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Review of Machine Learning System for Cardiovascular Diseases Detection and Classification Based on Big Data

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Abstract: Cardiovascular disease is one of the top causes of death throughout the world. The early detection of these diseases is necessary to save lives. Using machine learning classification algorithms in healthcare organizations produces impressive results that assist medical professionals in correctly and rapidly diagnosing diseases of these kinds. The academic community is not yet fully using the huge amounts of data that healthcare companies generate. It is possible to extract important information from datasets with the use of machine learning technologies, creating more accurate results. By the survey findings, combining the feature optimization techniques PSO and ACO with the machine learning techniques KNN and RF yields an accuracy level of 99.65% minimum. To assist healthcare practitioners in making sound decisions, it is possible that future research can concentrate on developing a sophisticated model that makes use of machine learning and optimization techniques.

Keywords: *Machine Learning, Cardiovascular, Diseases, Detection, Naïve Bayes, Random Forest and Support Vector Machine*

1. Introduction

Heart disease and other cardiovascular conditions are responsible for more than 70 percent of all fatalities globally, making them the major cause of morbidity and mortality[1] [2] . According to research that was released in 2017 as part of the Global Burden of Disease study[3], cardiovascular disease is responsible for around 43 percent of all deaths worldwide. Poor diet, smoking, excessive sugar consumption, and obesity or excess body fat are prominent risk factors for cardiovascular disease[4] . According to Mozaffarian et al. [5] and Maiga et al. [6], cardiovascular disorders estimated global economic burden between 2010 and 2015 was about 3.7 trillion US dollars. In addition, many of the diagnostic tools that are necessary for determining the presence of coronary heart disease, such as CT scans and electrocardiograms, are prohibitively costly and difficult to schedule for patients. In 2019, an estimated 17.9 million people died from CVDs, which is 32 percent of all deaths worldwide. In the United States, about 695,000 people die from heart disease each year, which is 1 in every 5 deaths **(WHO 2021)**. More than half a billion people around the world continue to be affected by cardiovascular diseases, which accounted for 20.5 million deaths in 2021 close to a third of all deaths globally and an overall increase on the estimated 121 million CVD deaths. The goal of reduce premature mortality from non-communicable diseases (NCDs) by 25% by 2025 [7], [8]. Workers who suffered from cardiovascular disease were responsible for between 25 and 30 percent of the annual medical expenditures incurred by the firms [9]. Looking at trends each year from 2010 to 2022, the researchers' findings show that the death rates from cardiovascular disease rose by 9.3% from 2020 through 2022, in contrast to a decline of 8.9% from 2010 to 2019. There were more than 228,000 more CVD deaths from 2020-2022 than would be expected had the pre-2020 trends continued [10]. According to a January 2024 update from the American Heart Association, 931,578 people in the United States died from cardiovascular disease (CVD) in 2023. Therefore, early detection is essential to decrease the financial and medical expenses that heart disease imposes on both people and organizations. According to projections made by the World Health Organization (WHO), the number of people who will pass away as a result of cardiovascular disease (CVD) will reach 23.6 million by the year 2030 [11]. It is necessary to employ methods such as data mining and machine learning to anticipate the possibility of acquiring heart disease to save lives and minimize the financial burden that heart disease places on society.

In the field of medicine, a substantial amount of data is gathered daily, and by using data mining techniques, we can be able to unearth previously concealed patterns that are beneficial to clinical diagnosis [12]. Therefore, research that has been carried out over the previous several decades has shown the crucial role that data mining plays in the field of medicine. Diabetes, high blood pressure, high cholesterol, and irregular pulse rate are some of the

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risk factors for cardiovascular disease that need to be considered when making a prognosis[13]. The fact that not all of the relevant medical information is now readily available can sometimes have an impact on the results of predicting heart diseases.

In the realm of medicine, machine learning is essential. The use of machine learning enables the diagnosis, detection, and prognosis of a wide variety of diseases. Recent years have seen a rise in interest in using data mining and machine learning techniques to estimate the likelihood of an individual developing a certain disease. In the work that has been published in the past, applications of data mining approaches for disease prediction are discussed. Although several studies have attempted to determine the chance that the disease will progress in the future, such studies have not yet yielded conclusions that can be considered credible [14][15][16].

2. Literature Review

Numerous research investigates heart disease expectation frameworks using various data mining methods. Using many calculations, datasets, test results, and framework work is yielding better results. Numerous investigations were undertaken to create efficient approaches and high accuracy in detecting heart disease.

Pattekari [17] examined prediction system for heart disease using naïve Bayes. A computer program lets users answer pre-set questions. It compares client values to a predetermined data collection and finds hidden data. It can address difficult heart disease diagnostic questions better than typical emotionally supportive networks, helping doctors make better clinical decisions. It reduces treatment expenses by providing effective remedies.

Kusprasapta M [18] shows the importance of cycling heart rate monitoring. Cyclists can measure their pulse while accelerating to gauge activity and adjust their rhythm. By regulating pedaling effort, bikers can prevent overtraining and heart failure. The pulse of a cyclist could indicate training intensity also wearable sensors can monitor pulse. Unfortunately, the sensor does not capture all data at one, two, or more-second intervals.It focuses on medical therapy based on these grounds. Remote communication has advanced for heart disease.

Karrar[19] shows that data mining (DM) helps locate and diagnose cardiac disease. Many single- and mixed-breed information mining calculations are compared to discover the best coronary disease predictor.

Yeshvendra[20] reports a rise in AI-based disease forecasts. This approach is crucial and diversified because an AI program can imagine a heart disease from a human perspective, improving prediction accuracy.Heart disease diagnosis is a crucial biological problem. Examples of tree information mining methods include decision trees, naïve Bayes, and support vector machines. These strategies created an emotionally secure support structure for their decision.

Tripoliti[21] believes that detecting common diseases including diabetes, breast cancer, and heart disease is an important biological test.

Gonsalves[22] used machine learning and medical information to predict coronary CVD.

Oikonomou[23] describes the different sorts of chronic disease information. They used machine learning to clarify the extreme value theory and quantify chronic disease severity and risk.

Ibrahim [24] thinks machine learning can anticipate and diagnose heart disease. Active learning (AL) improves classification accuracy by combining sparsely labeled data with user-expert system input. Pratiyush et al. [25] examined how ensemble classifiers, not the XAI (Explainable Artificial Intelligence) framework, can predict heart disease using CVD datasets. The classification challenge used KNN, SVM, naive Bayes, AdaBoost, bagging, and LR on 303 examples and 14 attributes with category, integer, and real type attributes.

Jasmine S. Sonawane et al.[26] proposed a multilayer sensory neural network for heart disease detection in 2014 having accuracy almost 80%. Independently trained subnetworks scale well because complicated Boolean functions and restricted data sources increase training time. Ketut Agung Enrico et al.[4] proposed employing the KNN algorithm with simplified parameters for predicting heart disease. Its accuracy is 81.85%. Increasing KNN parameters affects performance and uses 90% of data for training, which is computationally costly and achieves nothing.

M. Akhil Jabbar et al.'s [27] Lazy Associative Classifiction categorizing heart disease prediction in the massive area needed to store all the info. No abstraction is performed during training, therefore noisy input expands the case base needlessly. In 2015, Jaymin Patel et al. [3] recommended data mining for heart disease prediction. The accuracy rate is 56.76%. A downside of J48 is that the tree grows linearly with huge data. Poor accuracy, sluggish deployment, and lengthy duration characterize LMT.

Rifki Wijaya et al. [28] studied the conceptual design of heart disease assessment using machine learning artificial neural networks in 2013. The accuracy is 81.85%. The neural network needs training to function. Large neural networks take time to process. Emulating microprocessors is necessary owing to their architecture and history.

Carlos Ordonez et al. [29] suggested association criteria for this prediction system having 70% accuracy. Too many patient record parameters are employed, creating superfluous rules. Poor performance and hefty computing costs characterize this approach.

Jyoti Soni et al.[30] assessed WAC (Weighted Associative Classifiers) which yields 81.51% accuracy. No characteristic is equally essential in predicting class marks in the prediction model. Because of this, attributes could be weighted differently based on prediction.In 2013, Ibticeme Sedielmaci et al. [13] proposed diagnosing heart diseases using fractal dimension and chaos theory, 80% accuracy is achieved using this method. Fractal analysis was created to examine complex, irregular objects. Chaos Theory's restrictions are primarily down to input parameter choices. Parameter computation depends on data dynamics and the kind of analysis, which is frequently complicated and imprecise.

Jayshril S, et al.[31] proposed learning vector quantization for heart disease prediction . Its accuracy is 85.55%. Each class must have at least one prototype, but there is no restriction on the number.

Chen et al.[32] develop a heart disease prediction approach which was presented to aid clinicians in predicting heart disease based on patient data. C-programmed artificial neural networks identify and predict heart disease. System development uses C and C#. The method has 80% accuracy. Anbarasi et al.[14] proposed a genetic approach to predict heart disease using feature subsets in 2010 having accuracy almost 70% . The response must be defined with a powerful term.

Manpreet Singh et al. [33] proposed a structural equation model (**SEM**) and fuzzy cognitive map (**FCM**) for cardiovascular disease prediction system. FCM and SEM accuracy is 74%. It struggles with large data sets and accuracy. Kathleen H. Miao et al.[34] studied Deep Neutral Networks for coronary heart disease diagnosis in 2015. This yields 83.67% accuracy. Adopting novices is difficult. Classifiers are needed since understanding alone cannot assess performance. Jae Kwon Kim et al.[9] proposed a neural network-based feature correlation analysis technique for predicting the risk of coronary heart disease. The accuracy of this technique is 81.16%. Correlational research can only be carried out if two variables can be rated on a scale of their own. It is difficult to tell which factors are responsible for which effects, and it is possible that a significant correlation between variables could be misleading. Sairabi H. Mujawar et al.[11] proposed a modified K-means and Naïve Bayes model for heart disease prediction. The Naive Bayes model assumes that all predictors are independent and suffer from a problem known as the zero-frequency issue.

Narin et al.[35] developed a machine learning-based (CVD) prediction method to increase the accuracy of the Framingham risk score (FRS). The suggested system, which employs a quantum neural network to learn and detect CVD patterns, was experimentally verified and compared to the FRS using data from 689 CVD patients and a Framingham validation dataset. The suggested method's accuracy in predicting CVD risk was 98.57%, considerably outperforming the FRS (19.22%) and other techniques. The study found that the proposed technique can assist doctors in forecasting their patients' CVD risk, designing better treatments, and encouraging early identification.

3. Comparison of Existing Works

Conventional invasive methods for diagnosing heart disease were based on a patient's medical history, the results of physical exams, and the study of accompanying symptoms by the attending physician. When compared to other common diagnostic procedures for heart problems, angiograms are often held in high esteem as being among the most precise options. Angiography does, however, come with a number of substantial drawbacks, the most notable of which are its high cost, its wide range of adverse consequences, and the need of a solid technological foundation [27]. Because of the possibility of human error, traditional methods [28] often provide erroneous diagnoses and take much more time. In addition, the evaluation of this approach of disease detection is highly difficult computationally, as well as time-consuming, expensive, and complicated.

The relatively short dataset, which leads to an increased risk of overfitting, is the primary limitation of the previous research. It's possible that the known models don't work very well with large datasets. Instead, we selected a dataset on cardiovascular disease that had 11 features and 70,000 people. This significantly reduced the possibility that our model was overfitting the data. The authors [29] used every feature in the dataset and generated classification models with good accuracy; however, they did not manage the null values in the dataset and only used a small dataset to evaluate the accuracy of their respective models' predictions. In addition, they did not utilize any strategy for feature selection to uncover strongly associated traits that could potentially increase the accuracy of the classification model.

Researchers have been hard at work developing a variety of non-invasive smart healthcare systems that are based on predictive machine learning techniques. These techniques[30]include Decision Tree (DT), Naive Bayes (NB), K-Nearest Neighbor (KNN), and Support Vector Machine (SVM), amongst others. The goal of these researchers is to address the issues that are present with traditional invasive-based methods for the identification of heart disease. As a direct result of this, the mortality ratio for patients who suffer from heart disease has decreased. In this paper, researchers often refer to the Cleveland heart disease dataset. The given table shows a tabular analysis of existing work.

Table 1. Tabular analysis of existing works

Ref.No	Author	Technique	Dataset	Accuracy	Limitations
[3]	Jaymin Patel	Data mining technique Decision Tree model	Cleveland dataset	56.76%	• The drawback of J48 is that the tree increases linearly with large data • LMT is slower and takes a long time for implementation • Accuracy is low
[14]	M. Anbarasi	Feature subset selection using genetic algorithm	Hospital database	70%	• A bad fitness function option can cause serious issues, such as being unable to solve a problem or, even worse, returning an incorrect answer to a problem the solution to the issue
[29]	Carlos Ordonez	Association rules	Medical dataset from hospital	70%	• This technique is computationally expensive and performance is low.
[33]	Manpreet Singh	Structural equation modeling and Fuzzy cognitive mapping	Canadian Community Health Survey (CCHS) dataset	74%	• It doesn't work well with large data and accuracy is low.
[13]	Idticeme sedjelmaci	Fractal dimension and chaos theory	Hospital database	80%	• The drawbacks of applying Chaos Theory are primarily due to the input parameters chosen. The underlying dynamics of the data, as well as the type of analysis being done, which is usually complex and not always accurate, determine the methods used to measure these parameters.
[32]	Ah Chen	Artificial neural network algorithm	ML UCI repository	80%	• It exhibits a black box nature, which doesn't give information about how much time is required for prediction, or the amount of data required. It is computationally expensive.
[9]	Jae Kwon Kim	Feature correlation Analysis	KNHANE S-VI dataset	81.16%	• A correlational analysis can only be used when the variables are two measurable on a scale. Cannot conclude cause and effect, strong association between variables can be misleading
[30]	Jyoti Soni	Weighted Associative classifier	UCI machine learning dataset	81.51%	• All attributes are not equally important in predicting the class mark in the prediction model. As a result, different weights can be assigned to different attributes depending on their predictive performance.

[4]	Ketut Agung Enrico	K-Nearest Neighbours	Hungarian dataset	81.85%	• Using KNN, with an increase in several parameters the performance decreases and it considers 90% of data for training which is computationally expensive and does nothing during the training phase.
[34]	Kathleen j. Miao	Deep Neural Network	Cleveland Heart Disease Database	83.67%	• It is difficult to be adopted by less experienced people. It is difficult to comprehend performance based solely on understanding, and this necessitates the use of classifiers.

4. Significance and Scope of the Research

The modern, hectic way of life has a huge influence on the lives of other people. Because of the way people choose to live their lives, the stress they put themselves through, and in some circumstances, their genetic make-up, heart disease affects a significant number of people all over the globe, regardless of age. In order for medical experts to be able to take preventive measures and so save a significant number of lives, the purpose of this article is to foresee the early beginning of heart disease. The bulk of the conventional procedures that hospitals employ to treat heart issues are reactive [31],[32]. This means that physicians are unable to make accurate forecasts since hospitals are unable to manage the enormous quantity of data that is created everyday regarding the health of patients. For the purpose of prediction in this study, machine learning approaches are used due to their high level of performance as well as their capacity to manage enormous volumes of data. Because they are crucial to prediction, Machine Learning categorization models are used. The Random Forest approach, in combination with a few other classification strategies, is used in this investigation to make a prediction about coronary heart disease. This study hopes to cut down on the number of people who pass away from heart disease and improve our ability to predict when it can strike again.

5. Data Collection Methods

Depending on the sources, we can employ various methods to collect data:

- **Electronic Health Records (EHRs):** Collaborate with healthcare institutions to gain access to EHRs [33]. You could need to extract relevant information from structured databases or unstructured clinical notes.
- **Imaging Data:** Work with healthcare providers to obtain relevant imaging data [34]. This can involve partnerships with radiology departments or access to medical archives.
- **Surveys and Questionnaires:** Design surveys or questionnaires to collect patient-reported data, including lifestyle factors, family history, and symptoms.
- **Wearable Devices:** Explore the use of wearable devices (e.g., fitness trackers) to collect real-time data on heart rate, physical activity, and sleep patterns [35][36].
- **Publicly Available Datasets:** Consider using publicly available datasets related to cardiovascular diseases, such as those from government health agencies or research institutions [37].

6. Conclusions

An examination of supervised machine learning classification techniques for the diagnosis of cardiovascular disease is presented in this paper. Those who work in healthcare can apply machine learning to improve their decision-making abilities. Through research, algorithm combinations are investigated, and effective approaches are discovered. The accuracy of the model is dependent on the dataset, the number of attributes, the pre-processing procedures, and the classifier. Research was conducted on a number of different models for predicting cardiovascular disease, and experimental data was evaluated in order to find the most effective classifier. To detect these diseases, a variety of classifiers were utilised, such as Support Vector Machines (SVM), Decision Trees, Random Forests, Naïve Bayes, and Artificial Neural Networks (ANN). As a result of its low number of missing variables, the Cleveland dataset is quite popular. It has been determined via analysis that the approaches of optimisation and classification provide outstanding results. To develop a more sophisticated model, it is necessary to combine optimisation techniques with individualised classification methods. A large number of samples from a dataset of good quality are required.

References

[1] "Vanessa, Nadoo, Ashezua et al. / Procedia Computer Science 127 (2024) 430–443".

[2] "Azmi, Javed, et al. 'A systematic review on machine learning approaches for cardiovascular disease

prediction using medical big data.' Medical Engineering & Physics 105 (2022): 103825.".

[3] "Jaymin Patel, Prof. Tejal Upadhyay, and Dr. Samir Patel, Sep 2015-Mar 2016, 'Heart Disease Prediction using Machine Learning and Data Mining Technique', Vol. 7, No.1, pp. 129-137".

[4] "I Ketut Agung Enriko, Muhammad Suryanegara, Dinda Agnes Gunawan, ' Heart disease prediction system using a k-Nearest neighbor algorithm with simplified patient's health parameters', 2016.".

[5] "Dariush Mozaffarian, 'Dietary and Policy Priorities for Cardiovascular Disease, Diabetes, and Obesity' PT- Journal Article, DP - 2016, TA - Circulation, PG - 187-225, VI - 133, IP - 2, AID - 10.1161/CIRCULATIONAHA.115.018585.".

[6] "J. Maiga, G. G. Hungilo and Pranowo, 'Comparison of Machine Learning Models in Prediction of Cardiovascular Disease Using Health Record Data,' 2019 International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS), Jakarta, Indonesia, 2019, pp. 45-48, doi: 10.1109/ICIMCIS48181.2019.8985205.".

[7] "Vaduganathan M, Mensah GA, Turco JV, Fuster V and Roth GA (2022) The Global Burden of Cardiovascular Diseases and Risk: A Compass for Future Health. J Am Coll of Cardiol 80(25): 2361-2371".

[8] "World Heart Report 2023: Confronting the World's Number One Killer. Geneva, Switzerland. World Heart Federation. 2023."

[9] "Jae Kwon Kim and Sanggil, 'Neural Network-Based Coronary Heart Disease Risk Prediction Using Feature Correlation Analysis', 2017.".

[10] R. C. Woodruff *et al.*, "Trends in Cardiovascular Disease Mortality Rates and Excess Deaths, 2010-2022," *Am J Prev Med*, vol. 66, no. 4, pp. 582–589, Apr. 2024, doi: 10.1016/j.amepre.2023.11.009.

[11] "Sairabi H. Mujawar, and P. R. Devale, October 2015, 'Prediction of Heart Disease using Modified k-means and by using Naive Bayes', International Journal of Innovative Research in Computer and Communication Engineering(An ISO 3297: 2007 Certified Organization) Vol. 3, Issue 10, pp. 10265-10273.".

[12] "Saikumar, K., and V. Rajesh. 'A machine intelligence technique for predicting cardiovascular disease (CVD) using Radiology Dataset.' International Journal of System Assurance Engineering and Management (2022): 1-17.".

[13] "IbticemeSedielmaci; F. BereksiReguig, 'Detection of some heart diseases using fractal dimension and chaos theory', 2013, IEEE 8th International Workshop on Systems, Signal Processing and their Applications (WoSSPA).".

[14] "Anbarasi Masilamani, ANUPRIYA, N Ch Sriman Narayana Iyengar, 'Enhanced Prediction of Heart Disease with Feature Subset Selection using Genetic Algorithm', October 2010, International Journal of Engineering Science and Technology 2(10).".

[15] "Padmaja, B., et al. 'Early and accurate prediction of heart disease using machine learning model.' Turkish Journal of Computer and Mathematics Education (TURCOMAT) 12.6 (2021): 4516-4528.".

[16] "Amal, Saeed, et al. 'Use of multi-modal data and machine learning to improve cardiovascular disease care.' Frontiers in Cardiovascular Medicine 9 (2022): 840262.".

[17] "Shadab Adam Pattekari and Asma Parveen PREDICTION SYSTEM FOR HEART DISEASE USING NAIVE BAYES International Journal of Advanced Computer and Mathematical Sciences ISSN 2230-9624. Vol 3, Issue 3, 2012".

[18] "Kusprasapta M, Ichwan M, Utami DB. Heart rate prediction based on cycling cadence using feedforward neural network. In 2016 International Conference on Computer, Control, Informatics and its Applications (IC3INA), IEEE, 2016;72–76. https://doi.org/10.1109/IC3INA.2016.7863026".

[19] "Al-Jammali, Karrar. 'Prediction of heart diseases using data mining algorithms.' Informatica 47.5 (2023).".

[20] "Singh KY, Sinha N, Singh KS. Heart disease prediction system using random forest. In International Conference on Advances in Computing and Data Sciences, Advances in Computing and Data Sciences.

[21] ICACDS 2016. Communications in Computer and Information Science, Singapore. 2017;721:613–623. https://doi.org/10.1007/978-981-10- 5427-3_63".

[22] "Tripoliti E, Fotiadis ID, Manis G. Automated diagnosis of diseases based on classification: dynamic determination of the number of trees in random forests algorithm. EEE Trans Inf Technol Biomed 2012;16(4).".

[23] "Gonsalves AH, Thabtah F, Mohammad RMA, Singh G. Prediction of coronary heart disease using machine learning: an experimental analysis. In: Proceedings of the 2019 3rd International Conference on Deep Learning Technologies, 2019;51–56".

[24] “Oikonomou EK, Williams MC, Kotanidis CP, Desai MY, Marwan M, Antonopoulos AS, Thomas KE, Thomas S, Akoumianakis I, Fan LM, et al. A novel machine learning-derived radiotranscriptomic signature of perivascular fat improves cardiac risk prediction using coronary ct angiography. Eur Heart J. 2019;40(43):3529–43”.

[25] “El-Hasnony IM, Elzeki OM. Multi-label active learning-based machine learning model for heart disease prediction. Sensors. 2022;22(3):1184–8. https://doi.org/10.3390/s22031184”.

[26] “Guleria P, Srinivasu PN, Ahmed S. Ai framework for cardiovascular disease prediction using classification techniques. Electronics. 2022;11(24):1184–8. https://doi.org/10.3390/electronics11244086”, [Online]. Available: https://doi.org/10.3390/electronics11244086

[27] “Sonawane J, D.R Patil, 2014, ‘ Prediction Of Heart Disease Using Multilayer Perceptron Neural Network ’, IEEE International Conference on Information Communication and Embedded Systems (ICICES2014).”.

[28] “M. Akhil Jabbar; B. L Deekshatulu; Priti Chandra, ‘ Heart disease prediction using lazy associative classification’, : 2013, IEEE International Mutli-Conference on Automation, Computing, Communication, Control and Compressed Sensing (iMac4s)”.

[29] “Rifki Wijaya, ArySetijadiPrihatmanto, Kuspriyanto, ‘ Preliminary design of estimation heart disease by using machine learning ANN within one year’, 2013, IEEE Joint International Conference on Rural Information & Communication Technology and Electric-Vehicle Technology (rICT&ICeV-T).”.

[30] “Carlos Ordonez,2006, ‘Association Rule Discovery with the Train and Test Approach for Heart Disease Prediction’, IEEE Transactions on Information Technology in Biomedicine (TITB), pp. 334-343, vol. 10, no. 2”.

[31] “Jyoti Soni, Uzma Ansari, Dipesh Sharma, and SunitaSoni, June 2011, ‘Intelligent and Effective Heart Disease Prediction System using Weighted Associative Classifiers’, International Journal on Computer Science and Engineering (IJCSE), Vol. 3, No. 6, pp. 2385-2392”.

[32] “Jayshril S. Sonawane; D. R. Patil, ‘ Prediction of Heart Disease Using Learning Vector Quantization Algorithm ’, 2014, IEEE Conference on IT in Business, Industry, and Government (CSIBIG).”.

[33] “AH Chen, SY Huang, PS Hong, CH Cheng, and EJ Lin,2011, ‘HDPS: Heart Disease Prediction System’, Computing in Cardiology, ISSN: 0276-6574, pp.557-560.”.

[34] “Singh, M., Martins, L.M., Joanis, P. and Mago, V.K. (2016) Building a Cardiovascular Disease Predictive Model Using Structural Equation Model and Fuzzy Cognitive Map. IEEE International Conference on Fuzzy Systems (FUZZ), Vancouver, 24-29 July 2016, 1377-1382. https://doi.org/10.1109/FUZZ-IEEE.2016.7737850”.

[35] “Kathleen H. Miao, Julia H. Miao, ‘Coronary Heart Disease Diagnosis using Deep Neural Networks ’,(IJACSA)International Journal of Advanced Computer Science and Applications, Vol. 9, No. 10, 2018.”.

[36] “Narin, A.; Isler, Y.; Ozer, M. Early prediction of Paroxysmal Atrial Fibrillation using frequency domain measures of heart rate variability. In Proceedings of the 2016 Medical Technologies National Congress (TIPTEKNO), Antalya, Turkey, 27–29 October 2016”.

[37] “Shah, D.; Patel, S.; Bharti, S.K. Heart Disease Prediction using Machine Learning Techniques. SN Comput. Sci. 2020, 1, 345”.

[38] “Drozd˙ z, K.; Nabrdalik, K.; Kwiendacz, H.; Hendel, M.; Olejarz, A.; Tomasik, A.; Bartman, W.; Nalepa, J.; Gumprecht, J.; Lip, G.Y.H. ˙ Risk factors for cardiovascular disease in patients with metabolic-associated fatty liver disease: A machine learning approach. Cardiovasc. Diabetol. 2022, 21, 240”.