Research Methods and Ethics in Health and Genomics

How Can Artificial Intelligence and Big Data Advance Cardiovascular Disease Research?

Student Names:

Khadeejath Hafruza - 2100033902
Syeda Warisha Fatima Rizvi - 210021453

Instructor Name:

Dr. Nady El Hajj

Contents

Abstract

This paper focuses on how artificial intelligence (AI) and big data can be used in cardiovascular diseases (CVD) applications such as electrocardiography, echocardiography and angiography by reviewing existing literature. Key studies have been presented in this paper for these fields and how AI has helped the researchers in accomplishing their objective by enhancing the diagnostic and predictive accuracy of these tools. However, limitations exist still in this research such as data privacy concerns. Which is why future work to leverage the benefits of AI is necessary where clinicians are able to trust this technology for the betterment of human health especially in CVD research. This is because coupling AI with CVD presents a promising future for efficient methods for cardiovascular diagnosis and treatment.

1. Introduction

AI and Big Data are very beneficial in healthcare by providing many opportunities to improve disease diagnosis, prediction as well as treatment. With regard to cardiovascular diseases (CVD), it is crucial for accurate diagnosis on time. Therefore, the fusion of AI and CVD will help save many lives and make the entire diagnosis to treatment process more seamless.

2. Artificial Intelligence and Big Data

AI is the "branch of computer science that mimics the human mind process" which was invented by Alan Turing in 1950s (Krittanawong, et al., 2017). Even though there is no clear definition of what AI is, the use of AI will help in making our lives better and help in so many fields including healthcare (Kagiyama et al., 2019). In the health sector, the use of AI can be used for many applications which includes, "medical diagnosis, treatment, risk prediction, clinical care and drug discovery" (Gulshan, et al., 2016).

Machine learning (ML) is another term that is used alongside AI. ML algorithms identifies trends in the given dataset and builds a model capable of performing classification tasks on the training dataset (Rajkomar, et al., 2019). Subcategories of machine learning include "supervised learning, unsupervised learning and reinforcement learning" (Yan, et al., 2019).

Reinforcement learning (RL) is where the programmer sets a goal, and the algorithm accomplishes this goal based on either supervised or unsupervised learning which is the first part of RL (Yan, et al., 2019). The second part includes a "feedback mechanism" which is also known as a "reward" for the AI (Johnson, et al., 2018). Therefore, the aim of reinforcement learning algorithm is to have the highest reward in its training cycle (Yan, et al., 2019).

Deep learning (DL) is another topic that is discussed along with AI. DL falls under ML which is described as a "computational method that enables the algorithm to automatically program and learns from big data" (Gulshan, et al., 2016). It is a powerful tool that is capable of training neural network models to behave like a human mind. In addition to that, DL can understand complicated dependencies between the data set compared to ML (Esteva, et al., 2019).

Figure 1 illustrates the relationship between big data and AI and its application in the healthcare sector. It indicates that big data such as imaging & EHR, are applied to AI algorithms like ML and DL, for several applications in CVD like disease diagnosis, prediction of risk and imaging interpretation. The figure outlines the dependency between big data and AI, and one must utilize both to make a fully functional automated diagnostic or predictive algorithm.

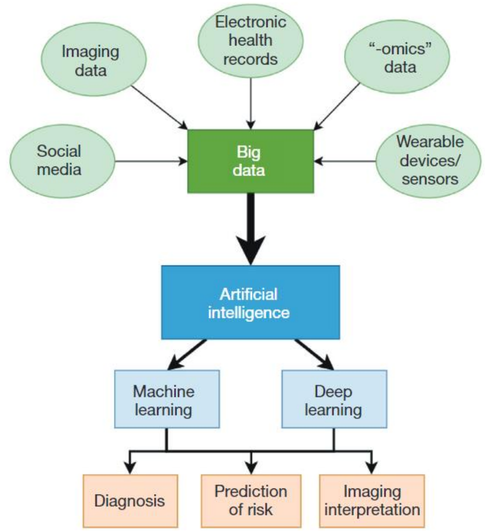

Figure 1: Overview of AI and big data in CVD applications (Haq, et al., 2021)

3. Artificial Intelligence and Big Data Application in Cardiovascular Diseases

AI and big data exhibit significant applications within the healthcare industry, aiding medical professionals in disease diagnosis as well as improving patient outcomes. Advancement of DL in medical imaging, and data analysis paired with AI models has helped clinicians in diagnosis and improved the results for patient-level predictions (Yan, et al., 2019). This literature review focuses on AI and big data application in CVD in the fields of electrocardiography, echocardiography, and angiography.

3.1 Electrocardiography

With techniques going back to the 1960s, the electrocardiogram (ECG) has shown to be a quite useful source of data for ML research (Perez, et al., 2019). Many studies have been done on this application, some of these will be discussed further.

Attia et al. have done a study where they utilized a dataset of 12-lead ECG, echocardiogram and the left ventricular ejection fraction from patients for training a convolution neural network (CNN) model to discover which patients have ventricular dysfunction by using the ECG data. The model, with an accuracy of 85.7%, is a low-cost but powerful test for asymptomatic patients to know if they possess Asymptomatic Left Ventricular Dysfunction (ALVD) (Attia, et al., 2019).

Moreover, a study was done by Hannun et al. in 2019 where they developed a deep neural network (DNN) for the classification of "12 rhythm classes" using single-lead ECG. This model outperformed cardiologists as its positive prediction were higher than that of clinical professionals. These findings indicate that having AI models for this purpose would help reduce misdiagnosis as well as improve test efficiency (Hannun, et al., 2019).

Furthermore, a retrospective cohort study by Kwon, et al. was done for the detection of Symptomatic Aortic Stenosis (AS) by applying DL techniques, specifically a combination of multilayer perceptron (MLP) and CNN model on ECG data. The study utilized both 12-lead ECG as well as single-lead ECG, with slightly better ROC performance by 12-lead ECG. However, both can be efficiently used to detect AS in a patient as the DL algorithm utilizes the “T wave of the precordial lead” to identify if the individual is suffering from AS (Kwon, et al., 2020).

Another retrospective cohort study was done by Kwon et al. on using AI to detect left ventricular hypertrophy (LVH). In this research, the dataset was of 21,286 patients from two different hospitals who had 12-lead ECG and echocardiography performed within 4 weeks. An AI model based on Ensemble Neural Network (ENN), was trained. The outcomes outdid the cardiologist’s clinical evaluation and showed that they have lower sensitivities at the same “specificity” than the ENN model (Kwon, et al., 2020).

Yao et al. designed a DL algorithm for detection of low ejection fraction (EF) by applying it to Electronic Health Records and using 12-lead ECG data. This is a randomized trial where there are clustering the health professionals to intervention (exposed to the AI tool) and control group (not exposed to AI tool). The trial incorporated about 20,000 patients and 400 health professionals. A pragmatic cluster RCT can test the tool and the results can guide future AI applications (Yao, et al.,2020).

A recent study by Valente Silva et al. developed and evaluated a DL model to predict Pulmonary embolism using 12 lead ECG with specificity of 100% and sensitivity of 50%. The study provides evidence to support the real-world application of AI in routine clinical practice. (Valente Silva et al., 2023)

3.2 Echocardiography

Two-dimensional echocardiography (2DE) helps in diagnosis and management of multiple CVDs. However, this procedure requires many resources and necessitates the expert analysis of a clinician, therefore, the use ML will make this procedure more efficient. There are various software that can perform diverse tasks by analyzing 2DE dataset (Al'Aref, et al., 2019).

A study conducted by Zhang et al, in 2018, was based on the automation of the understanding of echocardiogram pipeline. Their study utilized a dataset of 14,035 echocardiograms with training conducted on 8,666 echocardiograms using a CNN model. This model could classify 3 diseases: “hypertrophic cardiomyopathy, cardiac amyloid, and pulmonary arterial hypertension”. Results of this study indicated that automated outcomes are better than manual results (Zhang, et al, 2018).

Moving on, research done by Madani et al, focused on developing a CNN model which could classify “15 standard views (12 video, 3 still)”. The training was done by utilizing 267 labelled images and videos from “transthoracic echocardiograms”, which is data that comprises of “video clips, still images and Doppler recordings”, all obtained from various angles of the heart. The model demonstrated a high level of accuracy, with an overall accuracy of approximately 98% during the testing phase. These results shed light on how AI can significantly enhance the accuracy and efficiency of echocardiographic data analysis, thereby improving workflows. (Madani, et al., 2018).

A recent study conducted by Guo et al aimed to develop a novel CAD screening approach based on machine learning-enhanced echocardiography. Even though the model had high sensitivity, its low specificity lead to high false-positive rate. However, it demonstrated benefits such as good diagnostic performance in screening CAD patients and only required noninvasive echocardiography along with other commonly used clinical features (Guo, et al, 2023).

3.3 Computed Tomography Coronary Angiography (CTCA)

Oikonomou et al., developed a new AI based method to predict cardiac risk by analyzing the radiomic profile of coronary PVAT, developed and validated in patient cohorts acquired from three different studies. The experiment concluded that a combination of FAI (a component of FRP) and FRP facilitates the development of a more comprehensive individualized cardiac risk profile for each patient and that radiomic characterization of PVAT by means of the FRP is a novel, promising approach to capture adverse PVAT remodeling around the coronary arteries and its associated residual cardiac risk (Oikonomou et al., 2019).

Coronary artery disease (CAD) can be measured by assessing the quantity of atherosclerotic plaque from the CTCA test. This retrospective cohort study employed a DL algorithm, specifically a CNN, to quantify plaque levels and assess stenosis severity. The training dataset consisted of 921 patients who had CAD and got the CTCA done. On testing, the algorithm demonstrated reliability, aligning with clinician results, thus showing that there is great scope for AI advancement in CVD diagnosis (Lin, et al., 2022).

Coronary heart disease (CHD) causes so many deaths worldwide, therefore significant research has been conducted on improving the diagnosis of this disease. One of this research is by Lee, et al. where they developed a DL algorithm which can detect the CHD on CTCA data. It was a retrospective study where they collected data from 11,180 patients who had done CTCA, applied ANN with "multi-task learning" and selected 19 features (age, gender, cholesterol level etc.). The accuracy of the model for diagnosing CHD was 71.6%, which was more accurate compared to "pretest probabilities including the pooled cohort equation (PCE), CAD consortium, and updated Diamond-Forrester (UDF) scores" (Lee, et al., 2023).

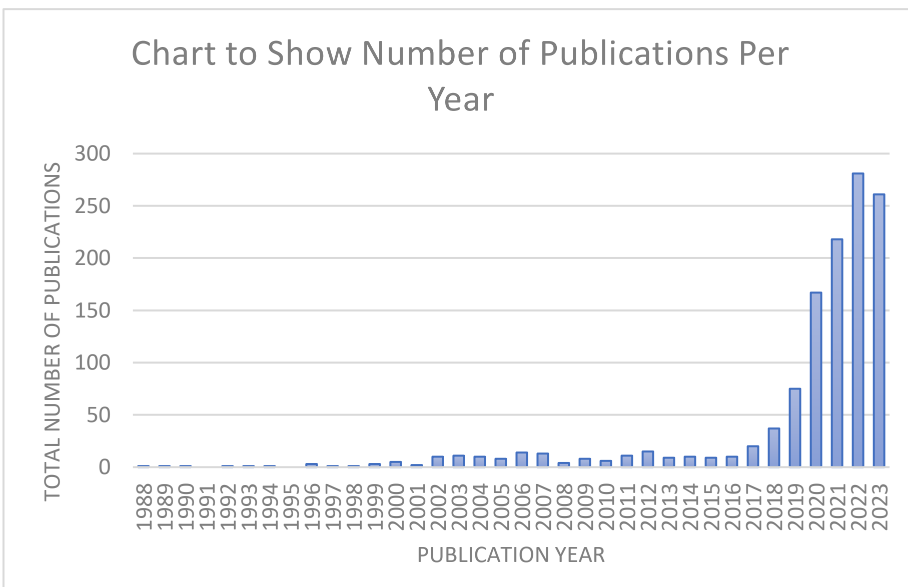

Figure 2: Number of publications published every year on this topic

Figure 2 shows a graph that visualizes the exponential increase in the number of publications annually. Starting from 1988, a lot of research has been done on the application of AI in CVD and the trend is continually increasing. Since 2019, there has been a boom in the number of publications per year which implies that the research on this field is still new and there are many opportunities for work within this sector.

Table 1: Summary of all the different studies referenced in this section.

Author	Field	Objective
Attia, et al., 2019	Electrocardiography	Detect left ventricular ejection fraction by using CNN and 12-lead ECG dataset
Hannun, et al., 2019	Electrocardiography	Classify 12 rhythm classes by using DNN and single-lead ECG dataset
Kwon, et al., 2020	Electrocardiography	Detect symptomatic aortic stenosis using MLP and CNN on ECG data
Kwon, et al., 2020	Electrocardiography	Detect left ventricular hypertrophy by using ENN and 12-lead ECG data
Valente Silva et al., 2023	Electrocardiography	Predict pulmonary embolism using DL and 12-lead ECG dataset
Zhang, et al, 2018	Echocardiography	Classify hypertrophic cardiomyopathy, cardiac amyloid, and pulmonary arterial hypertension by using CNN and echocardiograms dataset
Madani, et al., 2018	Echocardiography	Classify 12 standard views from transthoracic echocardiograms by using CNN
Guo, et al, 2023	Echocardiography	Developed a novel CAD screening approach by using ML and echocardiography
Oikonomou et al., 2019	Computed Tomography Coronary Angiography (CTCA)	Predict cardiac risk by analyzing coronary PVAT and using AI and CTCA dataset
Lin, et al., 2022	Computed Tomography Coronary Angiography (CTCA)	Detecting CAD by using DL and CTCA dataset
Lee, et al., 2023	Computed Tomography Coronary Angiography (CTCA)	Detect CHD by using DL and CTCA dataset

4. Limitations

Despite the numerous advantages of using AI based technology for classification of CVD, certain limitations remain. Primary limitation among them is the challenge of establishing trust in the technology, as people often struggle to understand the decision-making processes of AI algorithms, which prompts researchers to exhaust their efforts on transparency (Kwon, et al., 2020). Furthermore, another limitation is regarding assurance that this algorithm would perform on large scale, unseen, data reliably (Vaid, et al., 2022). As the model's training is based on historical data, there is a risk of poor performance on new, untrained data. This concept is also referred to as overfitting of the data (Haq, et al., 2021).

Additionally, there are also security and privacy concerns related to this field. This is due to the current guidelines not regulating research bodies on their use of private health information, how they store it and develop models based on them (Haq, et al., 2021). Another limitation with AI is the phenomenon of the 'black box' (London, 2019) which means the clinicians do not understand how the model was able to make the output based on the input it was provided. It is important to mention another limitation of incorporating AI to CVD is that training these algorithms requires a lot of computational power and necessitates the use of high-end machinery which adds to the cost (Xu, et al., 2020).

5. Future Work

According to Haq, et al. we learnt that a lot of literature focuses on research done on data produced by means of computer modelling therefore, the implication of future work is to incorporate "multi-center randomized control trials" with AI technology. This is important because it overcomes one of the limitations of ML that it does not generalize well on new data and produces improper results. It can be done by multi-centers correctly labelling data and making it available for many organizations whilst also considering the different diversities in the world. Data overfitting can be avoided while making the algorithm generalize well on unseen data (Haq et al., 2021).

Additionally, another limitation was the lack of published studies on this field. Therefore, the future prospective should be to increase funding for AI related research (Haq, et al., 2022).

Moreover, work should be done to improve the understanding of AI by clinicians to increase use of AI based applications or services. To address this issue, it is suggested to have courses that teach students about these topics at university level (Karatzia, et al., 2022).

6. Conclusion

CVD are the leading cause of death in the world which calls for robust systems to be deployed in the health settings for the disease diagnosis and prevention. Therefore, it is beneficial to use AI and big data in CVD applications such as electrocardiography, echocardiography, and angiography. This is proven by the numerous studies in this field who seem to show a positive impact on the patient's health. Despite the advantages, there are limitations also such as privacy concerns, overfitting, and lack of AI-related information amongst clinicians. Therefore, future work should focus on multi-center randomized control trials along with an increased funding for AI-based research and educational initiatives to gain the most of this technology.

Conflict of Interest Statement – none declared.

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