbalanced data issues are tackled through methods like SMOTE and CNN-based solutions. However, CNN needs more interpretability. Performance is superior under the intra-patient paradigm but poor under the inter-patient paradigm. Distinguishing heartbeats from noisy ECGs proves challenging. Models claiming success with imbalanced data should incorporate explainable AI. Conventional classification models prioritize accuracy without considering fluctuations in misclassification costs. Literature often involves multiple steps, making real-world implementation challenging.

A standardized process and presentation requirements are necessary for cross-disciplinary research. Studies vary in their emphasis on accuracy, AUC, ROC, sensitivity, and specificity. Table 5 summarises research papers focusing on cardiovascular disease (CVD) diagnosis, each with a distinct study emphasis and employing techniques. Notable topics include data preparation, effective machine learning classification, and evaluating diagnostic performance for congenital heart disease. Techniques range from content analysis to machine learning methods, emphasizing features, algorithms, and samples. The comprehensive overview aids in understanding diverse approaches in CVD research.

Table 4: Related Research.

Title of the Papers	Study Emphasis	Techniques	Content Analysis	Imbalance Issues	Meta Analysis	SLR	Performance Metrics
Data preparation for CVD diagnosis: A systematic review [13]	Data preparation	—	—		—	—	—
Effective classification of CVD using machine learning methods: a review[14]	Machine learning techniques	—				—	—
Machine learning-based cardiac disease prediction: a meta-analysiss[15]	Features, algorithms, and samples	✓	—				✓
Evaluation of the effectiveness of machine learning methods in detecting congenital heart disease: a review[4]	Estimating the diagnostic performance of ML.	—			—	—	—
An exhaustive scope review of machine learning and deep learning-based classification of cardiac disease[3]	Test data, patient signals, dataset origins, and feature reduction/extraction methods.				—		
Our study	Machine learning based on CVD classification	—	—	—	—	—	—

4. DISCUSSION

Selected papers undergo comprehensive evaluation based on predefined criteria, including the research problem, proposed approach, machine learning classification, and accuracy. Criteria assign the highest scores to models used in evaluating studies, typically applied to heart disease datasets from various sources, not limited to UCI. Researchers often use reduction strategies or feature selection when providing data to ML classifiers, focusing on key characteristics like chest discomfort, blood pressure, fasting blood glucose, cholesterol, ECG readings, pulse rate, exercise, age, and gender. While over 75% of systems rely on UCI heart disease data, multiple datasets and ML techniques yield similar results. Despite variations, Random Forest (RF) showed the highest accuracy frequency among the identified classifiers, with Support Vector Machine (SVM) ranking second. Seven classifiers addressed CVD prediction: decision trees (DT), RF, naive Bayes (NB), logistic regression (LR), artificial neural networks (ANN), k-nearest neighbors (KNN), and SVM. RF, SVM, and KNN demonstrated reasonably high accuracy, but reliability clarification on predictions was needed in literature sources. Constructing a machine-learning-based clinical diagnosis system requires unique models due to variations in training data. The stability of the model when parameters shift or update is critical for reliable diagnoses. The results from the literature sources are summarized in Table 5, providing a comprehensive understanding of machine learning-based heart disease diagnosis. Challenges arise from complex feature extraction and the need for domain expertise in clinical applications. A thorough evaluation of extensive clinical datasets is essential for the reliability of machine learning methods. Integrating machine learning into cardiovascular disease analysis can improve patient outcomes and significantly guide future research in cardiology[2].

5. LIMITATIONS

The study must thoroughly address biases and challenges related to imbalanced datasets in cardiovascular disease (CVD) classification, potentially affecting the reliability of machine learning models. Additionally, there needs to be more discussion on the generalization of machine learning models to diverse populations and external validation, which is essential for evaluating their robustness across various patient groups. The study briefly mentions the interpretability of CNN models. However, it does not sufficiently emphasize their critical importance in clinical settings, impacting healthcare professionals' understanding and trust in machine learning decisions for cardiovascular disease.

6. CONCLUSION AND FUTURE WORK

This thorough literature review provides a nuanced synthesis of the current research on machine learning applications for classifying cardiovascular diseases. Its primary focus is elucidating recent trends and techniques for diagnosing heart disease using machine learning (ML) and data-driven approaches. The central conclusion drawn from the analysis underscores the importance of broadening ML-based experiments to incorporate real-time patient data and providing a clear interpretation of the final predictions through interpretable machine learning. The amalgamation of findings highlights the potential of ML models to improve diagnostic accuracy and risk prediction substantially. Nevertheless, the expectation is that ML-based heart disease diagnosis with imbalanced data still involves unexplored aspects and holds significant potential for further exploration in the years to come.

For future work, This study recommends shifting focus from theoretical frameworks to practical datasets, promoting research engagement with advanced representation learning on CVD data. Collaboration among experts in computational fluid dynamics, cardiology, wearable sensors, and machine learning is crucial for advancing cardiovascular disease analysis.

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