Machine Learning Classification in Cardiology: A Systematic Mapping Study

Khadija Anejjar[1][a], Fatima Azzahra Amazal[1][b] and Ali Idri[2][c]
[1]LabSIV, Department of Computer Science, Faculty of Science, Ibn Zohr University, BP 8106, 80000 Agadir, Morocco
[2]Faculty of Medical Sciences, Mohammed VI Polytechnic University, Morocco

Keywords: Heart Disease, Machine Learning, Classification Techniques, Predictive Models.

Abstract: Heart disease, a widespread and potentially life-threatening condition affecting millions globally, demands early detection and precise prediction for effective prevention and timely intervention. Recently, there has been a growing interest in leveraging machine learning classification techniques to enhance accuracy and efficiency in the diagnosis, prognosis, screening, treatment, monitoring, and management of heart disease. This paper aims to contribute through a comprehensive systematic mapping study to the current body of knowledge, covering 715 selected studies spanning from 1997 to December 2023. The studies were meticulously classified based on eight criteria: year of publication, type of contribution, empirical study design, type of medical data used, machine learning techniques employed, medical task focused on, heart pathology assessed, and classification type.

1 INTRODUCTION

Heart disease is a major global health concern and ranks as one of the primary causes of mortality worldwide. Although conventional approaches to diagnosing and treating heart disease have seen notable progress, there is increasing acknowledgment of the potential advantages of machine learning (ML) in enhancing medical outcomes and optimizing cardiology practices (Hassan et al., 2022). This is fueled by the increasing availability of diverse medical data from electronic health records, medical imaging, and wearable devices (Almazroi et al., 2023).

Encompassing a range of conditions like coronary artery disease, arrhythmia, and myocardial infarction, heart diseases vary in complexity and require personalized approaches considering each patient's medical history, genetics, and environment (Collet et al., 2021).

ML classification techniques empower heart disease practitioners not only in disease prediction and detection but also in patient management, treatment, and ongoing monitoring (Esfandiari et al., 2014).

Classification as a subset of ML (Dangare & al., 2012; Noh & al., 2006; Seetharam & al., 2022) holds promise for accurately predicting heart disease and aiding doctors in making informed decisions (Dwivedi, 2018). There are two primary types of classification: binary classification, which categorizes elements of a set into one of two classes, and multi-classification, which involves assigning elements to more than two classes (Sun, 2008). These classification techniques are employed to identify patterns and relationships within the data, facilitating the categorization of patients into different risk categories in some cases (Araki & al., 2016; Chicco & al., 2020; Aziz & al., 2021), detecting the presence of a heart abnormality in others cases (Chicco & al., 2021; Hassan & al., 2022; Masetic & al., 2016; Rahman & al., 2015), or even identifying specific heart conditions (Juhola & al., 2018; Smole & al., 2021).

This research utilizes a Systematic Mapping Study (SMS) to examine ML classification in cardiology. As defined by Kitchenham et al. (2010),

[a] https://orcid.org/0009-0009-7299-2380
[b] https://orcid.org/0000-0002-9008-656X
[c] https://orcid.org/0000-0002-4586-4158

Anejjar, K., Amazal, F. and Idri, A.
Machine Learning Classification in Cardiology: A Systematic Mapping Study.
DOI: 10.5220/0012785600003756

In *Proceedings of the 13th International Conference on Data Science, Technology and Applications (DATA 2024)*, pages 409-416
ISBN: 978-989-758-707-8; ISSN: 2184-285X

SMS establishes a framework for categorizing research within a specific field. Notably, no prior comprehensive mapping study has been conducted to explore the development and current state of ML classification in cardiology, to the authors' knowledge. This SMS aims to: 1) Identify recent research (1997-December 2023) on ML classification in cardiology. 2) Evaluate and categorize the selected literature based on eight factors: publication year, contribution type, empirical study type, medical data, ML techniques, medical task, heart pathology, and classification type.

The methodology to conduct this SMS is presented in Section 2, followed by results (Section 3), discussion of implications (Section 4), and conclusions with future directions (Section 5).

2 RESEARCH METHODOLOGY

The systematic mapping method proposed by Kitchenham and Charters (Kitchenham & Charters, 2007) is applied in this investigation. A mapping study, according to Kitchenham, tries to categorize research works in accordance with a set of predetermined criteria and discover the research trends associated with a certain topic (Kitchenham & al., 2010). The following five steps make up the utilized mapping process: defining the mapping questions, selecting studies, extracting data, summarizing data, and conducting a thorough search for candidate articles.

2.1 Mapping Questions

This mapping investigation resulted in the formulation of eight mapping questions (MQs). The MQs and their major motivating factors are listed in Table 1.

Table 1: Mapping questions.

ID	Mapping question	Motivation
MQ1	What are the years and venues of publication of the selected studies?	Track publication trends and venue
MQ2	What types of contributions were presented in the selected studies?	Analyze study impact on knowledge and practice advancement
MQ3	What research approaches did the selected studies adopt?	Categorize the research approaches that were used in the selected studies
MQ4	Which medical tasks received the most attention in the selected studies?	Identify the most studied cardiology tasks
MQ5	Which heart disease did the studies focus on?	Identify prevalent vs. less explored heart diseases
MQ6	What types of data were used to conduct experiments in the selected studies?	Analyze data type usage (requirements and limitations)
MQ7	What type of classification was used in the studies?	Identify the employed classification types
MQ8	What ML techniques were used in the selected studies?	Identify dominant ML techniques

2.2 Search Strategy

To identify relevant publications addressing the research questions in Table 1 on ML classification in cardiology, seven electronic databases were searched: IEEE Xplore, DBLP, ScienceDirect, ACM Digital Library, PubMed, Springer Link, and Google Scholar. These choices align with prior systematic reviews in this domain (Amazal & Idri, 2019; Idri & al., 2018; Idri & al., 2015; Kadi & al., 2017; Kadi & al., 2019).

The search focused on articles published between 1997 and December 2023, utilizing a comprehensive search string targeting titles, abstracts, and keywords. This strategy ensured inclusion of the most recent version of each study and avoided duplicates.

The entire search string set was created in the way that is described below.

((cardi* or heart* or vascular or arter* or coronary or myocardial) and (defect* or disease or failure or abnormal) and ("machine learning" or ML) and (classif*) and (model or method or technique or algorithm or rule or tool or framework or approach)).

The search strategy targeted relevant articles using titles, abstracts, and keywords in the aforementioned libraries. Only the most recent paper for each study was included, avoiding duplicates from various publication channels.

2.3 Study Selection

Inclusion and exclusion criteria were applied to identify relevant articles addressing the research questions in Table 1.

2.3.1 Inclusion Criteria

- Studies aiming to predict heart diseases using ML-based classification or to enhance that process
- Studies aiming to compare different techniques for predicting heart diseases using ML classifiers
- Papers on the detection of other diseases directly related to heart diseases (symptoms of a heart disease or causes)

2.3.2 Exclusion Criteria

- Papers that center on predicting a variety of diseases, alongside heart diseases
- Papers predicting potential heart disease symptoms without explicitly targeting heart disease detection
- Papers employing classification techniques exclusively for the purpose of feature selection
- Papers utilizing classification techniques unrelated to ML
- Duplicate publications (only the most complete version is included)
- Other Systematic Mapping Studies (SMS) or systematic literature reviews

Applying the previously described criteria, the candidate papers were assessed, which included an examination of their abstract, title, and in some cases, the entire content. Subsequently, they were categorized as either "included" or "excluded".

2.4 Data Extraction Strategy and Synthesis Method

The extraction of data from all selected publications addressed the research questions in Table 1. A standardized form (Table 2) guided this process. The extracted data were then analyzed for each question using a narrative synthesis approach, supplemented by relevant visuals (tables, graphs, etc.).

Table 2: Data extraction form.

Data Extractor
Paper Identifier
Author(s) Name(s)
Paper Title
(MQ1) Publication Year and Channel
(MQ2) Contribution Type (Tool, Algorithm, Model, Framework, Metric, Comparison, Validation, Other)
(MQ3) Research Approach (Solution Proposal , History-based Evaluation, Case Study, Theory, Experiment, Other)
(MQ4) Medical Task Assessed (Screening, Diagnosis, Treatment, Prognosis , Management, Monitoring)
(MQ5) Heart Disease Studied (Arrhythmia, Coronary Artery Disease, Cardiac Arrest, Myocardial Infarction, Dilated Cardiomyopathy, Valvular Heart Disease, Other)
(MQ6) Type of Data Used (Patient Medical Characteristics, Medical Images, Electronic Health Records, Physiological Signals, Wearable Devices Data, Other)
(MQ7) Type of Classification Used (Binary Classification, Multi-class Classification)
(MQ8) Machine Learning Techniques Utilized

3 RESULTS AND DISCUSSION

The findings of our mapping study in relation to the Table 1 questions are discussed in this section.

3.1 Overview of the Selected Studies

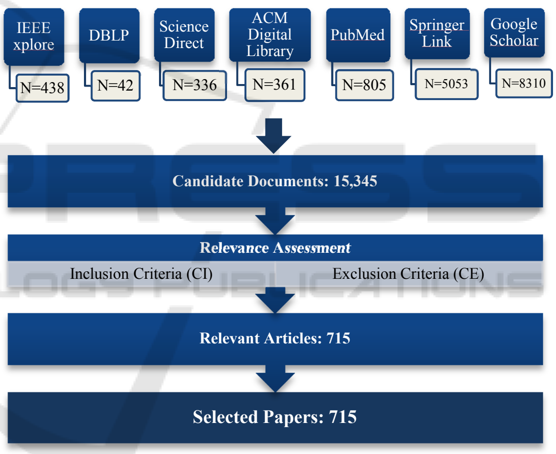

Figure 1: Overview of the selection process and its results.

The search across seven databases yielded 15,345 candidate publications (Figure 1). After applying inclusion/exclusion criteria and reviewing full texts, titles, abstracts, and keywords, 715 relevant studies were selected. Reference lists of included studies did not yield additional relevant publications.

3.2 Publication Trends and Venues (MQ1)

We examined how often ML classification appeared in cardiology studies over time (Figure 2). Publications rose steadily from 1997 to 2023. The jump after 2016 (93% of studies) suggests growing interest and use of ML in cardiology research.

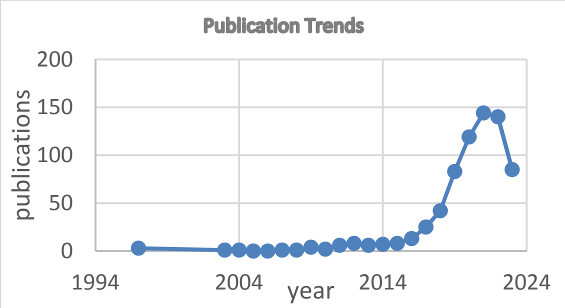

Figure 2: Publication trends of the selected studies.

Over half (57%) of the 715 studies were journal articles, while conferences presented 32%. The rest were chapters, symposia/workshops (each under 10%), and a single report (Figure 3). We found most journals on Google Scholar, PubMed, or SpringerLink, while conference papers were on IEEE Xplore or ACM Digital Library. Chapters were mainly on SpringerLink, and symposia/workshops and reports were found on ACM Digital Library and Google Scholar, respectively.

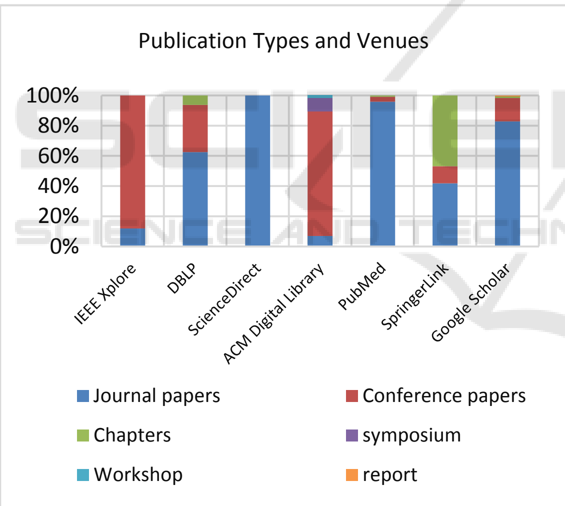

Figure 3: Publication sources and venues.

3.3 Contribution Types (MQ2) and Research Approaches (MQ3)

As depicted in Figure 4, the selected papers employed five primary research approaches: history-based evaluation, solution proposals, case studies, experiments, and surveys. Out of 715 studies, 693 were based on history-based evaluation, and 623 were solution proposals. In contrast, there were only 12 case studies, 5 experiments, and one survey.

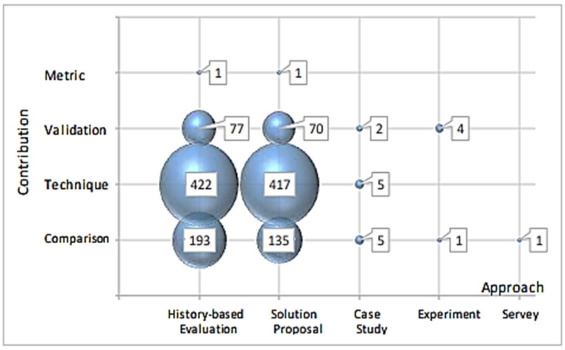

Figure 4: Research approaches used in the selected studies and their contribution types.

Most studies (around 61-67%) focused on developing new techniques, regardless of the research approach used (history-based evaluation, solution proposal, case study). Validation was the primary focus for experiments (80%) while case studies were more balanced between developing and comparing techniques (all around 40%). There were some overlaps, with studies often combining approaches (e.g., history-based evaluation and solution proposal) and contribution types (e.g., comparing and validating new techniques).

3.4 Medical Tasks (MQ4) and Heart Diseases Studied (MQ5)

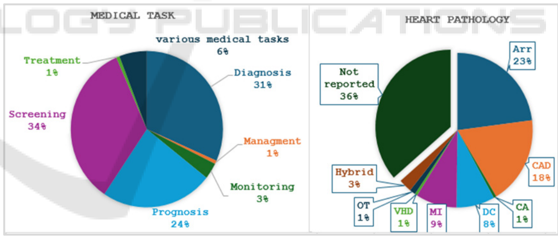

Figure 5: Medical tasks and heart pathologies studied.

Figure 5 shows that most research focused on screening (34%) and diagnosis (31%) of heart diseases, followed by prognosis (24%). Other tasks like monitoring, management or treatment were less common (5% total). Interestingly, some studies (6%) tackled multiple tasks simultaneously.

For heart conditions, a third (36%) didn't specify a particular type. Coronary artery disease (18%) and arrhythmias (23%) were the most studied, followed by myocardial infarction (9%) and dilated cardiomyopathy (8%). Less common conditions (3% total) included cardiac arrest (CA), valvular heart disease (VHD), and others. Some studies (3%) explored multiple conditions at once.

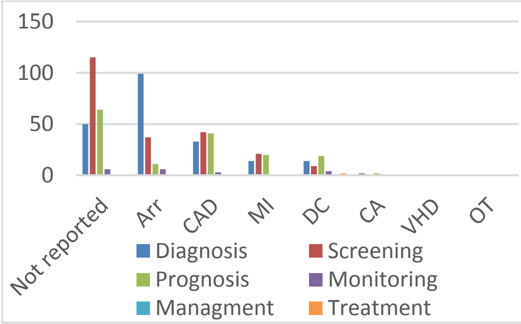

Figure 6: Medical task and heart pathology correlation.

As shown in Figure 6, studies concentrating on detecting arrhythmias primarily focused on the diagnosis task, aiming to identify specific types among various based on symptoms. For CAD, MI, and DC, the notable tasks associated with them were prognosis, diagnosis, and screening, each in close percentages.

Studies where heart pathologies were unspecified predominantly emphasized screening, reflecting uncertainty among professionals about the specific heart pathology they seek.

3.5 Types of Data Employed (MQ6)

The selected studies utilized various data types: physiological signals (29%), electronic health records (10%), patient characteristics (7.8%), medical images (6.4%), wearable data (0.6%), and others (1.8% - gene expression, voice recordings, etc.). While Table 3 focuses on single data types, table 4 focuses on studies combining different data types.

Table 3: Data types used in the selected studies.

Type of data	Description	# of studies
Physiological Signals (PhS)	Data from monitoring devices (heart rate, blood pressure, ECGs, etc.)	212
Electronic Health Records (EHR)	Digital patient records containing diagnoses, medications, lab results, etc.	73
Patient Medical Characteristics (PMC)	Demographic, medical history, lifestyle, and relevant health details	57
Medical Images (MI)	visual data from X-rays, MRIs, ultrasounds, CT scans	46
Wearable Devices data (WD)	Data from wearable technology monitoring activity metrics	4
Other types (OT)	Genetic data, omics data, or unspecified data type	13
Not reported	Refers to situations where the type of data used is not reported	17

Table 4 shows a trend towards combining data in arrhythmia research. A significant number of studies (175) combined electronic health records with patient characteristics. Medical images were frequently used with most data types. Wearable devices showed promise, with 17 studies combining their data with physiological signals and medical characteristics. Some studies even ventured into using three or four data types together. Importantly, physiological signals were the most used data, especially when studied alone, highlighting their significance in arrhythmia diagnosis.

Table 4: Data types combinations.

Data types combinations	# of studies
EHR+PMC	175
PMC+MI	14
PhS+MI	13
PhS+PMC	13
PhS+WD	13
EHR+MI	7
EHR+PhS	4
PMC+WD	4
EHR+PhS+PMC	23
EHR+MI+PMC	10
EHR+PhS+PMC+MI	2

3.6 Classification Approach (MQ7)

Figure 7 shows trends in heart disease classification. Binary classification, identifying presence or absence of any heart disease, dominates (65.73%, 470 studies). Multi-classification for specific disease type identification follows (28.67%, 205 studies). A small portion (2.94%, 21 studies) uses a hybrid approach for both presence and specific type. Notably, 2.65% (19 studies) lack classification details.

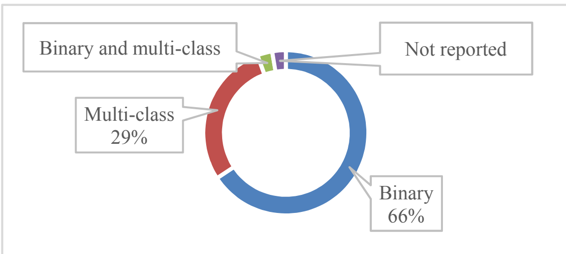

Figure 7: Classification approaches employed in the studies.

3.7 ML Techniques Used to Handle Heart Diseases (MQ8)

ML techniques usage in the selected studies revealed a predominance of multiple technique applications (75.62%) for comparison and model building, with some studies exploring up to 13 distinct techniques (Garg et al., 2022; Guo et al., 2023; Anton et al., 2021; Swathy et al., 2022). A smaller portion (23.92%) focused on a single technique, and a small minority (0.28%) developed entirely new algorithms.

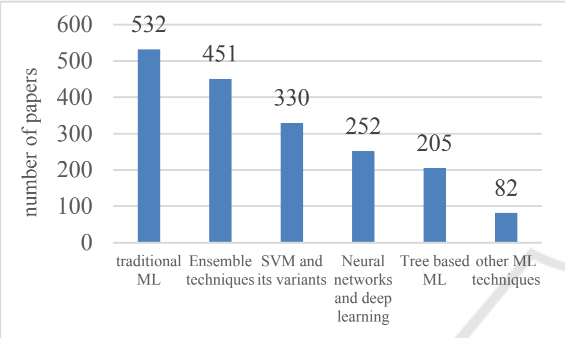

Figure 8: ML techniques used in the selected studies.

Figure 8 shows the use of several ML techniques in the selected studies. As can be seen, traditional ML models (74.4%) were the most common, followed by ensemble techniques (63.1%). Support Vector Machine (SVM) featured prominently (46.2%), while Neural Networks/Deep learning came fourth (35.2%). Other techniques were also used (e.g., tree-based methods: 28.7%). This variety highlights the widespread use of diverse ML approaches.

Similarly, Table 5 details the traditional ML techniques that were frequently used. KNN was the most applied (26%), followed by Logistic Regression (24.4%) and Naive Bayes (20.8%). K-Means and Genetic Algorithms were less frequent (2% and 3%).

Table 5: Traditional machine learning techniques.

Traditional ML models	# of papers	Total
KNN (k-Nearest Neighbours)	186	532
LR (Logistic Regression)	174	
NB (Naive Bayes)	149	
GA (Genetic Algorithm)	14	
K-means	13	

Table 6 showcases Random Forests as the most dominant ensemble technique (39.58%). XGBoost (10.07 %,) and AdaBoost (7.28%) followed at a distance. The inclusion of other techniques like CatBoost, Bagging, Voting, and Stacking highlights the variety of ensemble methods used in the research.

Table 6: Ensemble techniques.

Ensemble technique	# of papers	Total
RF	284	451
AdaBoost	52	
XGBoost	72	
Bagging/ Voting/ Stacking	32	
CatBoost	11	

Table 7 highlights SVM dominance (46%) in ML approaches. The classic SVM reigns supreme (95%), with minimal use of other variants (RBF-SVM: 1.54%, Quadratic SVM: 0.42%, and a few studies employing even less common variations).

Table 7: Support vector machines (SVM) and its variants.

Support vector machines (SVM) and its variants	# of papers	Total
SVM	312	330
RBF-SVM	11	
QSVM (Quadratic SVM)	3	
Incremental SVM/ SVM PEGASOS	2	
LSTSVM (Least Squares Twin SVM)/ KSVM (Kernel SVM)	2	

Table 8 showcases Artificial Neural Networks (ANNs) as the leading neural network technique (17.32%). Multi-Layer Perceptrons (MLPs) and Convolutional Neural Networks (CNNs) followed closely (7.52% and 6.84% respectively). While techniques like Deep Neural Networks (DNNs), Recurrent Neural Networks (RNNs), were less frequently present (combined total under 3.35%).

Table 8: Neural network and deep learning models.

Neural networks and deep learning models	# of papers	Total
ANN (Artificial Neural Networks)	124	252
MLP (Multi-Layer Perceptron)	54	
CNN (Convolutional Neural Network)	49	
DNN (Deep Neural Network)	14	
RNN (Recurrent Neural Network)	6	
Echo State Networks/ Bi branch network	2	
Layer-wise Quantized CNN/ EFCN (Efficient Fully Convolutional Network)	2	
Bi-LSTM (Bidirectional Long Short-Term Memory)	1	

Table 9 highlights Decision Trees (DT) as the dominant tree-based technique (22.38%). Decision tree variants like CART, C4.5, C5, J48, and J4.8 were employed in 5.73% of the studies. Notably, Extreme

Random Trees and Feature Ranking techniques (under 0.56%) were less frequent.

Table 9: Tree-based models.

Tree-based models	# of papers	Total
DT (decision tree)	160	205
CART	14	
C4.5 and C5	14	
J48 and J4.8	13	
ERT (Extreme Random Trees)	2	
FR (Feature Ranking)	2	

4 IMPLICATIONS FOR RESEARCH AND PRACTICE

This study examines the use of ML classification for cardiology, offering recommendations for researchers, cardiologists, and care units.

A key recommendation is for researchers to collaborate with practitioners on real-world case studies to bridge the gap between research and practical application.

The analysis also highlights a focus on ML for heart disease screening, diagnosis, and prognosis. Further research is needed for treatment, monitoring, and management tasks.

The study points to a dominance of physiological signals and electronic health records (EHR) data in current models. More exploration is encouraged for medical images, wearable device data, and standalone patient characteristics.

Finally, a gap is identified in the specific heart diseases studied. While arrhythmias and coronary artery disease (CAD) receive attention, many other conditions require further investigation.

5 CONCLUSION AND FUTURE WORK

This SMS explored the use of ML classification techniques in cardiology. Our analysis of 715 studies revealed that:

(MQ1): A surge in research interest, particularly after 2016, with journals as the main publication channel.

(MQ2 and MQ3): The publications primarily adopted solution proposal and history-based evaluation approaches. The main contributions were the development of new techniques, comparisons of existing ones, and their validation.

(MQ4) and (MQ5): The selected papers mainly focused on screening, diagnosis, and prognosis tasks. The heart disease handled is often not mentioned, and in some cases, the focus is on arrhythmias and CAD, leaving a research gap in other heart diseases and medical tasks, such as treatment.

(MQ6): Physiological signals and Electronic Health Records (EHR) were the main data types, highlighting the underutilization of other data types.

(MQ7): Binary classification, the dominant approach, was often linked to the screening task.

(MQ8): Traditional ML techniques were predominantly used in most studies, suggesting the need for researchers to investigate more innovative techniques for classification in cardiology.

REFERENCES

Almazroi, A. A., Aldhahri, E. A., Bashir, S., & Ashfaq, S. (2023). A Clinical Decision Support System for Heart Disease Prediction Using Deep Learning. *IEEE Access, 99, 1-1,* https://doi.org/10.1109/ACCESS.2023.328524.

Amazal, F. A., & Idri, A. (2019). Handling of categorical data in software development effort estimation: A systematic mapping study. *In Proceedings of the 2019 Federated Conference on Computer Science and Information Systems, FedCSIS 2019 (pp. 763–770).* https://doi.org/10.15439/2019F222.

Araki, T., et al. (2016, March). PCA-based Polling Strategy in Machine Learning Framework for Coronary Artery Disease Risk Assessment in Intravascular Ultrasound: A Link between Carotid and Coronary Grayscale Plaque Morphology. *Computer Methods and Programs in Biomedicine, 128(8).* https://doi.org/10.1016/j.cmpb.2016.02.004.

Aziz, F., et al. (2021, August). Short- and long-term mortality prediction after an acute ST-elevation myocardial infarction (STEMI) in Asians: A machine learning approach. PLoS ONE, 16(8), e0254894. https://doi.org/10.1371/journal.pone.0254894.

Chicco, D., & Jurman, G. (2020, February). Machine learning can predict survival of patients with heart failure from serum creatinine and ejection fraction alone. *BMC Medical Informatics and Decision Making*, 20(1). https://doi.org/10.1186/s12911-020-1023-5.

Collet, J.-P., et al. (2020, August). 2020 ESC Guidelines for the management of acute coronary syndromes in patients presenting without persistent ST-segment elevation. *European Heart Journal*, 42(14). https://doi.org/10.1093/eurheartj/ehaa575.

Dangare, C. S., & Apte, S. S. (2012, June). Improved study of heart disease prediction system using data mining classification techniques. *International Journal of Computer Applications*, 47(10), 44-48. https://doi.org/10.5120/7228-0076.

Dwivedi, A. K. (2018, May). Performance evaluation of different machine learning techniques for prediction of heart disease. *Neural Computing and Applications*. https://doi.org/10.1007/s00521-016-2604-1.

Esfandiari, N., et al. (2014, July). Knowledge discovery in medicine: Current issue and future trend. *Expert Systems with Applications*, 41(9), 4434–4463. https://doi.org/10.1016/j.eswa.2014.01.011.

Garg, P., Steen, J., & Mardon, A. A. (2022, February). An exhaustive comparative analytical study of 15 machine learning models for automated cardiovascular disease classification. *Paper presented at the 2021 4th International Conference on Recent Trends in Computer Science and Technology* (ICRTCST) https://doi.org/10.1109/ICRTCST54752.2022.9781828.

Guo, Y., et al. (2023, May). Machine learning-enhanced echocardiography for screening coronary artery disease. *BioMedical Engineering OnLine*, 22(1). https://doi.org/10.1186/s12938-023-01106-x.

Hassan, C. A. U., et al. (2022, September). Effectively predicting the presence of coronary heart disease using machine learning classifiers. *Sensors*, 22(19), 7227. https://doi.org/10.3390/s22197227.

Noh, K., Lee, H. G., Shon, H.-S., Lee, B. J., & Ryu, K. H. (2006, October). Associative classification approach for diagnosing cardiovascular disease. Intelligent Computing in Signal Processing and Pattern Recognition (pp. 721-727). *Lecture Notes in Control and Information Sciences*, 345. https://doi.org/10.1007/978-3-540-37258-5_82.

Sun, D.-W. (2008, January). Computer Vision Technology for Food Quality Evaluation. https://doi.org/10.1016/B978-0-12-373642-0.X5001-7.

Rahman, Q. A., et al. (2015, April). Utilizing ECG-Based Heartbeat Classification for Hypertrophic Cardiomyopathy Identification. IEEE *Transactions on Nanobioscience*, 14(5). https://doi.org/10.1109/TNB.2015.2426213.

Idri, A., Benhar, H., Fernández-Alemán, J. L., & Kadi, I. (2018, May). A systematic map of medical data preprocessing in knowledge discovery. *Computer Methods and Programs in Biomedicine*, 162. https://doi.org/10.1016/j.cmpb.2018.05.007.

Idri, A., Amazal, F. A., & Abran, A. (2014, August). Analogy-based software development effort estimation: A systematic mapping and review. *Information and Software Technology*, 58. https://doi.org/10.1016/j.infsof.2014.07.013.

Juhola, M., Joutsijoki, H., Penttinen, K., & Aalto-Setälä, K. (2018, June). Detection of genetic cardiac diseases by Ca2+ transient profiles using machine learning methods. *Scientific Reports*, 8(1). https://doi.org/10.1038/s41598-018-27695-5.

Kadi, I., Idri, A., & Fernandez-Aleman, J. L. (2017, January). Knowledge discovery in cardiology: A systematic literature review. *International Journal of Medical Informatics*, 97, 12-32. https://doi.org/10.1016/j.ijmedinf.2016.09.005.

Kadi, I., Idri, A., & Fernandez-Aleman, J. L. (2019, September). Systematic mapping study of data mining–based empirical studies in cardiology. *Health Informatics Journal*, 25(14), 146045821771763. https://doi.org/10.1177/1460458217717636.

Kitchenham, B., Budgen, D., & Brereton, P. (2010, January). The value of mapping studies: A participant-observer case study.

Kitchenham, B., Pearl, O., Budgen, D., Turner, M., Bailey, J., & Linkman, S. (2009, January). Systematic literature reviews in software engineering: A systematic literature review. *Information and Software Technology*, 51(1), 7-15. https://doi.org/10.1016/j.infsof.2008.09.009.

Puyol Anton, E., et al. (2021). Statistical Atlases and Computational Models of the Heart. M&Ms and EMIDEC Challenges 11th International Workshop, STACOM 2020, Held in Conjunction with MICCAI 2020, Lima, Peru, October 4, 2020, Revised Selected Papers. *Lecture Notes in Computer Science. Springer*. https://doi.org/10.1007/978-3-030-68107-4.

Seetharam, K., et al. (2022). Applications of Machine Learning in Cardiology. *Cardiology and Therapy*, 11(24). https://doi.org/10.1007/s40119-022-00273-7.

Smole, T., et al. (2021). A machine learning-based risk stratification model for ventricular tachycardia and heart failure in hypertrophic cardiomyopathy. *Computers in Biology and Medicine*, 135, 104648. https://doi.org/10.1016/j.compbiomed.2021.104648.

Swathy, M., & Saruladha, K. (2021). A comparative study of classification and prediction of Cardio-Vascular Diseases (CVD) using Machine Learning and Deep Learning techniques. *ICT Express*, 8(3). https://doi.org/10.1016/j.icte.2021.08.021.