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Heart Disease Prediction using Artificial Intelligence and Machine Learning

N R Chinmayi[1]*

1 MedRite Division, Ascentia Innovations, Davangere, 577004, Karnataka, India

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* **Corresponding author**.

chinmayinramrigi@gmail.com

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Abstract

Heart-related medical conditions, often known as cardiovascular diseases (CVDs), have emerged as the main cause for death worldwide over the past several decades and are now recognized as the most serious medical conditions in both India and the rest in the entire world. This study focuses on the development of a machine learning-based artificial intelligence system for the identification of heart disease. Diagnose, risk stratification, and management are basically a few of the critical thinking-intensive aspects of medical treatment that have been mechanized because of the development of artificial intelligence (AI) and data science, which has reduced the strain on doctors and decreased the possibility of human error. Using the primary clinical outcomes of each CHD (Congenital heart defects) and the right computational algorithms, risk stratification as well as the prediction of treatment results are feasible. Cardiovascular diseases (CVDs) have a significant economic burden for healthcare systems all over the world and are associated with high morbidity and mortality. In the United States, adults had a prevalence of 7.2% for coronary artery disease, which is one disease category included under the CVDs umbrella. In the years 2016–2017, this disease entity damaged the United States economy 360 billion US dollars. The domain of cardiovascular medicine has expanded in new directions because of the development of artificial intelligence (AI) as well as machine learning over the past two decades. It will be highly beneficial to the treatment of this disease if we are able to predict cardiac arrest in the early stages. A quick and effective detection method must be developed in order to decrease the enormous number of deaths caused by cardiovascular diseases. In order to increase the model's ability for predicting heart disease in every individual, an effective approach was utilized to control how it can be used.

Keywords: Artificial intelligence; Pediatric cardiac surgeries; Heart disease detection system; Cardiovascular diseases; Coronary artery disease; Congenital heart defects

Introduction

Cardiovascular conditions are frequently traded for heart diseases. The problems that result in blocked even narrowed blood arteries, which can cause a heart attack, a stroke, or chest pain known as angina, are the main focus of these types of diseases. There are also different forms of cardiac diseases, including those that damage the heart's muscle, valve, or rhythm. Machine learning, on the other hand, is essential for evaluating whether person has experienced heart disease. In both scenarios, if these are predicted in advance, doctors would find it much simpler to collect vital information for diagnosing and treating patients. [1] In 2015, approximately 17.7 million people died as a result of cardiovascular disease worldwide. To address cardiac risk, accurate decision-making and optimal treatment are required. Another Canadian study used five machine learning models to analyse 1-month mortality in congestive heart failure patients admitted to the hospital. Intrahospital predictions for myocardial infarction patients have been studied in South Korea and China. [2] On the other hand, it has been discovered that cardiovascular disease is the cause of one out of every four deaths in the United States. Cardiovascular disease affects approximately 92.1 million American youngsters. The success of machine learning techniques has aided medical experts' work. [3] As a result, a cardiovascular risk prediction system must be highly accurate and specific. [4] There are 17.7 million deaths worldwide from CVDs like ischemic heart disease, which are the main cause and include cerebrovascular diseases like stroke. [5] According to the World Health Organization, India is responsible for one-fifth of these global deaths, particularly among the younger population. According to the findings of the Global Burden of Disease study, India has an age-standardized CVD death rate, 272 per 100,000 people, significantly higher than the global average of 235. Indians are affected by CVDs for a decade earlier than people in the western parts. [6,7] One of the largest global burdens of cardiovascular disease (CVD) is seen in India. According to projections, there would be 4.77 million CVD-related deaths annually in India by 2020, up from 2.26 million in 1990. [8] Coronary heart disease prevalence rates in India have been estimated over the past several decades and have ranged from 1.6% to 7.4% in rural populations and from 1% to 13.2% in urban populations. [9,10] Heart disease is mainly an incorrect symptom of coronary artery disease. It is also known as a cardiac disease; therefore, it is not with cardiovascular disease, which is any blood vessel disease. [1] Cardiovascular disease is the main cause of death in the modern world. Cardiovascular disease prediction is a critical challenge in the medical data processing. The emergence of machine learning techniques has demonstrated their effectiveness in disease prediction from massive amounts of healthcare data. [11]

Since 1960, the development of artificial intelligence i.e., AI in the terms of medicine has made a significant contribution to the simplification of clinical procedures and decision-making in the healthcare industry. [12,13] The development of AI depends on the idea of machine learning (ML). The definition of machine learning (ML) is the capacity of a machine to learn tasks from a huge amount of previous data along with have the ability to predict the same for future occurrences. [13] As a result, artificial intelligence (AI) has numerous important applications in the surveillance, diagnosis, prevention, as well as intervention of congenital heart conditions and has led to significant advancements in the field of pediatric cardiology. [14] Machine Learning (ML) is an application of Artificial Intelligence (AI) that provides systems with the ability to automatically learn and improve from experience without being explicitly programmed. [15,16]

Problem Statement

Recent research in the field of medicine has been able to identify risk factors that may contribute toward the development of heart disease but more research is needed to use this knowledge in reducing the occurrence of heart diseases. Diabetes, hypertension, and high blood cholesterol have been established as the major risk factors of heart diseases. Life style risk factors which include eating habits, physical inactivity, smoking, alcohol intake, obesity is also associated with the major heart disease risk factors and heart disease. There are studies showing that reducing these risk factors for heart disease can actually help in preventing heart diseases. There are many studies and researches on the prevention of heart disease risk. [17] Data from studies of population has helped in prediction of heart diseases, based on blood pressure, smoking habit, cholesterol and blood pressure levels, diabetes. These prediction algorithms have been modified by researchers into simplified score sheets that patients can use to determine their risk of developing heart disease.

Prognosis and Risk Stratification

The clinical evaluations, diagnosis, management of cardiac interventions, as well as procedural planning have been shown to be greatly benefited by AI-based algorithms in pediatric cardiology. [13] The extraction of patient data from wearables for risk stratification as well as ambulatory health monitoring has also been facilitated by AI models. [18] Even having nonlinear data and patients with a history of congenital heart surgery, machine learning (ML)-based models like optimum classification trees (OCTs) have been able to predict hospital length of stay (LOS), postoperative mechanical ventilatory support time (MVST), and mortality. [19] Similar to this, machine learning (ML) algorithm-based models, RCRnet and extreme gradient boosting (XGBoost), have correctly predicted preoperative mortality odds in patients having CHDs as well as statistically significant prognostic indicators including risk stratification markers in patients having Tetralogy of Fallot as well as left-to-right shunt CHDs, respectively. [20,21] The capacity of AI-based models to be trained to work with different data cohorts is important for their broad utility in risk stratification as well as prognostic predictions. [22]

AI in Cardiac Surgeries

In the preoperative, intraoperative, as well as postoperative phases of surgery, artificial intelligence may revolutionize pediatric surgery. Because of AI-enabled algorithms' incredible processing as well as analysis ability, decision-making and preoperative risk assessment can be made much simpler. Predicting post-operative results and preventing morbidity and mortality brought on by inadequate preoperative risk assessment are two benefits of utilizing ANN in surgical decision support systems. A paradigm shift in telesurgery can be brought about by technologically advanced (Hitech) operating theaters, which can enable intraoperative interventions and decision assistance. [22,23] This is especially helpful for cardiac operations, where manual segmentation of retrieved images i.e., CT/MRI might take an excessive amount of time. When Xu et al. used AI to do a cardiac operation remotely on a patient who was suffering from complications of long-standing ASD using the foundation of 5G technology, humans successfully started down this route. This was made possible because AI took the place of manual segmentation, which typically takes 2-3 hours even for experts. AI segmentation produced accurate results in just 2 minutes. [24,25] The authors in this case assisted a patient who, due to their poor condition, was unable to be transported to another hospital; the same benefit may be extended to a remote, inaccessible site, particularly in rural areas and developing nations. [25] Postoperative AI can assist in a number of applications, including automated risk classification of patients to enable more stringent follow-ups and ambulatory patient monitoring following discharge with AI devices. An ECG-based AI algorithm was described by Mahayni AA et al. that predicts post-operative ventricular dysfunction and long-term mortality in cardiac operations. These algorithms can be implemented as well as developed to significantly enhance the outcomes of pediatric surgical procedures. [26]

AI in other Pediatric Heart Diseases

Acute coronary syndrome as well as coronary artery aneurysms can result from the acquired pediatric vasculitis known as Kawasaki disease (KD). [27] The pathogenic mechanisms of Kawasaki disease are poorly understood, however a recent study employing AI-guided signatures suggests a similar pathology with COVID19 related vasculitis in children and Multisystem inflammatory syndrome in children (MIS-C). Similar cytokines like IL15/IL15RA and a systemic inflammatory storm are present in each of these disorders. These AI-based study approaches will clarify the disease's complex pathogenic mechanisms and assist in the identification of novel diagnostic and treatment targets. [28] The cardiovascular consequences of Kawasaki disease, which have a substantial impact on adult mortality, can be greatly reduced with appropriate and timely monitoring for Kawasaki disease. [29] Artificial Intelligence (AI)-based techniques have the potential to be extremely significant for predicting the chances of developing a cardiac aneurysm. Although the increased incidence of coronary artery aneurysms in Kawasaki patients having intravenous immunoglobulin resistance is well established, the majority of scoring models currently used to predict the resistance are not practical. A machine learning-based (ML) model on patient data, presented by Wang T et al., is able to accurately predict intravenous immunoglobulin resistance in Kawasaki diseases patients. With the development of AI, the potential for several such prediction models has increased, and they can support clinical decisions to enhance patient outcomes. [30] In these participants, acute coronary disease can be predicted using changes in coronary artery distensibility. The severity of the OCT i.e., Optical coherence tomography results of KD-related CA damage was associated with the calculation of these changes in KD by Benovoy M et al. utilizing an automated deep learning approach. [31] Despite limited number of studies utilizing AI-based methods, AI has the potential to change Kawasaki disease risk stratification as well as prognosis estimate as well as open up possibilities for additional therapeutic targets by elucidating the pathophysiology. RHD—Screening for RHD necessitates a clinician's expertise, and as a result, the availability of skilled manpower at the grassroots level is constrained. It is possible for RHD to be automatically diagnosed, which would reduce the workload of experts and serve as the foundation of future screening systems. [32] With an overall accuracy about 96.1%, 94.0% sensitivity, as well as 98.1% specificity, recent data has also demonstrated promise for a deep learning method based on convolutional neural networks to identify heart sounds as "rheumatic." [33] As a result, AI can serve as the backbone of future worldwide RHD screening systems.

AI: An Efficient Physician Assistant

Doctors and other medical professionals still resist the entire implementation of AI out of concern for inaccuracies the exclusion of social factors, as well as possible unemployment. The traditional medical establishment is frequently skeptical about the health care mechanization, loss of empathy, as well as personal touch in health care. Despite the skepticism as well as fear mongering around the loss of human touch and employment, we believe AI can be a valuable help rather than a replacement for doctors. [34] It can speed up insurance reviews, offer real-time data analysis, plus help with research.

It may lower physician workloads and rates of burnout in the medical profession. Therefore, use in the correct areas can help improve the overall quality of receiving healthcare and the patient experience.[35]

Challenges to AI in Pediatric Cardiology

There are many difficulties in implementing AI in pediatric cardiology. In order to train AI systems to recognize, evaluate, and decrease inherent biases and overfitting, there is still a severe lack of data accessible for pediatric cardiology. Additionally, it is challenging to incorporate AI and data accessibility into pediatric cardiology due to the variability of cardiac anatomy and the rarity of specific disease types. By combining data from all the many hospitals to create a considerable data set, we are able to address this limitation.[36] Because of their smaller size and more frequent movements while imaging, which result in increased motion artifacts, imaging in the pediatric population presents another challenge. This serves a technical problem, for example whose solution calls for a better spatial resolution in the MRI.[24] The application of AI to replace the existing protocols may be resisted by the doctor and the patient. Health care professionals will need to develop their ability to effectively understand the numerous model parameters and model architectures as a result of AI integration. Different strategies are being used to tackle this challenge. For instance, several works have included easier-to-use interfaces in the models to make interpretation simpler.[37] The ethical implications of AI are also developing as it develops. Privacy and Data security, biases and algorithm fairness, and transparency are among the concerns mentioned. Informed consent to data access is also among them.[38] The application of AI in healthcare settings may give rise to legal and ethical difficulties, but there are currently no clear rules or regulations in place to handle them. To guarantee algorithmic transparency and safeguard data privacy, rules and regulations can undoubtedly be investigated as AI develops and is utilized more widely.

Risk Prediction Models and Imaging Modalities for Estimating Pretest Probability of CAD

Pretest probability (PTP) estimates of CAD have traditionally been used to stratifying patients who report with stable chest pain in order to aid in decision-making regarding subsequent testing and the selection of an appropriate diagnostic modality. Historically, a clinician's risk- stratification technique for predicting the PTP of CAD was the Diamond-Forrester model, which was created using age, sex, as well as characteristics of chest pain.[39] However, multiple studies demonstrated its limitations, particularly in women, where it overestimated PTP by almost threefold.[40] This resulted in the creation of the CAD consortium score and the updated Diamond-Forrester model (UDF).[41–43] These scores, which include clinical and demographic risk variables, have been shown to be more accurate at predicting the risk of CAD. Given the potential to lower downstream testing and even associated costs, it is crucial to increase the ability to predict CAD utilizing more precise risk-assessment modelling. The PTP of CAD has been estimated using ML models using clinical as well as demographic variables.[44–46] In current multicentre cross-sectional research, a deep neural network algorithm based on an individual's facial profile was able to outperform traditional risk scores in predicting the PTP of coronary artery disease (PTP of CAD) (AUC with the ML model 0.730 vs. 0.623 for Diamond-Forrester as well as 0.652 for the CAD consortium, $p < 0.001$).[47] The study is constrained by its lack of external validity as well as low specificity (54%), but such methods could result in a paradigm change in the management of CAD by enabling earlier detection and the beginning of primary prevention using easily accessible parameters, such as a person's facial profile. The PTP of CAD has been shown to increase when a CAC score is available, with a CAC score of 0 indicating low-risk patients who might not require further testing.[48,49] When predicting the PTP of obstructive CAD, ML models that combine clinical and imaging factors have been demonstrated to have superior predictive ability than conventional risk scores.[50,51]

Limitations

This study also considers angiography and traditional invasive-based approaches to be appropriate and well-known diagnostic methods for diagnosing heart problems. It is a limitation in the prediction of heart disease. Apart from this, intelligent learning is dependent on computational techniques that are upright and efficient in predicting the occurrence of heart disease. The goal of this prediction method is to assist in the diagnosis and prediction of cardiac disease. This classification technique depends on different pruning as well as data cleaning techniques. This technique is prepared as well as developed a dataset that is suitable for data mining and selects the proper technique, which provides much better accuracy of this application.[1]

Conclusions

AI has the potential to bring about the next medical revolution. It has a wide range of uses in the working environment and in the management of patients, from making physicians' jobs easier to easily facilitating research. A considerable amount of cognitive and interpretational skills is needed for the specialty of pediatric cardiology, which makes it an excellent candidate for AI integration. Clinical assessment, imaging interpretation, diagnosis, risk stratification, prognosis, precision medicine, as well as treatment in pediatric cardiology have all been successfully incorporated using AI. The advent of AI has helped medicine become more precise and accurate, yet it is still a work in progress with challenges and limitations. Despite these obstacles, we believe that with AI's current pace of development, pediatric cardiology approaches will become more efficient.

AI has the unmatched potential to revolutionize healthcare and improve the capacity of the current system to serve vast populations while offering tools to concentrate on providing specific yet comprehensive as well as precise care.

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