

Performance Improvement of Cardiovascular Disease Prediction with Machine Learning and Classifiers: A Survey

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Abstract

Nowadays, the term "heart disease" is often used interchangeably with the term "cardiovascular disease." covering any disorder of the heart. Since from the past few years majority of research studies shows that more number of deaths occur due to heart diseases, which increased drastically in India. People in India now are getting heart attacks at a much, much younger age. Predicting and monitoring cardiovascular disease is often expensive and tenuous; thus, involving most popular technologies of AI is called machine learning which empowers the algorithms to study and understand the data and its properties. Therefore, machine learning can be used to predict and possibly determine future data. The aim of this paper is to summarize some of the current research on predicting heart diseases using machine learning techniques.

Keywords: Cardiovascular disease, Classification, machine learning, predictive analytics.

I. INTRODUCTION

Cardiovascular disease (CVD) is the leading cause of death universal with 17.9 million deaths a year. Cardiovascular disease is a group of cardiovascular disorders and includes coronary heart disease, cerebrovascular disease, rheumatic heart disease and other conditions. Four out of five heart deaths are caused by heart attacks and strokes, and one third of these deaths are caused by premature death in people under 70 [1]. People at risk for CVD suffer from high blood pressure, glucose and lipid levels, as well as overweight and esophageal cancer. All of this can easily be measured in primary care. Identifying people at risk for cardiovascular disease and providing appropriate treatment can prevent premature death. All primary care settings require access to all non-communicable medicine and basic health technologies.

Millions of people around the world find it difficult to control the risk factors that cause cardiovascular disease and many are unaware that

they are at high risk. Lifestyle and treatment interventions, if available, can help prevent a large number of heart attacks and strokes by controlling important risk factors. The World Health Organization (WHO) assists Member States in preventing, managing and monitoring cardiovascular disease through the development of global strategies to reduce disease, disease and death. [1] These strategies include reducing risk factors, developing standards of care, increasing the capacity of the healthcare system to care for patients with cardiovascular disease [2], and monitoring trends and models. Diseases to inform national and global operations. WHO works with partners and countries to develop cost-effective and equitable health care innovation in disease management.

Risk factors for cardiovascular disease include smoking, malnutrition, harmful alcohol and physical activity, as well as high blood pressure (hypertension) [3, 4], high cholesterol and blood sugar, or high blood sugar. It has to do with decision makers and social leaders such as aging,

income and urbanization.

Machine learning (ML) provides an alternative approach to standardized sensitive modeling [5] within today's boundaries. Using "big data" to develop algorithms is likely to restore the state of the drug. ML arises from the identification of models and from research in computer science (called 'artificial intelligence'). It uses a computer to learn complex and non-linear interactions while minimizing error between observed and observed results [6]. In addition to improving estimation, ML can detect important latent variables, but they can be confused with other variables. The workflow for processing heart disease data is shown in Figure 1.

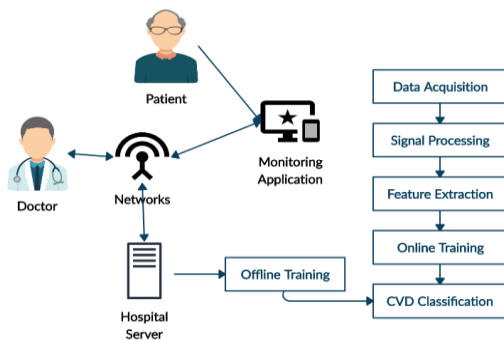


Figure 1. Workflow of Heart data acquisition and processing

To date, large-scale machine learning has not been used to evaluate analyzes in a broader population using daily clinical and medical data [7]. The purpose of this evaluation study is to understand whether machine learning improves the accuracy of cardiovascular risk assessment in a large generalized primary care population. Determine which branch of machine learning algorithms has the highest predictive accuracy.

II. RELATED WORK

Heart disease is the leading cause of gloom and death in today's lifestyle. Separating evidence from cardiovascular disease is an important yet complex task that requires careful and skillful application, and appropriate robotization is extremely attractive. Not all people have the same skills as professionals. Not all professionals have the same talent in every claim to fame, and in

many places people do not have readily available gift and authority professionals. The mechanical framework for therapeutic analysis improves inhalation assessment and also reduces costs.

In this study, Purushottam et.al. [8](2015) have developed a system that allows us to effectively find theories to assess the level of patient risk with respect to a given patient's health parameter. The key contribution of the study is to provide the assistance to the doctors who do not specialize in making the precise decision about the risk of any of the heart diseases. The instructions developed by their proposed system take precedence over real rules, abridged rules, duplicate rules, eligibility rules, regulated rules and polishing. The effectiveness of system implementation has been evaluated and the results show that the system has an excellent ability to more accurately assess the risk of coronary heart disease. Through their research work, authors have provided an effective system for the purpose of heart disease prediction through data mining. The system helps physicians make an effective decision based on a defined parameter.

Impact of visual assessment on risk of accidental cardiovascular disease (CVD) using a risk prediction tool based on data quality variability and electronic health records and general data collection. The design methodology is based on longitudinal coordinate research. There were 392 general procedures related to hospitalization data (covering 3.6 million patients). Li Yan [8] (2019) has adopted methods such as data quality change using SEZ consistency metrics that measure the effectiveness of each practice. Statistical decline models analyzed the difference between the accuracy of QRISK3 estimates in the individual estimates and the effect of the total risk factor (linear predictor).

There are significant differences between CSD event practices that are not measured by QRISK3. When practice variability is included in disorder statistical models, QRISK3 predicts a 10% risk for women from 7.1% to 9.0%; for most quintiles, the rate is between 10.9% and 16.4%. The quality of the data (using smart metrics) and its completeness can be compared to different levels of statistical deterioration. Significant differences

in cardiovascular disease rates between practices cannot be explained by differences in data quality or the effect of risk factors. QRISK3 risk prediction should include clinical judgment and evidence of additional risk factors.

Studies by Alik et al. [9] (2017) provide a summary of machine learning methods for the classification of diabetes and cardiovascular disease (CVD). The authors used artificial neural networks (RNA) in conjunction with Bayesian networks (BN) for this purpose. A comparative analysis of some articles was published between 2008 and 2017. Multilayer neural network with direct operation with the ANN-type learning algorithm Levenberg-Marquard, commonly used in individual articles. Alternatively, the naive Bayesian network mainly uses the BN type, which has the highest precision values for the classification of diabetes and CVD, with a retrospective rating of 99.51% and 97.92%. In addition, the calculation of the average accuracy of the experimental networks showed better results using RNA, indicating a higher probability of more accurate results in diabetes and / or CVD classification when applied to RNA.

A comparison of 10 scientific articles on diabetes classification and 10 articles on cardiovascular disease showed that in both cases ANN was more accurate (87.29 in diabetic patients and 89.38 in cardiovascular disease). Due to the independence of the nodes observed, the Naïve Bayesian network used may be less accurate than the ANN approach. Thus, according to the result obtained, the classification of diabetes can be determined to have better accuracy in NCL and / or CVD when applied to an artificial neural network.

Traditional clinical decision support systems are usually built with a single classification or moderate performance in a generic set of these models. Search by Eoma et.al. [10] (2008), they provide a classification-based approach to support the diagnosis of cardiovascular disease (CVD) under optimal conditions. This OptasidSS-E system provides a solution to the limitations found in traditional methods using different classifications. Cardiovascular disease is one of the leading causes of death according to recent

surveys and can save considerable lives if accurate diagnosis is made. For CVD diagnostics, their system encounters a set of four different classifiers with groups.

Support vector machines and neural networks are accepted as basic classifications. In addition, decision trees and Bayesian networks have been developed to improve system performance. Four optometric-based biochip data sets, including CVD data with 66 samples, were used to train and test the system. Three other related datasets are used to minimize data errors. Comparing the results with models based on a single classification, the authors explore the benefits of a complex system with multiple aggregation approaches.

The performance of the AptaCDSS-E system was evaluated using mutual qualification tests. The authors say that variance intervals (<6%), demonstrating its worth of the clinical decision making of the diagnosis.

The use of medical data sets has attracted the attention of researchers worldwide. Data mining methods are widely used to develop decision support systems for the assessment of disease groups. Medical data sets. Nilashi et al. [11] (2017) proposed a new knowledge-based system for disease assessment using noise prevention and assessment methods. The authors used classification and regression trees (CART) to indicate fuzzy rules for use in a knowledge-based system. The authors reviewed many of the methods proposed in public medical data sets. The Indian Diabetes Pima, Mesothelioma, Wisconsin Diagnostic Breast Cancer, Cleveland, Starlog and Parkinson telemonitoring data illustrate that the proposed method can significantly improve the accuracy of diagnosis. Results are based on fuzzy rules, and group methods can be effective in predicting disease from CART and real-world medical datasets, reducing noise. As a clinical analysis practice, a knowledge-based system helps physicians to heal.

In order to evaluate the effectiveness of the proposed method and to standardize the system, several experiments were conducted with national medical data sets. The datasets are from the University of California, Data Mining Repository,

Irvine (UCI) Indian Diabetes Pima, Mesothelioma, Wisconsin Diagnostic Breast Cancer, Starlog, Cleveland, and Parkinson Telemonitor databases. The results show that the combination of clustering methods, PCA and methods based on fuzzy rules provides better forecasting accuracy.

The approach proposed in this study evaluates public UCI datasets that include input and output parameters for a specific diagnosis. In addition, the nature of the data contained in these datasets is not complex compared to the large data on health care. Plus, big data on health care.

Artificial intelligence (AI) has helped transform important aspects of human life. As a subset of AI machine learning (ML), which automatically retrieves information from large databases, is increasingly being used by the medical community and especially in the field of cardiovascular disease. Al-Aaref et.al. [12] (2018) gave a brief overview of the ML methods used to construct inferential and data-based models. They have highlighted several areas of application of ML, such as echocardiography, electrocardiography, and have recently introduced non-invasive imaging techniques, such as coronary calcium and coronary angiography evaluation. They made their observations by exploring the limits of modern application of the ML algorithm in cardiovascular disease. The rapid digitalization of healthcare allows ML to answer important medical questions. While traditional statistical methods are still the language of medical research, ML has proposed new tools to navigate a rapidly changing landscape. In addition, ML can provide an effective platform for integrating clinical data with imaging data, which can be useful in many complex cardiac conditions, such as heart failure.

In this review, the authors highlight recent applications of ML in cardiovascular medicine with an emphasis on cardiac imaging. Machine learning promises to transform medical research into systematic optimization of the clinical workflow.

Previous studies have shown an association between ambient air pollutants and congenital heart defects (CHD), but the effect of

aerodynamic diameter cells CH10 man(PM10) on CHD is unstable. RenJoupeng et.al. . The authors conducted a birth cohort study based on 39,053 children born in Beijing. GB and RF methods were used to estimate the coronary heart disease coefficient associated with increased exposure to PM10 associated with maternal and perinatal symptoms. In all machine learning models, maternal exposure to PM10 has been identified as a major risk factor for coronary artery disease.

From 3 to 8 weeks in pregnancy, PM10 is more susceptible to coronary artery disease because this period is in the window of prenatal heart development. Machine learning models offer the opportunity to investigate the complex and linear relationship between air pollution and maternal exposure to congenital defects. Other studies should look at the effects of various air pollutants on susceptibility and risk of coronary heart disease at different times.

Classification is a powerful machine learning technique commonly used for evaluation. Some classification algorithms predict satisfactory accuracy while others predict limited accuracy. This study was supported by Lata et.al. [14] (2019) discussed a technique known as mass classification that combines several classifications to improve the accuracy of weak algorithms. This tool was used to experiment with heart disease data.

Algorithms Table 1 is an example of precision improvement using a set of functions with stacking algorithms.

Table 1. Performance comparison when feature is not used vs. when feature set is used.

Stacking Algorithm with Random Tree	Accuracy	Feature set	Accuracy with feature selection
Naïve Bayes, Bayes Net, C4.5	77.89	FS3	78.55
Naïve Bayes, Bayes Net, C4.5	77.89	FS4	78.55
Naïve Bayes, Bayes Net, C4.5, PART	77.56	FS3	78.22
Naïve Bayes, Bayes Net, C4.5, PART	77.56	FS1	77.89
Naïve Bayes, Bayes Net, C4.5, PART, MLP	75.58	FS2	80.21
Naïve Bayes, Bayes Net, C4.5, PART, MLP	75.58	FS4	76.24

A comparative analytical approach was used to find out how generic technology can help improve the accuracy of heart disease assessment. The purpose of this article is to increase the accuracy of poor classification algorithms and to implement an algorithm with medical data to demonstrate its effectiveness in early disease assessment. Studies on common methods such as wrapping and wrapping are effective in improving the accuracy of low estimation prediction and are satisfactory in determining the risk of heart disease. The advantage of mass classification is that weak classifiers have a maximum accuracy of 7%. Implementing feature selection further improves process performance and results show significant improvement.

Classification of multiple cardiovascular diseases by electrocardiogram signal (ECG) is necessary for the prompt and effective treatment of the patient. Hasans et al. From the input signals, each ECG signal is first subdivided by empirical mode division (EMD) and connected to higher order internal mode (IMF) mode functions integrated in the ECG signal. The use of EMD is believed to provide detailed information and reduce degrading performance. This processed signal is then supplied as an input to the CNN architecture, which has a cardiovascular disease record using a network-end softmaxregressor.

It is observed that the structure of the CNN learns the properties of a modified ECG signal that does not correspond to the raw ECG signal. This method applies to three publicly available ECG databases that are superior to other classification accuracy methods. The proposed

technology reaches maximum accuracy of 97.70%, 99.71% and 98.24% in the MIT-BIH, St. Petersburg and PTB databases.

In addition, the proposed technique was compared with the other training methods with different IMF signal combinations. The proposed method has been shown to give better results than any other method. The proposed approach has been evaluated in three publicly available databases and therefore has the ability to classify strong and widespread cardiovascular disease.

One of the most common forms of cardiomyopathy is advanced cardiomyopathy (DCM), which is associated with poor outcome. In addition, poor evaluation during short-term follow-up was seen in DCM patients with poor discharge section. During this process, Machine Learning (ML) helps clinicians classify risks and monitor patients after a relationship between multiple symptoms and outcomes has been tested. According to Chen et.al. [16] (2019) evaluated cardiovascular events during the year in patients with severe DCM using ML. The process includes assisting physicians with risk classification and patient monitoring. From both centers, a database of 98 patients with severe DCM (LVEF <35%) was used to determine the ML model. The ML algorithm recorded 32 clinical data characteristics. Information Acquisition (GI) was used to select cardiovascular events to identify the most important features.

A naive Bayesian classification is constructed and its approximate performance is calculated by crossing the validation ten times using the receiver's operating area under the curve (AUC). During the year of follow-up and treatment, 22 patients met the study evaluation criteria. Major features with GI > 0.01 were carefully selected for the ML model, which included left atrium (GI = 0.240), QRS duration (GI = 0.200), and systolic blood pressure (IG = 0.151). ML has been shown to be effective in predicting cardiovascular events in patients with severe DCM (AUC, 0.887 [95% confidence interval, 0.813-0.961]). Effectively evaluate the risk of ML in patients with acute DCM within one year of follow-up that can guide risk stratification and future patient management.

Cardiovascular disease (CVD) refers to narrow or congested blood vessels that cause cardiac arrest (angina) or stroke, or any combination of these. Cardiovascular disease is the leading cause of silent, massive heart attacks and serious death. A current assessment of the presence or absence of a CSD is not necessary in the current circumstances. Instead, it is important to evaluate the CSD, gain knowledge of the CSD, and the possibility that the person will experience cardiac arrest. Ultimately, the goal of creating a personal risk assessment for a CSD is Vivekanandan et.al. [201] (2019) using a hybrid model.

A person's cardiovascular disease is caused by a variety of regulatory and regulatory factors. Calculation and analysis of all identified factors is complex and time consuming. Only a

few codes turn out to be more complex. Therefore, the optimization of complex properties is performed using an advanced differential evolution (DE) algorithm. The factors are sufficient to assess the presence / absence of a CSD. The study takes into account the identified critical characteristics of individuals through Cox regression analysis that assesses the emergence of critical symptoms. These individual event levels measure the proportion of cumulative events for the individuals concerned.

The process of effectively performing a medical imaging survey is a key component of the diagnostic field and diagnostic techniques have yet to be developed. At this point, DL can be considered a black box that requires knowledge of its core business and therefore Wang et.al. [18] (2019) presented some important technical challenges that require further procedural progress. With a proper diagnosis, you can use a preoperative computer simulation plan to use the appropriate surgical intervention technology.

The authors have raised important questions about the diagnosis of cardiovascular disease (CVD) using this influential technique, which is still not well understood. It looks at the challenges posed by the AI and DL paradigm shift in CVD diagnostics, provides probable solutions for the problems. Further the process describes the future of related artificial intelligence applications. The issues discussed in relation to the classification,

segmentation and identification of CVD images are broken down into modular aspects of DL. A good perspective in managing these issues is essential for the successful technical application of DL in contemporary medical science.

III. BACKGROUND

A. Cardiovascular Diseases

- Heart attacks, as well as strokes, serious events and obstacles prevent blood from flowing to the heart or brain. The most common cause is the accumulation of fat in the inner walls of blood vessels that supply the heart or brain [19]. Bleeding from blood vessels in the brain or blood clots can also cause a stroke. The severity of a heart attack and stroke is a combination of risk factors such as smoking alone or smoking, malnutrition and deterioration, physical laxity and alcoholism, hypertension, hyperlipidemia and diabetes.
- Cardiovascular disease (CVD) is a group of cardiovascular disorders and includes:
- coronary artery disease, a disease of the blood vessels that nourish the heart muscle;
- cerebrovascular disease, a disease of the blood vessels that nourishes the brain;
- peripheral arterial disease, a disease of the blood vessels that can damage the legs and arms;
- R rheumatic heart disease, heart valves caused by rheumatic fever, damage to the heart muscle and streptococcal bacteria;
- congenital heart disease, structural heart problems at birth;
- Deep vein thrombosis and pulmonary embolism, venous leg thrombosis which purifies the heart and lungs.

B. Machine Learning Algorithms

The rapid growth of the available computing power in the world in recent years has led to the use of numerous algorithms in machine learning. Machine learning for signal processing is very common in adults. In particular, it is commonly used in the areas of image recognition and speech [21]. One of the most interesting applications I've seen in these areas is the use of machine learning in medical diagnostics. As machine learning is used to diagnose cancer, malaria and other major diseases, I would like to explore ways to make these medical applications more accessible, as many cheap computing devices are available today. Increases. : Smartphones. This machine learning (ML) application demonstrates the potential to help the healthcare industry and the most vulnerable in our society.

C. Machine Learning Algorithms for CVD

Decision Tree: It is considered to be one of the most commonly used data mining algorithms in classification and estimation problems. Each interior node corresponds to an input variable and is divided into child nodes according to the values of the input variables. Each page node represents a specific value of the output variable [22]. When the decision tree is executed, samples of each internal node are split according to the attribute, and the process is repeated for each subset of the recursive partition. At each stage, one of the input variables is selected for the partitioning models during decision tree growth. With the variable selected, the value of the attribute is determined by the position of the new compartment, and the most frequently performed tests are impurity and entropy.

Support Vector Machines: Because of its automated training system, it is commonly used to effectively address assessment and classification problems. When a mathematical model is proposed for regression and classification problems, they are based on a statistical learning system [23]. Several other researchers claim that SVM is an edge classifier which is created with data along with feature vectors. The SVM seeks to find the optimal boundary for separating two

classes along with the vectors of various characteristics with maximum margin (the distance between the optimal hyper plane and the nearest vector). In order to classify an indivisible data set, a non-linear SVM kernel function based on radial parameters, such as a kernel function, projects an entity vector over a large space.

Support for vector machine architecture (SVM) is a kernel function - a kernel trick that depends on modifying or projecting a dataset in the n dimension, taking into account the large dimensional space applicable. From this newly created location, data can be seen as a linear problem that is solved no matter the size of the data.

Some of the advantages of support vector machines are: primarily, it has a solid mathematical basis; subsequently, it incorporates the idea of structural risk reduction, which reduces the likelihood of misclassification in the newly generated examples. This is very common when there is very little workout data. Besides the above two, the third advantage is the availability of influential tools and algorithms to discover a solution quickly and efficiently.

Naïve Bayes: As an alternate to the traditional expert systems, Bayesian networks are considered which underpin decision-making and evaluation in the event of potential uncertainty. The top level consists of a set of variables connected to the nodes whereas arrows are associated with impact words. On the subsequent stage, stages and states can be found, which are also called state spaces. From these stages and states each of the model variables can be taken for the process [24]. The third point is that, a set of functions for conditional probability can be found, one for each node. In addition, the probability that each condition of a conditional variable will occur for possible values. Recently, a lower level set of algorithms was developed that allows the network to recompute the probabilities dispensed to each level when specific model suggestion is known.

K-Nearest Neighbours: It is an algorithm used for data classification and regression. The

algorithm registers and classifies all known cases or assigns attributes to new case bases with similar properties. This method is one of the first tools of classification research without prior knowledge or knowledge of data dissemination [25, 26]. This method was developed considering the need for non-discriminatory analysis when it is difficult to determine reliable estimates of probability density parameters. The main difficulty of this method is the determination of the value of k , since if the value is greater than k , most of the data is at risk of categorization, and if the value of k is too small, then there is little choice of classification comparison case.

One of the main advantages of the K-NN method is that its classification results can be grouped without changing structures by changing only the distance metric used [27]. Solution providers should choose indicators based on experience. The great advantage of changing a metric is that you can get different results without changing the method's algorithm and the way distances are measured.

D. Scope of Machine Learning Algorithms for CVD prediction

From the physician's point of view, the current practical pattern of use in health care may focus on assessing the dynamics of the model's treatment processes (goals and milestones). Both types of models can be repeated. These models are made up of data that includes processing parameters, processing parameters, and result events. Laboratory indicators are very objective and accessible, very objective data that can be used in similar models [28, 29]. The significance of the events, as well as the choice and interpretation of the commentary, depends on the establishment of standardized assessment criteria (hospitalization, need for intervention, loss of life) that are consistent with the expert assessment activities. In this case, the dynamics of the fact and indicator (such as the entrance lab index or changes over a limited time) can be considered an event.

On the other hand, multiplications can be calculated using automated training methods

under expert control. Such a policy allows you to cover related topics and identify missing links. The purpose of this approach is to select indexes and modules. Machine learning policies can be tailored to the decision making process with the subject of assessment. Models developed from machine learning methods can more accurately describe the results of visitation model search [30]. Issues addressed include assessment of cardiovascular emergencies and strategic cardiovascular mortality (myocardial infarction, acute coronary syndrome, persistent angina).

Aspects of machine learning methods are subjectively complicated by the availability of data, its growth and complexity of medical data, the dynamic changes in the composition of indicators and important correlation factors, their diversity and variety [31]. Progressive interpretation of the results is also of scientific importance. From the clinic's point of view, it is possible to make the results understandable.

E. Challenges

- The availability of big data analytics tools for use in cardiovascular tools and research is growing rapidly,
- Big data analytics, such as risk to at-risk patients and the presence of resource use patterns, can have a significant impact on improving cardiovascular quality of care and patient outcome.
- Analysis of big data in cardiac care is still in its early stages of growth and evaluation and there is no evidence that it improves the quality and outcomes of patient care,
- It is important to build a Big Data application evidence base on cardiovascular quality and care outcomes. Therefore, the analysis of big data should be seen as a positive intervention in the healthcare sector,
- Big data methods do not allow database quality. However, Big Data tools are more useful and clinically beneficial in heart

care based on high quality data,

- More attention and resources needed to validate big data analytics applications in cardiac practice.

IV. CONCLUSIONS AND SUGGESTIONS

The work proposed in this article involves an in-depth study of the various authors' acknowledged work on cardiovascular disease (CVD). While investment in the use of machine learning algorithms for accurate CVD estimation has been proposed, it has been observed that incorporating them in classification techniques improves performance. This article focuses on the study of various machine learning methods, their relevance, and their impact on the performance of each system when classification algorithms are not used in addition to machine learning algorithms.

REFERENCES

- [1] World Health Organization. Global Plan of Action for the prevention and control of non-communicable diseases 2013-2030, 2013.
- [2] Fabio Mendoza Pachelor, Alexis De la Mantos, Paola ArizaColpas, Jorge Sepulveda Ojeda, Roberto Morales Ortega, Marlon PiñeresMelo, "Cardiovascular Disease Analysis Using Supervised and Unsupervised Data Mining Techniques," Accessed December 11, 2019.
<http://www.jsoftware.us/vol12/231-JSW15177.pdf>.
- [3] Weng, Stephen F., Jenna Reys, Joe Kai, Jonathan M. Garibaldi and Nadeem Qureshi. "Can Machine Learning Routine Improve Cardiovascular Risk Prediction Using Clinical Data?" *Plows One* 12, no. Page 4 of 2017
<https://doi.org/10.1371/journal.pone.0174944>.
- [4] Mezzatesta, Sabrina, Claudia Torino, Pasquale de Mio, Giacomo Fiomara and Antonio Vilasi. "An Machine-Based Approach to Estimating Cardiovascular Disease Prevalence in Dialysis Patients." *Computer Methods and Applications in Biomedicine*, 177(2019):9-15.
<https://doi.org/10.1016/j.cmpb.2019.05.005>.
- [5] Shamir, Qadar, Kip W. Johnson, Benjamin S. Glicksburg, Joel T Dudley and Partho P. Sengupta. "Machine Learning in Cardiovascular Medicine: Are We Still There?" *Hart*, Vol.104, No.14 (2018): 1156-64.
<https://doi.org/10.1136/heartjnl-2017-311198>.
- [6] SathyaBalaji, 2019, Smart Health Care Prediction for Cardiovascular Disease-A Systematic Review, *International Journal of Engineering Research & Technology (IJERT)* Vol.08, No.11, 2019, Paper ID: IJERTV8IS110376.
- [7] Purushottam, Kanak Saxena and Richa Sharma. "An Effective Heart Disease Prediction System Using Decision Tree." *International Conference on IT, Communications and Automation*, 2015.
<https://doi.org/10.1109/cca.2015.7148346>.
- [8] Li, Jan, Matthew Sperrin, Glen P. Martin, Darren M. Ashcroft and Tiedt Peter van Sta. "Check data quality and electronic health records for patient cardiovascular disease evaluation." *International Journal of Medical Informatics* 133 (2020): 104033.
<https://doi.org/10.1016/j.ijmedinf.2019.104033>.
- [9] Alik, Berin, Lezla Gurbeta and Almir Badjevic. "Machine learning methods for classifying diabetes and cardiovascular disease." *6th Mediterranean Conference on Embedded Computing (MECO) 2017*, 2017.
<https://doi.org/10.1109/meco.2017.7977152>.
- [10] Yeom, J, S Kim and B Zhang. "OptacidSS-E: A Clinical Decision Support System Based on a Collective Classifier to Predict Cardiovascular Disease Levels." *Expert Systems with Applications* 34, no. 4 (2008): 2465-79.
<https://doi.org/10.1016/j.eswa.2007.04.015>.
- [11] Neelashi, Meherbagh, Othman bin Ibrahim, Hussein Ahmadi and Leila Shahmoradi. "An Analytical Approach to Assessing Disease Using Machine Learning Methods." *Computers & Chemical Engineering* 106 (2017): 212-23.
<https://doi.org/10.1016/j.compchemeng.2017.06.011>.
- [12] Al Arefs, Subhi J, Khalil Ankouche, Gurpreet Singh, Piotr J Slomka, Kranti K Kolli, Amit Kumar, Mohit Pandey et al. "Clinical Applications of Machine Learning in Cardiovascular Disease and its Imaging v. Cardiac Imaging." *European Heart Journal* 40, no.24(2018):1975-1986.
<https://doi.org/10.1093/eurheartj/ehy404>.
- [13] Ren, Zhupeng, Jun Huu, Yanfang Gao, Qianxin, Maogu Hu, Li Dai, Changfeng Deng, etc. "Exposure to ambient PM10 during pregnancy increases the risk of congenital heart defects: evidence from machine learning models." *Common Environmental Science* 630 (2018): 1-10
<https://doi.org/10.1016/j.scitotenv.2018.02.181>.

- [15] Latha, C. Beulah Crystal and Art. Carolina Jeeva. "Increased accuracy of heart disease risk based on collective classification methods." *Medical Informatics Unlocked* 16 (2019): 100203.
<https://doi.org/10.1016/j.imu.2019.100203>.
- [16] Hasan, NahyanIbn and ArnabBhattapproach to the Classification of Cardiovascular Disorders Using a Modified ECG Signal from Empirical Decomposition." *Biomedical Signal Processing and Management* 52 (2019): 128-40.
<https://doi.org/10.1016/j.bspc.2019.04.005>.
- [17] Chen, Rui, Aijia, Xingjiang Wang, Xiaohai Ma, Li Zhao, Wangjia Wu, Jicheng Du, et al. "Using machine learning to evaluate one-year cardiovascular events in patients with severe dilated cardiomyopathy." *European Journal of Radiology* 117 (2019): 178 - 83.
<https://doi.org/10.1016/j.ejrad.2019.06.004>.
- [18] Vivekanandan, T. and Swati Jamjala Narayanan. "A Hybrid Risk Assessment Model for Cardiovascular Disease Using Coke Regression Analysis and Two-Way Clustering Algorithm." *Computers in Biology and Medicine* 113 (2019): 103400.
<https://doi.org/10.1016/j.compbimed.2019.103400>.
- [19] Wang, K. K. and Derek Abbots Fortini. "Cardiovascular Imaging Diagnostics Based on Deep Learning: A Promising Challenge." *Computer Systems of the Future*, 2019.
<https://doi.org/10.1016/j.future.2019.09.047>.
- [20] Ajanne, Daniel. 2019. Cheap cardiovascular disease diagnostic tool. Bachelor thesis at Harvard College.
- [21] Baskaran, Lohendran, Gabriel Maliyakal, Subhi J. Al Aref, Gurpreet Singh, JuwaranJu, Kelly Michalak, Christina Dolan and others. "Identification and Quantification of ACTC Cardiovascular Structures." *JACC: Cardiovascular Imaging*, 2019.
<https://doi.org/10.1016/j.jcmg.2019.08.025>.
- [22] Amin, Muhammad Shafenur, Yin Chia Chiam and Kasturi Devi Vrathan. "Identifying Important Symptoms and Data Acquisition Techniques for Assessing Heart Disease." *Telematics and IT* 36 (2019): 82-93.
<https://doi.org/10.1016/j.tele.2018.11.007>.
- [23] Ujar, Kan, and AhmetIlhan. "Diagnosis of heart disease using repeated trained neural networks based on genetic algorithms." *Procedia Computer Science* 120 (2017): 588-93.
<https://doi.org/10.1016/j.procs.2017.11.283>.
- [24] Metzker, Oleg, Sergei Sikorsky, Alexei Yakovlev and Sergei Kovalchuk. "Dynamic prediction of mortality using machine learning methods in acute cardiovascular cases." *Procedia Computer Science* 136 (2018): 351-58.
<https://doi.org/10.1016/j.procs.2018.08.279>.
- [25] Su, Xiao, Jinpeng Hu, Jingchi Jiang, Jing Xi, Yang, Bin Hee, Jinfeng Yang and Yi Guan. "Obtaining Cardiovascular Risk Factors from Chinese Electronic Medical Documentation." *Computer Methods and Applications in Biomedicine* 172 (2019):1-10
<https://doi.org/10.1016/j.cmpb.2019.01.007>.
- [26] Ting, Daniel Shu Wei, and Tian Shin Wang. "Looking at cardiovascular risk factors." *Natural Biomedical Engineering* 2, no. 3 (2018): 140-41.
<https://doi.org/10.1038/s41551-018-0210-5>.
- [27] Wang, Huang, Huangshan Ding, FatemehAzamianBidgoli, Brian Zhou, Carlos Iribaren, Sabi Molloy and Pierre Baldy. "Detection of Cardiovascular Diseases from Mammograms through Deep Learning." *IEEE Transactions on Medical Imagery* 36, no. 5 (2017): 1172-81.
<https://doi.org/10.1109/tmi.2017.2655486>.
- [28] Nakanishi, Rine, DaminiDey, Frederic Commandeur, PiotrSlomka, Julian Betancur, Heidi Gransar, Christopher Dailing, Kazuhiro Osawa, Daniel Berman, and Matthew Budoff. "Machine learning for the prediction of coronary heart disease and cardiovascular disease: results from the Multi-Ethnic Study of Atherosclerosis (MISA)." *Journal of the American College of Cardiology* 71, no.11 (2018).
[https://doi.org/10.1016/s0735-1097\(18\)32024-2](https://doi.org/10.1016/s0735-1097(18)32024-2).
- [29] Ramachandran, Diya, VanathiPonusamyThangapandian and HarikumarRajaguru. "Computerized Approach to Determining Cardiovascular Risk Level Using Photoplasmographic Signals." *Measure* 150 (2020): 107048.
<https://doi.org/10.1016/j.measurement.2019.107048>.
- [30] Popeline, Ryan, Avinash V. Varadarajan, Katy Bloomer, Eun Liu, Michael V. McConnell, Greg S .. Colorado, Lily Peng, and Dale R. Webster. "Prediction of Cardiovascular Risk Factors from Retinal Uterine Photographs Using Deep Learning." *Natural Biomedical Engineering* 2, no. 3 (2018): 158. - 64.
<https://doi.org/10.1038/s41551-018-0195-0>.
- [31] Eichel, Stefans, Patrick Rabbitt and Paulo Ghisletta. "Symptoms of cardiovascular disease and longitudinal declines in treatment rates differentially predict white brain damage in the elderly." *Archives of Gerontology and Geriatrics*

78 (2018): 139-49.
<https://doi.org/10.1016/j.archger.2018.06.010>.
[32] Al-Mallah, Mouz H., Sheriff Sakr and Ada al-Khunaibet. "Cardiovascular Conditioning and

Prevention of Cardiovascular Disease: An Update." Current Reports of Atherosclerosis 20, no. 1 (2018).
<https://doi.org/10.1007/s11883-018-0711-4>.