Use of Artificial Intelligence in Cardiology: Where Are We in Africa?

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Abstract. Cardiovascular diseases are the leading cause of death. Their inherent silent nature makes them often challenging to detect very early. The management of these diseases also requires many resources. Meanwhile, Artificial Intelligence (AI) in cardiology has recently showed its ability to fill the gap. Indeed, several scoring methods and prediction models have been developed to understand the different aspects of these pathologies. The purpose of this paper is to review the state-of-the-art of the use of AI and digital technologies in cardiology in developing countries and to see the place of Africa. We have conducted a bibliometric analysis with 222 papers and an in-depth study on 26 papers using real and local databases. The words arrhythmia, cardiovascular disease, deep learning, and machine learning come up most often. Support vector machine algorithms, decision tree-based assemblers, and convolutional neural networks are more used. Among the 26 papers studied, only one comes from Africa, 24 from Asia, and one is a joint work between researches from Uganda and Brazil. The results show that countries using these AI-based methods often have accessible health databases, and collaborations between health specialists and universities are frequent. The finding of the African studies is that they focused, in most instances, on medical research to find risk factors or statistics on the epidemiology of heart disease.

Keywords: Artificial Intelligence · Cardiology · Cardio-vascular disease · Algorithm · Machine Learning · Africa

1 Introduction

Cardiovascular diseases (CVDs) are the leading cause of death in the world, according to the World Health Organization (in short, WHO). Approximately,

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17, 7 million of deaths are due to cardiovascular diseases, which represents 31% of total world mortality. Among the 17 million of dead persons whose age is under 70 and caused by non-communicable diseases, 82% occur in low- and middle-income countries while 37% are imputed to cardiovascular diseases [6]. Several risk factors, e.g. sedentary lifestyle, high cholesterol, obesity, hypertension, etc., can cause this high prevalence of CVDs worldwide. Prevention and early treatment are necessary to better fight against complications related to cardiovascular diseases. For instance, technology is currently used in the medical field for the prevention of stroke. In this direction, a real progress has been made in the fields of theoretical and applied research on cardiovascular diseases and particularly the application of Artificial Intelligence (AI) in developing countries like Asia ones. Indeed, AI techniques are used in several countries for the understanding, prevention, and management of stroke. Such existing techniques are often built on machine learning models allowing the prediction with a high accuracy of a cardiovascular anomaly.

In practice, notable advances are also noted in the medical field with intelligent systems such as the one implemented in a cardiology department in the Netherlands, which allows not only the consultation of statistics on interventions and aortic valve operations in the past but also the risks of surgeries. Another example of an invention that targets the prediction of the dangers of cardiac arrhythmia called Torsade de Pointes [12] has been set up by a collaboration between IRD ("Institut pour la Recherche et le Développement Français"), Sorbonne University and AP-HP ("Assistance Publique – Hôpitaux de Paris"), and DeepECG4U. At last, the Volta medical company in Marseilles envisioned setting up Artificial Intelligence to predict the most severe forms of atrial fibrillation [40].

Unfortunately, in Africa, it isn't easy to access reliable socio-demographic and clinical data to help better understand and prevent CVDs. According to [1], the disease is not considered as a public health problem in the African continent despite its increasing mortality and morbidity rates. The WHO provides guidelines for diagnosing cardiovascular diseases [30] however, there are still disparities in managing the diseases in low-income countries. This paper provides an in-depth review of the progress made in developing countries regarding the use of AI to tackle CVD issues. This review helps us identify and present the barriers to the effective use of AI for better management and prevention of CVDs in African countries. We propose answers to the following open question: *how can we do in Africa to have reliable, available, and exploitable health databases to propose intelligent systems that can be adapted and allow remote management?*

The rest of this paper is organized as follows. Firstly, Sect. 2 describes the methodology used for collecting the most relevant research papers and details the proposed multi-dimensional review of the state-of-the-art of the current studies about CVDs and AI with the purpose to gain more insights into risk factors and specific diseases. We also review the AI models and their performance measures regarding the pathology of interest and used data sources. Then, Sect. 3 discusses the limitations of the existing African studies regarding the state of the art in the rest of the world.

2 Multi-dimensional Data Profiling Framework

To motivate the relevancy of our study, we refer the readers to a recent survey in [2] about research works worldwide on cardiovascular diseases and the use of AI. In our framework, we first perform a typical bibliometric analysis with 222 papers before restricting ourselves to a subset of this latter selected based on the database provenance (see Fig. 1). We then proceed to an in-deep analysis by considering various aspects related to CVD challenges and AI.

2.1 Targeted Data Collection

Considering that we aim to illustrate through this review that there is a need to perform an analysis of the state-of-the-art from diverse areas and see where Africa stands on the application of AI in cardiology compared to other continents, we have targeted different research papers with topics covering the development of an intelligent system for cardiology. We have searched for studies performed in developing countries according to the list available on the website `DonnéesMondiales.com`[1], in combination with the keywords ("cardiovascular disease" OR "heart disease") AND ("Artificial intelligence" OR "machine learning") on `PubMed` and `ScienceDirect` from 2000 to 2020. This process results in 3713 records, out of which several filters were applied, as summed up in Fig. 1, after removing the duplicates.

2.2 Filtering Out the Most Relevant Research Papers

We started by eliminating the papers not related to cardiovascular diseases, and the papers that did not exploit databases from the target areas. Then we conducted our in-deep analysis of the 26 remaining papers, 16 from `PubMed` and 10 from `ScienceDirect`. We also looked at sources like IEEE, which allowed us to find other papers on research about cardiology in Africa.

2.3 Multi Dimensional Analysis of the Literature

In this section, we introduce and detail a multi-dimensional analysis approach of the existing research studies about the use of AI and digital technologies for CVDs worldwide and a focus on Africa. We start by presenting a common bibliometrics analysis.

Basic Bibliometrircs Analysis. `VOSviewer` is free software that facilitates visualizing information about newspapers, scientific papers, etc. It allows analysis of co-occurrences with titles, keywords, or authors. `VOSviewer` helps us generate maps of the most frequent terms. We consider only the keywords that appear at least 5 times and obtained results depicted in Fig. 2(a). The expression "deep learning" has 16 occurrences and "machine learning" 15 with the same

[1] https://www.donneesmondiales.com/pays-voie-developpement.php.

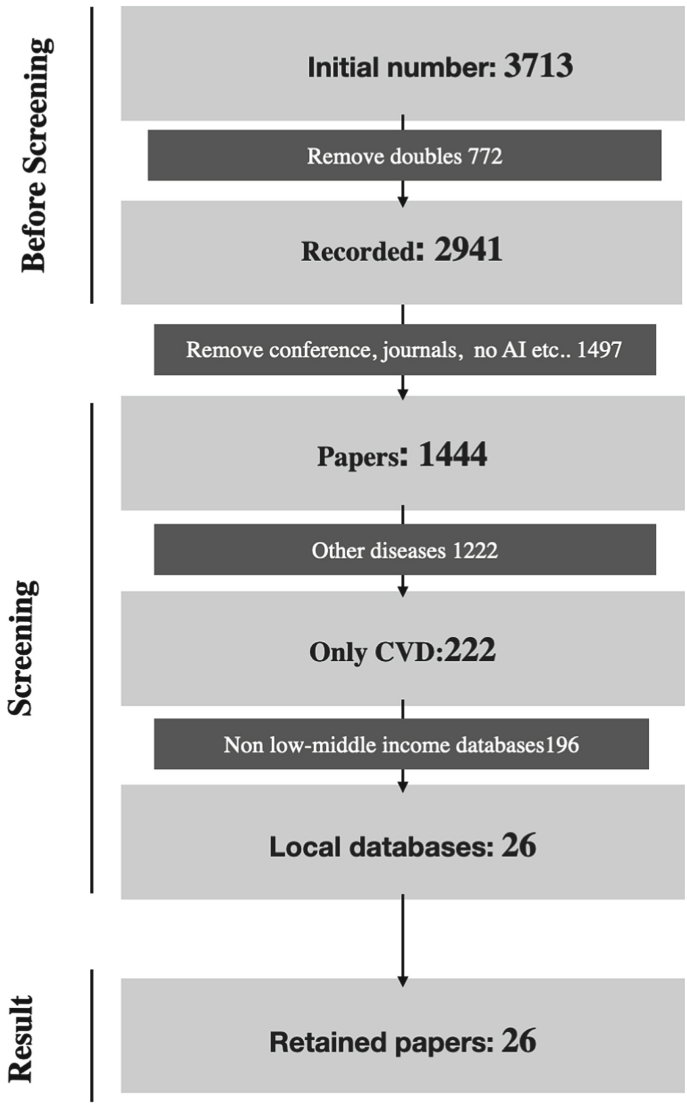
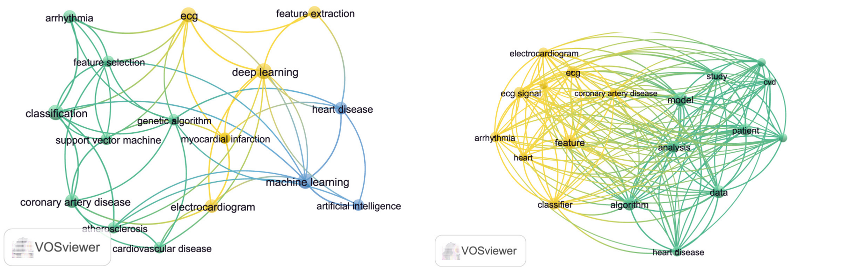


Fig. 1. Methodology of collection of the relevant research papers

total link strength 8. The word "classification" appears 15 times, "ecg" 13 times. For diseases, "coronary artery disease" appears 10 times with a full link strength of 8 followed by "arrhythmia" which appears 8 times with a total link strength of 6. The only machine learning model appears is "support vector machine" with occurrences 6.

A co-occurrence analysis performed on the 222 papers on titles and abstracts resulted in the most frequent terms with a minimum number of occurrences of 25. 32 terms are concerned, but 19 are retained as being part of the 60% most relevant. In Fig. 2(b), two clusters are formed: the green cluster concerns mainly the models, the data counts 10 terms, while the yellow cluster is formed by the pathology and counts 9 terms.



(a) Analysis of the co-occurrence terms based on the keywords

(b) Analysis of the co-occurrence terms based on abstract and title

Fig. 2. Results of the bibliometric analysis (Color figure online)

In-Depth Analysis. To go further than the common bibliometrics analysis of the state-of-the-art, we propose an in-depth analysis of the 26 selected papers to have a deeper insight into the most studied CVDs using AI, common risk factors, developed algorithms, and their performance measures.

Research on Specific CVDs Using AI. Table 1 presents the list of diseases studied on the 26 papers selected. We notice that *arrhythmia* is the most studied pathology using machine learning methods. Nearby come *heart failure* and *stroke* with machine learning and deep learning, respectively for the most AI method used.

In more developed countries, other disorders may be the priorities for their populations. For example, atherosclerosis, left ventricular hypertrophy [36], atrial fibrillation [38], coronary artery disease, deep vein thrombosis, abdominal aortic aneurysm, and type 2 diabetes [32] have already been predicted thanks to machine learning or deep-learning models. This proves that each region will have to perform studies on local data to know the top priorities for its population and thus propose solutions in accordance. This raises the following question: *what is the most urgent pathology to study using AI in Africa?*

Research on Risk Factors Using AI. Cardiovascular diseases are often difficult to diagnose in time and can have disastrous consequences (e.g., death or physical handicap). They may have already altered some of the body's functionality when detected late. Knowing the risk factors that cause these complications can help prevent and detect them earlier. Studies have been conducted to this end, in different areas and in different population samples. The studies about the factors that can promote or increase the risk of CVDs will help know which

Table 1. Heart diseases with common used AI methods

Pathologies	Methods		References
	Machine learning	Deep Learning	
Arrhythmia	4	2	[10,13,25,28,42,45]
Heart failure	3	2	[9,17,19,39,46]
Stroke	2	3	[5,11,15,20,44]
Cardiac disease	3	1	[7,31,35,37]
Rheumatic heart disease	–	1	[22]
Coronary Disease	–	1	[21]
Left ventricular dysfunction	–	1	[8]
Valvular heart disease	1	–	[33]
Peripheral arterial disease	1	–	[16]

factors are most considered or neglected in the research related to CVDs. Risk factors can be discovered by exploring comorbidity or physiological factors. To distinguish sick patients from healthy ones, factors such as renal insufficiency and hyper-coagulation are crucial [3]. Gender can also be a parameter that helps to understand the treatment of CVDs [41] compared to the country's income level. The standard of living can have an impact that promotes cardiovascular disease. In low-income countries, populations do not always have access to primary health care, so getting the information needed to prevent cardiovascular diseases is often difficult.

The social level must be considered for middle or low-income countries, e.g. those in sub-Saharan Africa do not necessarily have the same factors as other areas [47]. Changes in risk factors in middle and low-income countries can be due to urbanization or an adaptation to new lifestyle habits. It has been proven that it is essential to know that considering social and family factors is necessary because it can improve the management of patients [43] based on a risk score developed and compared to the Framingham score. Most of the research studies are epidemiological regarding the results obtained in Africa in this direction [18]. The socio-economic level, poor oral hygiene, and morbid associations are factors favoring arrhythmia according to [14], who finds that the socio-economic status is low in 14 cases (82.3%) of the 17 patients and poor oral hygiene in 14 cases $(93,3\%)$ out of 15 patients examined. When we consider the research for risk factors in Africa compared to other areas, we realize that the methods used are quite different. Some developing countries, such as China and India have available databases that facilitate this task, whereas, in Africa, the first obstacle is the availability of the required data. Indeed, there are few health structures with computerized equipment for managing CVDs.

Machine Learning and Deep Learning Models. AI is used in cardiology worldwide, and developing countries have integrated it well in managing cardiovascular diseases over the last 20 years. Classification, prediction, and data mining are some techniques that allow better management and understanding of some pathologies. To construct models, one needs input data. Table 2 shows that most studies used data from hospitals in the concerned countries or national registries. For machine learning models, algorithms based on decision trees: Random forest [33], gradient boosting tree [17,28] and Support Vector Machine [7,16,29] are the most used algorithms. We also observe the use of the multi-marker algorithm [46] and the sparse decomposition algorithm [25]. Convolutional neural networks are widely used for deep learning algorithms. New algorithms set up for mortality with a deep learning algorithm that predicts mortality due to acute heart failure [19]. Adaptive Neural Fuzzy Inference System (ANFIS) is built for the identification of Congenital Heart Disease or Defect (CHD) [37]. Regarding the results in Table 2, we may note that these new algorithms do not perform better than others based on standard algorithms.

Several performance measures have been used to evaluate the models' performance. The accuracy in evaluating the correctness of the model allows having a percentage of good prediction. The sensitivity measures the true positive rate of the model: the higher it is, the better the model predicts for sick subjects. The specificity measures ate of true negatives to identify the subjects who are not sick: the higher it is, the more the model can make a good prediction for patients who do not have the disease. The metrics AUC (Area Under the Curve), F1 score, precision, or the Kappa are also used.

The Case of Africa. The application of AI in health requires the availability of reliable and up-to-date data. One of the main research challenges regarding the application of artificial intelligence in Africa remains the lack of data. Indeed, IT tools are poorly integrated into hospital management, and data collection is not done regularly, leading to a lack of work on AI and health. In a systematic review of 451 references between 2012 and 2015 [2], categorized by country, research on machine learning and heart disease, no African country appeared in the results. Africa, with its lack of health facilities and adequate care [24], should be at the forefront of AI and health research to prevent, help diagnose, and provide early care and monitor patients in areas without such structures. Information about cardiovascular diseases in Africa is mostly from prospective studies conducted by medical teams Table 3. In the study done by Diouf et al. [34] for understanding comatose stroke and evaluating the survival of patients, the results show that coma is the leading disease and the first cause of death in neurology in Dakar. The study was conducted between 2006 and 2007 in the neuroanimation department of CHU Fann in Dakar on 105 patients admitted to the department. The results show that mortality is estimated at 82.9%, survival of 71 days, and survival at day 90 is 9.5%. The mean age was 61.914.2 years. The study also shows that ischemic strokes accounted for 51.4% and hemorrhagic strokes for 48.6%. People between 61 and 70 years of age were most at risk with 40% of cases. On the other hand, people coming from their homes represent the largest proportion of cases with 38.1%, which may be due to late detection or management [14].

Table 2. Different studies from middle low-income countries about CVDs

Type of Model	Reference	Algorithm	Performance of the model								Studied anomalies
			Acc (%)	Se (%)	Sp (%)	Re (%)	Pr (%)	F1	Ka	AUC	
Machine Learning	[42]	Lasso-logistic model	–	–	–	–	–	–	–	0.905–0.867	Malignant arrhythmia
	[29]	Co-SVM	–	–	–	–	–	0.723	–	–	–
	[17]	Gradient boosting	–	–	–	89	90	–	–	–	Heart failure
	[39]	model	–	–	–	93.28	94.12	0.9370	–		Heart failure
	[46]	Multi-marker model	–	94.4	90.3	–	–	–	–	0.956	Heart failure
	[11]	gradient boosted trees	76–80	76–67	76–81	–	–	–	–	–	Stroke
	[20]	model	–	–	–	99.92	97.33	–	–	99.94	Stroke
	[13]	CatBoost	99	99.17	99.25	–	–	0.99	–	–	Heart Rate
	[7]	SVM (linear)	95.40	92.70	–	–	–	–	–	–	Myocardial Infarction
	[33]	Random Forest	96.34	99.38	–	–	–	–	–	–	Valvular Heart Diseases
	[35]	Classification and regression tree (CART)	–	–	–	92	96	0.94	–	–	Cardiac disease
	[31]	Logistic Regression	85.2	81.3	859.	–	31.7	0.456	–	0.836	Cardiac disease
	[16]	SVM	96.36–97.91	–	–	–	–	–	0.91–0.96	–	Peripheral arterial disease
	[25]	Sparse decomposition algorithm	93.27 2.78	91.27,	93.46	–	–	–	–	–	Arrhythmia
	[28]	Gradient Boosting Tree	70.00 7.82	–	–	–	–	–	–	0.767 0.08	Heart rate
Deep Learning	[19]	Deep-learning-based artificial intelligence algorithm for predicting mortality of AHF	–	–	–	–	–	–	–	0,782–0,813	Acute heart failure
	[8]	–	–	72.1–86.9	88.0–89.6	–	–	–	–	0.94	Left ventricular dysfunction
	[9]	Deep convolutional neural network	74.29–93.94	–	–	–	–	–	–	–	Acute left heart failure
	[22]	3D convolutional neural network	72.77	–	–	–	–	–	–	–	Rheumatic heart disease
	[45]	Fast CNN	96.24	97.96	–	–	–	0.9807	–	–	Arrhythmia
	[10]	Neural network model	–	–	–	–	–	0.84	–	–	Cardiac Arrhythmia
	[44]	Deep learning algorithm-based Computed Tomography Perfusion	–	93.66	96.18	–	–	0.84	–	–	Acute Ischemic Stroke
	[21]	BioBERT (bidirectional encoder representations from transformers for biomedical text mining)	–	–	–	–	–	–	–	0.822–0.858	Coronary insufficiency
	[5]	Neural network	92.4	93.7	–	–	–	–	–	–	Acute ischemic stroke
	[37]	Adaptive Neuro Fuzzy Inference System (ANFIS)	84.4	96.7	82.3	–	–	0.9673	–	–	Truncus Arteriosus congenital heart defect
	[15]	Convolutional neural network	98.77–93.33	–	–	–	–	–	–	–	Stroke

Table 3. Heart diseases studies in Africa

Reference	Focus of the study	Research Type	Disease of Interest	Year of the study
[23]	Recommendation	Survey	–	2001
[34]	Prevention	Prospective study	comatose stroke	2008
[24]	Recommendation	Survey	–	2010
[1]	Risk factors	Survey	–	2010
[26]	Risk factors	Case control study	–	2021

3 Discussion

Regarding research and studies on this subject, it is not always easy to find concrete results that integrate health personnel and researchers in informatics or AI in Africa. Nevertheless, publications concerning African countries are available to all and can serve as a lever to improve the management and prevention of CVDs. While the strategies for management and prevention of stroke are far from reaching the goals when considering the burden of the disease, we can see in Table 3 that most of the studies conducted in Africa are medical or retrospective studies. There is therefore a lack of investigations in the digital domain concerning the prevention, diagnosis, and management of CVDs. It is necessary to find early management strategies but also to introduce solutions to allow a remote follow-up of patients. To achieve this, it is necessary to include new technologies in the management and prevention of CVDs, as pointed out by [1], who believe that modern information and communication techniques should be used to develop telemedicine. According to [4], there is a need for Africa to connect cardiology. A significant part of the research related to CVDs is the recommendation aspect, which allows us to know the concepts to consider before jumping in, whether it is about prevention, treatment, management, or behaviors to adopt when in doubt. WHO believes that "People with heart disease or at high risk of heart disease (due to the presence of one or more risk factors such as hypertension, diabetes, hyperlipidemia, or existing disease) require early detection and management, including psychological support and medication, as appropriate" [6]. In the management component, some risk factors may be overlooked or not considered at all. Several other aspects, such as living conditions or access to health care, must also be taken considered because each population, depending on its diversity, may react differently to the risks of cardiovascular disease. Mosca et al. suggest conducting essays based exclusively on women and limited to studies of unique or predominantly female conditions, consideration of gender-specific living conditions and publication of gender-specific analyses to reduce the prevalence gap [27]. Research is being conducted to facilitate management and to better understand the disease. Indeed, studies must be conducted on the methodologies used for the management of CVDs and comparisons by introducing factors that have often been neglected. Asian countries are well ahead in the use of AI for cardiology. In Table 1, all the research mentioned comes from there except one that comes from Tunisia and another one from Brazil and Uganda, so it is normal to ask ourselves what is slowing down countries like us from getting involved and integrating these technologies in the management of cardiovascular diseases. Looking at the sources of data used in each study, on the Table 4, some studies used data from field collection, others from government databases accessible for exploitation and better integration of intelligent techniques to find features that define their population for cardiovascular diseases, others used data from hospital databases that can allow having clinical highlights that identify patients through collaboration with health structures. The method of collecting these data may depend on the final objectives of the study, but having databases already available or being in collaboration with structures may allow having a history of the disease for the given area, but also to have a follow-up of the cases to make a better diagnosis, classification, prediction with intelligent tools and up-to-date data. It can be noted that there is a lack of this kind of policy based on the establishment of a national or hospital database in Africa and as in the study we must fall back on the collection of specific data knowing the purpose of the study which may limit the overall impact and sustainability of the research. Therefore, quality data are needed for Africa to develop new technologies for cardiology. Collaborations between specialists and digital technicians must be encouraged and popularized to set up tools adapted to Africa.

What can we do in Africa to have reliable, available, and exploitable health databases to propose intelligent systems that can be adapted and allow remote management? There are difficulties accessing medical data in Africa, but we can highlight other blockages. There is a need to establish collaborations between specialists in cardiology and computer scientists, which will allow the establishment of platforms for data management and a better understanding of the urgent needs for cardiology in Africa.

Table 4. Data source for the different studies and their countries

References	Data Sources	Countries
[42]	Anhui HF cohort	China
[29]	International Heart Hospital, Rizhao	China
[17]	Nine public hospitals for heart failure from Hong Kong	China
[31]	Tel-Aviv Sourasky Medical Center	Israel
[16]	Collaborating medical center database	India
[39]	The Joint Chinese University	China
[46]	Cardiology Department of Anzhen Hospital	China
[11]	10 areas in China	China
[8]	Tri-Service General Hospital, Taipei	Taiwan
[20]	National stroke screening	China
[19]	Korean AHF registry	Korea
[13]	National Institute of Technology Rourkela	India
[7]	Medical College and Hospital, Kolkata	India
[33]	Tunisian University Hospital Lä Rabta	Tunisia
[35]	B & J Super speciality Hospital, Navi Mumbai, other hospitals in Navi Mumbai	India
[9]	Affiliated Hangzhou First People's Hospital	China
[22]	Brazil and Uganda	Brazil and Uganda
[45]	The Second Medical Center and National Clinical Research Center for Geriatric Diseases	China
[10]	China Physiological Signal Challenge (CPSC) 2018	China
[44]	Department of Medical Imaging Centre, First People's Hospital of Xianyang	China
[21]	Taichung Veterans General Hospital	Taiwan
[5]	Huaxi Hospital of Sichuan University, Hangzhou First People's Hospital of Zhejiang University	China
[37]	Nearby hospitals and medical diagnostic centers	India
[15]	Himalayan Institute of Medical Sciences (HIMS), Dehradun	India
[28]	India volunteers	India
[25]	Tehran arrhythmia clinic database	Iran

4 Conclusion

In this work, we have conducted a review to understand what blocks the use of AI in cardiology in Africa compared to other continents. We found that research in other developing countries is facilitated by the availability of data and the existence of health care structures to conduct the tests. The gap is more felt because there is an almost absence of public health data, and collaborations between hospitals, professionals, and academics are not too much valued.

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