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HEART ATTACK PREDICTION USING MACHINE LEARNING: A COMPREHENSIVE SYSTEMATIC REVIEW AND BIBLIOMETRIC ANALYSIS

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ABSTRACT

Studies on predicting heart attacks using Machine Learning demonstrate that there is a wide variety of algorithms and methodologies highlighting their impact on heart attack prediction. This can help in reducing the risk of lifestyle-related complications. To understand the current state of the art, a systematic literature review (SLR) was conducted from 2017 to 2021. A key step in this SLR was the search strategy, which identified 3,525 articles from various sources of information such as Taylor and Francis, IEEE Xplore, ARDI, ACM Digital Library, ProQuest, Wiley Online Library, and Microsoft Academic. Exclusion criteria were applied, such as articles older than five years, non-English articles, and papers not published in conferences or journals, to ensure only the most relevant studies were included, ultimately resulting in 82 articles. The findings from the systematic review focused predominantly on studies predicting heart attacks, detailing the best methodologies and algorithms used to enhance the accuracy of these predictions. The conclusions indicate that, despite different approaches, the articles exhibit common themes and objectives in achieving better heart attack predictions using Machine Learning.

Keywords: *Heart Attack Prediction, machine learning, cardiac problems, ML, cardiac disease, Systematic Literature Review*

1. INTRODUCTION

The early prediction of heart disease is crucial for saving patients' lives. Yet, there is a noticeable gap in understanding the progress made in employing machine learning for the effective prediction of heart attacks. This underscores the need for a system that can diagnose and predict heart disease early. Traditional invasive diagnostic methods for heart disease typically depend on the patient's medical history, physical examinations, and medical professionals' interpretations of physical symptoms [1]. Research has shown that classification and regression methodologies significantly enhance the accuracy of heart attack predictions in individuals. These studies also shed light on the limitations of other methodologies. Notably, Artificial Neural Networks have been instrumental in creating automated diagnostic systems for identifying heart valve diseases [21], [8]. Overall, the use of machine learning in predicting heart attacks is advancing well, with current methodologies and algorithms contributing to improved prediction accuracy.

Heart attack prediction using Machine Learning is a problem that requires attention for several fundamental reasons: High Prevalence of Heart Disease, Potential of Machine Learning, Limitations of Traditional Methods, Need to Improve Early Warning Systems, Challenges in Clinical Implementation, Gaps in Current Research, and Impact on Public Health Policy. For all these reasons, the research addresses a vital and highly relevant topic. The originality of this research lies in addressing crucial issues and analyzing the actual impact of Machine Learning on heart attack prediction, a topic not yet thoroughly explored. This study has succeeded in identifying deficiencies, gaps, and current trends in this field, thus providing a solid foundation for future research. Its main

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contribution is to offer a valuable guide for researchers interested in Machine Learning and heart attack prediction, as well as for professionals implementing this advanced technology, helping them to improve the efficiency of their work. Although there are still aspects to perfect, this study distinguishes itself from existing literature by covering specific research areas not previously addressed. These include the most productive authors, the criteria for measuring the effectiveness of heart attack prediction using Machine Learning, the most used Machine Learning algorithms, and the identification of keywords with the highest co-occurrence in the field.

The aim of this study is to understand the state of the art on Predicting Heart Attacks using Machine Learning. The study is divided into the following sections: Section II presents works related to the topic. Section III describes the methodology used for the present Systematic Literature Review, based on Kitchenham's guidelines [83] and the PRISMA diagram. Section IV presents the results and comparison with other authors to answer each research question. Finally, Section V presents the conclusions of the study and recommendations for future research.

2. BACKGROUND

During the Systematic Literature Review process, a consistent search technique was employed to identify articles and compare their findings. Despite this uniform approach, there were instances where the results did not precisely reflect the effectiveness of various algorithms and methodologies in enhancing the value of Machine Learning for heart attack prediction. Consequently, some research questions remained inadequately addressed. The focal point of these studies was to assess the impact of Machine Learning on heart attack prediction, with a particular emphasis on both descriptive and analytical research questions. The scope of the reviewed studies was from 2017 to 2021. Nevertheless, it is crucial to broaden the research scope to include studies from subsequent years, as this would provide a more comprehensive understanding and potentially more conclusive results.

In a separate analysis by B. I. Perry and colleagues [85], the age of participants was artificially increased to the mean age used in the original studies' algorithms. This was done to assess how age influences predictive accuracy. Their exploratory analysis showed that calibration graphs for three algorithms consistently underestimated cardiometabolic risk in younger participants. These findings suggest that current algorithms might not accurately assess risk in younger individuals, even when other high-risk factors are present. Therefore, it becomes necessary to either recalibrate existing algorithms or develop a new, tailored algorithm for this demographic.

On the other hand, D. Chicco and G. Jurman [86] applied various machine learning classifiers to predict patient survival and classify corresponding characteristics of the most important risk factors. This discovery has the potential to impact clinical practice and become a new supporting tool for doctors when predicting whether a patient with heart failure will survive or not. According to authors D. Mpanya, T. Celik, E. Klug, and H. Ntsinjana [87], clinical risk prediction is one of the strategies implemented for selecting high-risk patients and guiding therapy in heart failure. However, most predictive risk models have not been adequately integrated into the clinical environment. This is due in part to inherent limitations, such as creating risk prediction models using static clinical data that do not consider the dynamic nature of heart failure. Finally, the author [89] shows that the most addressed medical task by selected studies was diagnosis. Additionally, the most commonly adopted approaches by studies were empirical type based on experiments and evaluation-based research type. This mapping study aims to provide a deeper understanding of the application of ensemble classification methods in cardiovascular diseases. Most studies reported positive comments on the ability of ensemble methods to perform better than individual methods.

A significant contribution to this research was the use of the Mendeley program, which facilitated the classification of all collected articles for better organization. The application of search equations in various information sources also allowed for more precise finding of appropriate articles for the study. The application of exclusion and quality criteria helped determine which articles were suitable for analysis. Additionally, the graphs shown in the research questions results were generated with the help of the RAj research assistant developed by Dr. Javier Gamboa-Cruzado. It is important to note that this SLR was carried out with the aim of obtaining greater knowledge about the main studies related to the use of Machine Learning.

3. REVIEW METHOD

The methodology for the review was designed in accordance with the guidelines set forth

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by B. Kitchenham [83]. To implement this review method, the steps outlined in Figure 1 were followed.

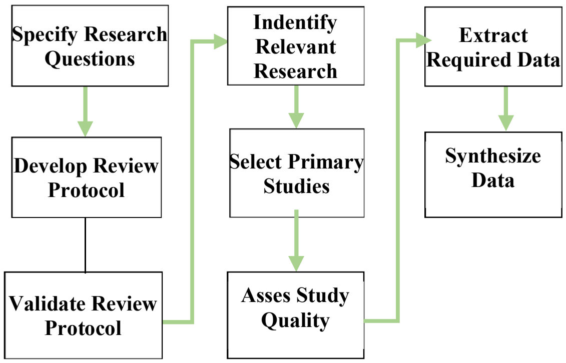

Figure 1: Description of SLR steps

3.1 Research Problems and Objectives

Research questions play a crucial role in the search, extraction, and analysis phases of data strategy, as they form an essential component at the outset of a systematic review. For this study, five research questions were formulated, each accompanied by its specific objectives. These questions and objectives are detailed in Table 1.

Table 1: Research Questions and Objectives.

Research Question	Research Objective
RQ1: Who are the most productive authors in research on Heart Attack Prediction using Machine Learning?	Identify the most productive authors in research on Heart Attack Prediction using Machine Learning.
RQ2: What methodologies are being used for Machine Learning development?	Detail the methodologies being used for the development of Machine Learning.
RQ3: What are the criteria for measuring the overall effectiveness of Heart Attack Prediction using Machine Learning?	Identify criteria that measure the overall effectiveness of Heart Attack Prediction using Machine Learning.
RQ4: What are the most commonly used algorithms for Machine Learning development?	Recognize the most used algorithms for the development of Machine Learning.
RQ5: What are the most used topics in research on the prediction of heart attacks using Machine Learning?	Determine the most used topics on Heart Attack Prediction using Machine Learning.

3.2 Search Sources and Search Strategies

The various search sources used for the study were: Taylor & Francis Online, IEEE Xplore, ARDI, ACM Digital Library, ProQuest, Wiley Online Library, and Microsoft Academic. The search strategies were developed based on the descriptors and their synonyms for each variable, as presented in Table 2.

Table 2: Search Descriptors.

Descriptor	Variable
Machine Learning	Independent
Heart disease prediction	Dependent
Prediction of heart attack	
Prediction of cardiac arrest	
Prediction of heart problems	
Heart Failure Prediction	

Regarding the search procedure, specific search equations were used for each information source, which are detailed in Table 3.

Table 3: Information sources and search equations.

Source	Search equation
Taylor & Francis Online	[[All: "machine learning"] OR [All: ml]] AND [[All: "heart disease prediction"] OR [All: "heart attack prediction"] OR [All: "cardiac arrest prediction"] OR [All: "heart problem prediction"] OR [All: "heart failure prediction"]]
IEEE Xplore	(("All Metadata":"machine learning" OR "All Metadata":ML) AND ("All Metadata":"heart disease prediction" OR "All Metadata":"heart attack prediction" OR "All Metadata":"cardiac arrest prediction" OR "All Metadata":"heart problem prediction" OR "All Metadata":"heart failure prediction")
ARDI	("machine learning" OR ML) AND ("heart disease prediction" OR "heart attack prediction" OR "cardiac arrest prediction" OR "heart problem prediction" OR "heart failure prediction")
ACM Digital Library	[[All: "machine learning"] OR [All: "ml"]] AND [[All: "heart disease prediction"] OR [All: "heart attack prediction"] OR [All: "cardiac arrest prediction"] OR [All: "heart problem prediction"] OR [All: "heart failure prediction"]]
ProQuest	("machine learning" OR ML) AND ("heart disease prediction" OR "heart attack prediction" OR "cardiac arrest prediction" OR "heart problem prediction" OR "heart failure prediction")

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Wiley Online Library	""machine learning" OR "ML"" anywhere and ""heart disease prediction" OR "heart attack prediction" OR "cardiac arrest prediction" OR "heart problem prediction" OR "heart failure prediction"" anywhere
Microsoft Academic	("machine learning" OR ML) AND ("heart disease prediction" OR "heart attack prediction" OR "cardiac arrest prediction" OR "heart problem prediction" OR "heart failure prediction")

3.3 Identified Studies

At the end of the article search, the results are shown in Figure 2.

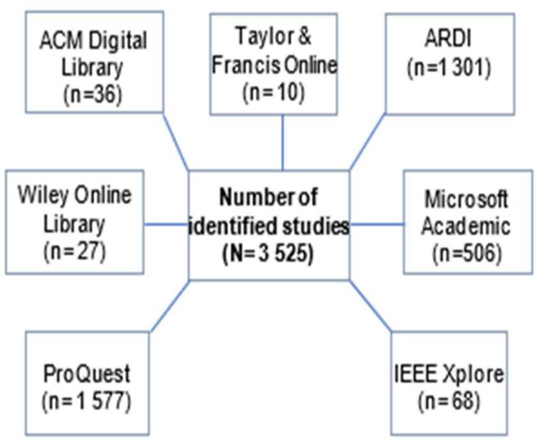

Figure 2: Number of identified studies

3.4 Selection Criteria

The exclusion criteria were meticulously established to ensure the removal of articles that did not fulfill the necessary requirements for the review. This was done to retain only those studies that were deemed relevant and useful for the analysis.

The criteria used are detailed below:
CE1: Articles are older than 5 years.
CE2: Articles are not written in English.
CE3: Articles are not published in conferences or journals.
CE4: Titles and keywords of articles are not very suitable.
CE5: Articles are not unique.
CE6: The abstract of articles is not very relevant.

3.5 Study Selection

The search was conducted using synonyms and keywords for each variable, which allowed obtaining a total of 3,525 articles for subsequent review. After applying the steps detailed in Figure 3, 82 articles were obtained as a result of this stage.

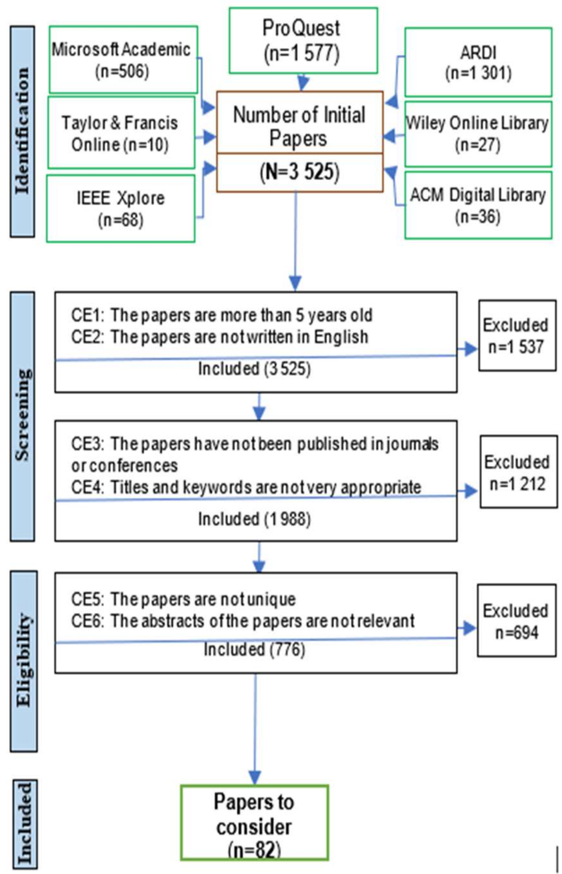

Figure 3: PRISMA flow chart

3.6 Quality Assessment

The quality assessment was conducted to ensure that the study findings could make a valuable contribution to the review. Seven quality assessment

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criteria (QAs) were identified to evaluate the quality of the articles found, which are as follows:

QA1. Are the research objectives clearly identified in the document?
QA2. Is the experiment performed adequate and acceptable?
QA3. Does the document explain the context in which the research was conducted?
QA4. Is the document well-organized?
QA5. Are the methods used to analyze the results appropriate?
QA6. Is the dataset used clearly identified?
QA7. Are the results of the experiments conducted clearly identified and reported?

Rigorous criteria were used for quality assessment, resulting in the retention of the 82 articles evaluated. This confirms that the reviewed articles met the established quality criteria. It should be noted that any disagreements during the evaluation process were resolved through discussion among the authors to determine the articles to be analyzed in the next stage of the study.

3.7 Data Extraction Strategies

In this stage, an exhaustive analysis of all the articles was conducted, enabling the extraction of pertinent information required to address the research questions. The key details extracted from each article encompassed various elements such as the article ID, title, URL, source, publication year, country of origin, page count, language, type of publication, name of the publication, list of authors, their affiliations, citation count, abstract, keywords, sample size, and other relevant data.

It is important to mention that not all articles helped answer all research questions; however, excellent overall results were obtained.

To efficiently extract and organize the data, the Mendeley program was used, as shown in Figure 4.

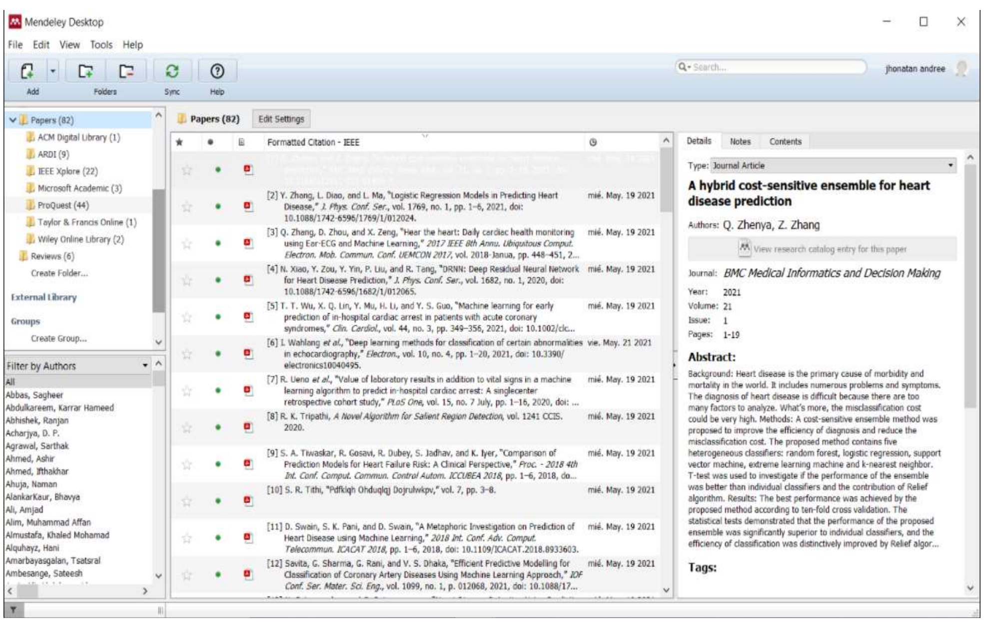

Figure 4: Document Management with Mendeley

3.8 Synthesis of Findings

During this stage, a precise search was conducted to find articles that could answer each of the research questions: RQ1-RQ6. Each study found contributed to obtaining a clear perspective on the different types of research related to the topic and was therefore fundamental to conducting a good study.

4. RESULTS AND DISCUSSION

4.1 General description of studies

The outcome of the study selection process culminated in the identification of 82 papers, which were then chosen for detailed analysis. These studies, as depicted in Figure 5, span publication years ranging from 2017 to 2021.

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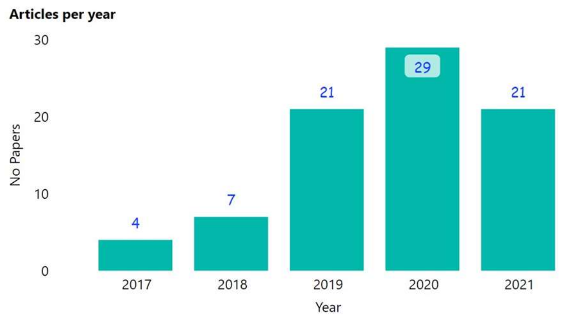

Figure 5: Papers published per year

Figure 6 shows the geographical distribution of the countries where the 82 selected papers were published. This information is important, as it allows researchers to identify the countries where most research in the field of predicting heart attacks using machine learning is being conducted. The countries with the highest number of studies are India with 24 (29.27%), the United Kingdom with 18 (21.95%), and the United States with 14 (17.07%).

Figure 6: Georeferential Map of Papers by Country

4.2 Answers to the Research Questions

This section meticulously presents the results acquired, enabling us to address each of the formulated research questions (RQs). Moreover, it includes comprehensive discussions pertaining to each of the findings obtained.

RQ1: Who are the most productive authors in research on Heart Attack Prediction using Machine Learning?

To answer this question, Table 4 was elaborated, which presents the distribution of the most productive authors in predicting heart attacks using Machine Learning. During the study selection process, a total of 82 valuable papers were obtained for data extraction and analysis.

Table 4: Most Productive Authors in Heart Attack Prediction Using Machine Learning.

Authors	2017	2018	2019	2020	2021	Total
Seyedamin Pouriyeh, Sara Vahid, Giovanna Sannino, Giu.	65	0	0	0	0	**65**
Maragatham G, Devi Shobana	0	0	34	0	0	**34**
Dogan Meeshanthini V, Grumbach Isabella M, Michaels.	0	27	0	0	0	**27**
Safdar Saima, Saad Zafar, Zafar Nadeem, Naurin Farood.	0	27		0	0	**27**
Nishant Gupta, Naman Ahuja, Shikhar Malhotra, Anju	25	0	0	0	0	**25**
Syed Muhammad Saqlain, Muhammad Sher, Faiz Ali Sh.	0	0	24	0	0	**24**
Carlo Ricciardi, Kyle J. Edmunds, Marco Recenti, Sigurdu.	0	0	0	19	0	**19**
Dimopoulos Alexandros C, Nikolaidou Mara, Francisco	0	13	0		0	**13**
Lal Hussain, Imtiaz Ahmed Awan, Aziz Wajid, Sharjil Sae.	0	0	0	13	0	**13**
Amanda H. Gonsalves, Fadi Thabtah, Rami Mustafa A. M.	0	0	10	0	0	**10**
Kauser Ahmed P., D. P. Acharjya	0	0		10	0	**10**
Li Fen, Liu Ming, Zhao Yuejin, Kong Lingqin, Dong Liqua.	0	0	10	0	0	**10**
Halil Ibrahim Blbl, Nese Usta, Musa Yildiz	9	0		0	0	**9**
Younas Khan, Usman Qamar, Nazish Yousaf, Aimal Khan	0	0	8	0	0	**8**

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Abderrahmane Ed-daoudy, Khalil Maalmi	0	0	7	0	0	**7**
Amin Ul Hag, Jianping Li, Muhammad Hammad Memon.	0	0	6	0	0	**6**
Ganesan, N.Sivakumar	0	0	6	0	0	**6**

It can be observed that Seyedamin Pouriyeh and Maragatham G. are the authors who have obtained the highest number of citations, with 65 and 34 respectively, suggesting that their research has been widely recognized and cited in the literature. The other authors have also made significant contributions in the field of predicting heart attacks using Machine Learning, although with fewer citations compared to the authors mentioned above. As pointed out by Rodrigo, G., Aledo, J. and Gámez, J. [88], the number of citations obtained by an author can be an indicator of the reach and relevance of their work in the field of study.

RQ2: What methodologies are being used for Machine Learning development?

In the review, eight Machine Learning methodologies for predicting heart attacks were identified, as shown in Table 5.

Table 5: Methodologies for Heart Attack Prediction Solutions using Machine Learning.

Methodology	**Reference**	**Qty. (%)**
Classification	[1] [2] [3] [4] [5] [6] [7] [8] [10] [12] [13] [14] [15] [16] [17] [18] [19] [20] [21] [22] [24] [25] [26] [27] [28] [29] [30] [31] [32] [33] [34] [35] [36] [37] [38] [39] [40] [41] [42] [43] [44] [45] [46] [47] [48] [49] [50] [53] [54] [56] [57] [58] [61] [62] [63] [64] [65] [67] [68] [69] [70] [71] [72] [74] [75] [76] [78] [79] [80] [81] [82]	71 (39)
Regression	[1] [2] [3] [4] [8] [9] [10] [11] [12] [13] [16] [17] [19] [20] [21] [23] [26] [27] [29] [31] [32] [33] [34] [35] [36] [37] [38] [42] [43] [44] [45] [47] [48] [49] [50] [51] [52] [53] [54] [55] [57] [58] [60] [61] [62] [63] [64] [65] [67] [68] [69] [70] [71] [72] [74] [75] [76] [78] [79] [80] [81] [82]	62 (34)
Artificial Neural Network	[3] [5] [18] [21] [23] [25] [26] [31] [32] [35] [41] [42] [47] [48] [53] [56] [58] [59] [61] [63] [66] [67] [68] [69] [71] [74] [78] [79]	28 (16)
Deep Learning	[8] [12] [14] [15] [18] [21] [23] [25] [26] [27] [36] [37] [40] [41] [42] [59] [63] [64] [66] [68] [75] [76] [79]	23 (13)
Group	[1] [4] [7] [11] [14] [24] [26] [29] [38] [81]	10 (6)
Dimensionality reduction	[4] [14] [26] [33] [47] [62] [64] [78]	8 (4)
ATTICA	[15]	1 (1)

Classification (39%) and Regression (34%) methodologies are the most relevant for predicting heart attacks, according to the evidence gathered from the reviews, as shown in Table 5. Although Artificial Neural Network is also widely used, its impact on predicting heart attacks is lower compared to Classification. In line with what authors Animesh Kumar Dubey and Kavita Choudhary [84] state, these methodologies allow for early prediction or diagnosis, thus increasing the chances of recovery from heart attacks that may occur.

RQ3: What are the criteria for measuring the overall effectiveness of Heart Attack Prediction using Machine Learning?

In this research, a series of criteria were identified to measure the effectiveness of machine learning, as shown in Table 6.

Table 6: Criteria for Measuring the Effectiveness of Heart Attack Prediction using Machine Learning.

Effectiveness criterion	**Reference**	**Qty. (%)**
Confusion matrix / Contingency table	[2] [3] [6] [8] [16] [18] [19] [21] [24] [27] [28] [30] [31] [42] [51] [62] [75] [77] [80]	19 (12)
PCA (Principal Component Analysis)	[1] [4] [14] [18] [31] [47] [50] [58] [62] [64] [71] [76] [78]	13 (8)
ROC (Receiver Operating Characteristic Curve)	[8] [12] [16] [17] [69]	5 (3)

AUC (Area under the roc curve)	[33] [54] [57] [79]	4 (3)
Accuracy Metric	[29]	1 (1)

It was found that Confusion Matrix (12%) and PCA (Principal Component Analysis) (8%) are the most commonly used criteria for measuring the effectiveness of machine learning. However, the other effectiveness criteria also showed good values, but with less precision.

Authors D. Mpanya, T. Celik, E. Klug, and H. Ntsinjana [87] mention that model performance is also evaluated with a confusion matrix, which allows for calculating accuracy, precision, recall, and specificity results to enable the prediction of heart attacks.

RQ4: What are the most commonly used algorithms for Machine Learning development?

Table 7 shows, in a detailed and clear manner, the most commonly used algorithms for developing Machine Learning.

Table 7: Algorithms for developing Machine Learning.

Algorithm	Reference	Qty. (%)
RNA (Red Neural Network)	[1] [2] [3] [4] [5] [7] [8] [12] [14] [18] [19] [21] [23] [25] [26] [27] [31] [32] [33] [34] [35] [36] [37] [38] [40] [41] [42] [43] [44] [46] [47] [48] [49] [50] [51] [53] [54] [55] [56] [58] [59] [60] [61] [62] [63] [64] [66] [67] [68] [69] [70] [71] [72] [74] [75] [76] [77] [78] [79] [80] [82]	61 (36)
Random Forest	[1] [2] [4] [6] [8] [10] [11] [12] [13] [14] [15] [16] [17] [21] [23] [24] [25] [31] [38] [40] [42] [43] [44] [46] [47] [48] [49] [50] [51] [53] [55] [56] [57] [58] [62] [64] [65] [68] [69] [72] [73] [74] [76] [77] [78] [79] [80] [81]	48 (28)
Decision Tree	[2] [3] [6] [8] [10] [13] [15] [21] [25] [29] [30] [31] [34] [38] [41] [42] [43] [44] [47] [48] [49] [51] [53] [56] [57] [58] [61] [62] [65] [72] [74] [75] [78] [81]	34 (20)
Naive Bayes classification	[1] [3] [9] [20] [21] [28] [31] [38] [44] [45] [46] [47] [48] [49] [53] [57] [61] [67] [68] [70] [72] [75] [77] [80] [81] [82]	26 (15)
Genetic algorithm	[1] [10] [14] [18] [21] [25] [26] [30] [31] [33] [34] [42] [43] [46] [49] [50] [51] [58] [59] [64] [68] [76] [78]	23 (15)
Support Vector Machines (SVM)	[7] [8] [12] [14] [15] [26] [29] [32] [33] [37] [44] [45] [48] [53] [57] [58] [70] [71] [74] [75] [79] [82]	22 (14)
MLP (Multilayer Perceptron)	[1] [8] [19] [26] [31] [37] [38] [42] [46] [47] [54] [56] [63] [64] [67] [68] [76] [78]	18 (11)
Gradient Boosting	[11] [13] [38] [42] [43] [62] [68] [72] [76] [79] [80]	11 (7)
Logistic regression	[70] [71] [72] [74] [76] [77] [78] [79] [80] [81] [82]	11 (7)
Adaboost	[7] [8] [24] [31] [42] [47] [49] [60] [62] [77]	10 (6)
KNN (k-nearest neighbors)	[1] [4] [15] [34] [45] [51] [67] [77]	8 (5)
XGboost	[7] [8] [13] [31] [33] [72] [76] [80]	8 (5)
Dimension Reduction	[4] [62]	2 (1)
LogitBoost	[42]	1 (1)
HellenicSCORE	[15]	1 (1)

The results show that the three most used Machine Learning algorithms are: Artificial Neural Network (36%), Random Forest (28%) and Decision Trees (20%), although the other algorithms also present very satisfactory results, they are not comparable to the Artificial Neural Network.

The authors Perry, B. I., Upthegrove, R., Crawford, O., Jang, S., Lau, E., McGill, I., Carver, E., Jones, P.B. and Khandaker, G. M. [85], endorse that the presented algorithms help to predict and resolve acute coronary syndrome, coronary artery disease, acute myocardial infarction and valvular heart disease.

RQ5: What are the most used topics in research on the prediction of heart attacks using Machine Learning?

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To answer this RQ, bigrams consisting of two words that appear together and form an idea were generated through natural language processing (NLP), as shown in Table 8, and trigrams consisting of three words that appear together are presented in Table 9.

Table 8: Paper Bigrams by Source.

Bigram	ACM	ARDI	IEEE Xplore	Microsoft Academic	Pro Quest	Taylor & Francis Online	Wiley Online Library	Total
machine learning	4	4	20	2	35	1	2	**68**
heart disease	3	4	22	3	19	1	2	**54**
neural network	4	2	10	1	25	0	1	**43**
data mining	4	3	11	2	11	0	1	**32**
decision tree	4	1	11	1	14	0	1	**32**
random forest	2	4	10	0	13	0	1	**30**
support vector	2	1	13	1	12	0	1	**30**
logistic regression	1	2	8	0	17	0	0	**28**
blood pressure	2	1	4	1	15	1	0	**24**
heart diseases	0	2	10	2	9	0	0	**23**
feature selection	2	0	6	1	11	0	1	**21**
vector machine	2	1	9	1	7	0	0	**20**
decision trees	1	1	7	0	8	0	0	**17**
naive bayes	1	1	7	0	7	0	1	**17**
…	**….**	**….**	**….**	**….**	**….**	**….**	**….**	**…**
Total	**230**	**162**	**983**	**131**	**2018**	**45**	**77**	**3646**

Table 8 shows that the concept of "machine learning" is the most used with a total of 68 mentions, followed by "heart disease" with a total of 54 mentions found in papers from different sources of information.

Table 9: Paper Trigrams per Year.

Trigram	2017	2018	2019	2020	2021	Total
Support vector machine	2	2	9	11	3	**27**
Machine learning algorithms	1	1	4	5	6	**17**
Machine learning techniques	1	3	2	5	4	**15**
Heart disease prediction	1	1	4	4	4	**14**
Heart disease dataset	1	0	4	5	1	**12**
Vector machine svm	2	0	5	3	1	**12**
Data mining techniques	1	0	2	5	2	**11**
Coronary heart disease	0	0	2	4	4	**10**
Heart disease diagnosis	0	1	3	3	2	**9**
Cleveland heart disease	1	1	1	4	1	**8**
Artificial neural network	0	1	2	4	0	**7**
convolutional neural network	0	1	1	2	2	**6**
Coronary artery disease	0	2	1	3	0	**6**
Recurrent neural network	0	0	1	4	0	**5**
Disease prediction system	0	0	3	0	1	**4**
Heart disease using	0	0	1	2	1	**4**
….	**….**	**….**	**….**	**….**	**….**	**….**
Total	**77**	**193**	**309**	**683**	**374**	**1636**

Regarding the most used concepts in papers from the last five years, it is highlighted that the trigram "support vector machine" is the most recurrent with a total of 27 mentions, followed by "machine learning algorithms" with 17 mentions. These results coincide with what is stated by authors D. Chicco and G. Jurman [86], who also highlight the relevance of concepts such as "Machine Learning" and "Support Vector Machine" in their research on the prediction of heart attacks.

5. CONCLUSIONS

This research was founded on an extensive systematic and bibliometric review aimed at underscoring and tackling issues associated with predicting heart attacks through Machine Learning. A total of 82 pertinent articles, spanning from 2017 to 2021, were identified to address both descriptive and analytical research questions (RQs). Notably, this study is among the first to employ bibliometric networks to respond to the research questions in this specific area of study. An in-depth analysis was carried out to pinpoint the articles that significantly contribute to heart attack prediction using Machine Learning techniques. In investigating the questions raised in this systematic review on the prediction of heart attacks using machine learning, significant results were obtained. For the first research question (RQ1), focused on identifying the most influential authors, Seyedamin Pouriyeh and Maragatham G. stand out as the most cited, with 65 and 34 citations respectively. In relation to the second question (RQ2), which examined the methodologies used in the studies, it was found that classification (39%) and regression (34%) approaches are predominant in the field of heart attack prediction. Artificial Neural Network is also frequent, although with a lesser impact compared to classification. For the third question (RQ3), which analyzed the criteria to evaluate the overall effectiveness of machine learning in predicting heart attacks, it was found that the Confusion Matrix and Principal Component Analysis (PCA) are the most used. Although other effectiveness criteria showed positive results, they did not reach the same level of precision. Regarding the fourth question (RQ4), which inquired about the most used algorithms in machine learning, it was observed that the Artificial Neural Network, Random Forest, and Decision Trees are the most used. While other algorithms also provided satisfactory results, they do not compare to the Artificial Neural Network. Finally, the sixth question (RQ6) focused on identifying the most concurrent keywords in studies on the prediction of heart attacks using machine learning. Through a bibliometric analysis, four key combinations were identified: "machine learning" with "heart disease" in 22 articles, "heart disease" with "machine learning" in 8 articles, "heart disease" with "data mining" in 7 articles, and "machine learning" with "random forest" in 6 articles. These results highlight the most relevant trends and approaches in the field.

Nonetheless, this systematic literature review has certain limitations that ought to be considered in subsequent research efforts. One such limitation is the selection of search sources, which yielded a restricted number of articles on the topic. To gain a more comprehensive perspective, it is advisable to encompass studies spanning a broader range of years. Additionally, researchers are advised to incorporate bibliometric network graphs in addressing their research questions, as this approach can yield more accurate and detailed results.

Despite the comprehensive analysis performed, this study is limited to articles published between 2017 and 2021 and uses specific search sources, which could have restricted the scope of the findings. Therefore, a relevant question for future research would be: how do approaches and results in heart attack prediction using Machine Learning vary when including studies from a wider temporal range and accessing a more diverse variety of publication sources? This question would allow us to explore whether the trends and methodologies identified in this study hold or change significantly with a larger and more varied body of research.

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