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ORIGINAL ARTICLE

Classification of Artificial Intelligence Based Coronary Artery Stenosis

YILDIZ ECE[1], TUNCAY ÇOLAK[2], SÜLEYMAN UZUN[3], AYŞE OYA SAĞIROĞLU[4]
[1]Department of Anatomy, Faculty of Medicine, Kocaeli University, Kocaeli, Turkey. tuncayc@kocaeli.edu.tr
[2]Department of Computer Engineering, Faculty of Technology, Sakarya Applied Sciences University, Sakarya, Turkey. suleymanuzun@subu.edu.tr
Correspondence to: Yıldız Ece, Email: yildizece@sakarya.edu.tr, Cell: +905457160668

ABSTRACT

Background: Despite major advances in diagnoses and treatments, cardiovascular disease (CVD) continues to be the leading cause of morbidity and mortality worldwide. To improve and optimize CVD results, AI techniques have the potential to radically revolutionize the way we practice cardiology, especially in imaging and provide with new tools to interpret data and make clinical decisions.
Aim: Establishing strategies are necessary to improve the diagnosis and treatment of CVD in the future. Nowadays, artificial intelligence (AI) may have the potential to solve this problem. The application of AI in heart diseases aims to facilitate the detection of radiology patients.
Methods: The machine learning algorithms used in this study are K-Nearest Neighbor (KNN), Support Vector Machines (SVM), Naive Bayes, and Decision Tree. In our study, a total of 600 patients, 300 female and 300 male, who were diagnosed with IHD as a result of the findings obtained from the reports of the patients who underwent CAG in the Fırat University Hospital were included in our study. Accuracy, precision, sensitivity, specificity, and F1-score performance values were obtained by the classification.
Results: Among the algorithms we have used, KNN had the highest success rate. It was followed by SVM in the second success rate. The success rate of RCA was 83% in KNN, and it was 75% in SVM. While the success rate of LCx in KNN was 76%, it was 68% in SVM. Similarly, the success rate of LAD in KNN was 73%, and it was 71% in SVM.
Conclusion: The demand for CAG will be rising in the coming years, owing to an increase in HR. Therefore, new strategies will be sought to reduce the duration of CAG. We consider the application of AI in routine clinical practice.
Keywords: Right coronary artery, Left coronary artery, Stenosis, Artificial intelligence

INTRODUCTION

Despite major advances in diagnoses and treatments, cardiovascular disease (CVD) continues to be the leading cause of morbidity and mortality worldwide (1). The incidence of CVD was responsible for 17.6 million deaths, with an increase of 14.5% from 2006 to 2016. Therefore, establishing strategies are necessary to improve the diagnosis and treatment of CVD in the future. Nowadays, artificial intelligence (AI) may have the potential to solve this problem (2). Right coronary artery (RCA) and left coronary artery (LCA) are vascular accesses in the capillary beds in the myocardium starting from the sinuses of the ascending aorta, valvulae semilunaris dextra, and sinistra (3). Ischemic heart disease (HRD) is the most common type of CVD resulting from atherosclerosis (4). Atherosclerosis is a systemic arterial disease that affects blood vessels of all sizes, frequently medium-sized elastic arteries (5). It usually begins with the formation of fatty streaks in the vessel lumen in childhood. Its clinical symptoms are observed in the middle and later ages. As there is less blood flow resulting from narrowing in the coronary arteries, it may cause chest pain called angina pectoris or myocardial infarction (6). In cases where the causes of atherosclerosis can be diagnosed and treated, it can be stopped or regressed (7). A strong correlation was identified between the number of cigarettes smoked and CVD in gender groups, the young, the elderly, and all racial groups (8). Malnutrition and physical inactivity are well-known as significant risk factors for a variety of diseases. An ‘obesogenic’ environment, which stimulates overeating and physical inactivity, has been reported to have a direct effect on obesity (9). Some modifiable factors that can be modified by lifestyle; such as smoking, obesity, and physical inactivity, or drug-modifiable lipid abnormalities, hypertension, and diabetes mellitus; and unmodifiable risk factors such as age, gender, and family history play a significant role in the formation and prognostic of CVD (10, 11). Smoking alone increases the risk of CVD by about two to three-folds; however, combining smoking with other factors will elevate the risk even more (10, 12). Due to the aging of society and the rapid increase in diseases such as diabetes mellitus and obesity, this frequency is expected to gradually elevate over the next decade (13, 14). Coronary angiography (CAG) is a method of advancing a catheter inserted into a peripheral artery through the origin of the coronary artery and imaging the coronary artery lumen anatomy radiographically under x-ray with radiopaque materials injected through the catheter (15). Contrast agents in coronary angiography may cause complications such as arrhythmia, congestive heart failure, acute pulmonary edema, vasovagal attacks, allergic reactions, and nephrotoxicity. Minor complications are usually local complications at the vascular interference site. Major complications, however, are acute MI, paralysis, and death (16). To improve and optimize CVD results, AI techniques have the potential to radically revolutionize the way we practice cardiology, especially in imaging and provide with new tools to interpret data and make clinical decisions (1). Artificial intelligence, commonly referred to as machine intelligence, is an area of computer science that simulates the process of human intelligence. Alan Mathison Turing proposed this idea more than 60 years ago. According to the Turing test, if a human being is unable to distinguish whether a machine's response is from a machine or a human, then the machine is called 'intelligent' (2). The application of artificial intelligence (AI) in heart diseases aims to facilitate the detection of radiology patients (17). In particular, AI applications may serve to image analysis, risk estimation, reduction of diagnosis time, and medical treatment (2, 18, 19). In addition, it may assist detecting myocardial ischemia (20). Similarly, the utilization of developing communication and information technologies is critical in terms of establishing a widespread health service that allows elderly and chronically ill patients to receive medical care at home, reducing hospitalizations, and enhancing the quality of life (1). The diagnosis of coronary artery stenosis is usually time-consuming, and the accuracy of coronary arteries' diagnosis depends on the stage in the cardiac cycle and the experience of the specialist physician (17). Soon, the AI will be able to identify coronary atherosclerotic plaques with more accuracy than clinicians using a deep learning approach (21). Artificial intelligence has changed essential aspects of human life. The AI created by human beings may have weak or strong sides. Weak AIs may only think and make judgments to the extent that humans have programmed them. However, strong artificial intelligence is a system capable of building its own program by performing computations, employing self-learning algorithms, and unrepeating its errors that have previously been done via learning from its own mistakes (22). The AI techniques such as machine learning (ML), deep learning (DL), and cognitive computing can play a critical role in the early detection and diagnosis of CVD, as well as outcome prediction and prognosis assessment. The continual development of the AI techniques, particularly in the sub-branches of ML and DL, has rapidly grasped clinicians' interest to create new integrated, reliable, and efficient approaches for providing quality healthcare (1). Machine learning (ML), a subset of artificial intelligence (AI), is becoming more widely employed in the medical community, particularly in the field of cardiovascular diseases, where machines learn knowledge autonomously through extracting patterns from enormous databases (1,23). Machine Learning (ML) is referred to the process of learning that uses algorithmic and statistical methods, which operate with the data provided in the computer system and make conclusions by verifying what they have learned (24). This model, which is designed to make predictions, takes on the task of predicting the future. As a result, the data is divided into two categories: training and test. The inference is provided as a percentage from the data included in the algorithm (25). Deep learning is a sub-branch of machine learning that uses neural networks and requires supervised, less touched, but more data than machine learning. It is also characterized by automatic algorithms that extract meaningful models from data sets (26). The use of deep learning became popular in the 2010s, and it now plays a significant role in big data. Deep learning is a method that processes data in many layers in machine learning at once, uses the libraries of machine learning and identify the parameters defined in it, calculates and processes which parameter will give the best value and produce the best ratio, and finds closer results in studies and researches. Machine learning is applied in many fields. Medicine is the most prominent and efficient of these fields. After consulting a physician, machine learning serves physicians to perform necessary examinations and make an early diagnosis. All medical devices have become digital as technology has advanced. This progress ensures the development of algorithms and the generation of sufficient datasets for machine learning. Significant researches have been carried out in this regard, particularly for diseases of vital importance. The use of algorithms with high predictive power and success rate increases the accuracy of early diagnosis. The importance of machine learning in the field of medicine is highlighted by studies on the subject and the effectiveness of the devices that have been used. These methods are utilized in several countries, including our own. Thanks to learning-based algorithms, early diagnosis of diseases can save lives. There are several algorithms in different libraries of machine learning (27). The machine learning algorithms used in this study are K-Nearest Neighbor, Support Vector Machines (SVM), Naive Bayes, and Decision Tree.

K-Nearest Neighbor Algorithm is the most widely used and straightforward algorithm. The K-nearest neighbor algorithm is a lazy algorithm that memorizes the training data rather than analyzes it, implying that it does not learn the data. An estimate must be made at the end of the study, and the algorithm searches the entire data set by checking its neighbors that it remembers to find this estimate. There is a K value determined in the study, and this value indicates the number of elements that the algorithm will search in the data set. It is a statistically based approach. When a value is entered into the algorithm, that algorithm selects and processes the K number of elements closest to that value. The Euclidean function is used to determine this distance. Manhattan and Minkowski functions are also used. The data calculated in these functions are sorted and classified by the appropriateness of the value. Due to its resistance to complex training data, it is one of the most well-known machine learning algorithms. It is not advantageous in large data sets since it memorizes rather than understands the data, requiring more memory (27).

Support Vector Machines is a learning algorithm based on the statistical learning theory discovered in 1963 by Alexey Chervonenkis and Vladimir Vapnik. Vapnik and his team continued to enhance SVM in 1995, giving it its current form. It is applied with the assistance of a line. It is used to separate data divided into two parts as appropriate. When compared to other machine learning algorithms, it has numerous advantages such as being effective in cases where the number of samples in the study is less than the number of dimensions, using different core functions in the decision mechanism, producing more effective and successful results in large data sets, and being able to work with a large number of independent variables (28).

Naive Bayes is a classification algorithm named after a scientist Thomas Bayes. The basis of this classification algorithm is purely probabilistic in nature. It assigns a categorization to the data in the data set based on probability estimates. The Naive Bayes algorithm, a lazy algorithm, can work on unbalanced and irregular data sets. It calculates all probabilities for each element in the data set separately and categorizes them based on the highest probability value. The more training data there is, the more accurate the results; yet, it can work with fewer data and have a high success rate. If the data in the test set has no counterpart in the training set, or conversely, if the data in the training set has no equivalent in the test set, then it cannot calculate probability, can make predictions, and outputs the result as ‘0’ probability. It is utilized in a variety of applications such as suggestion systems, survey analysis, mail spam detection, and text categorization. It has a substantially greater success rate, especially in applications that require real-time prediction (29).

Decision Tree is the most widely used method among classification and regression models since the methods are easy to interpret, integrate easily with other systems, expose understandable rules owing to its structure, and are reliable (30). Its structure is a probability-based and statistics-based algorithm. In decision trees, a decision tree is initially created, then the rules generated from the decision tree and the database entries are classified. In decision trees, several algorithms can be utilized including ID3, C4.5, Sliq, Sprint, CART, REP Tree, Random Forest, Logistic Model Tree. Firstly, the data is sent to one of these decision tree algorithms. The algorithm analyzes this data and generates a decision tree. This newly generated decision tree class is used to determine the classes of unknown data (30). Nodes are the acquisitions that come from the data set. These nodes respond the questions like on-off, true-false, yes-no, dividing the data in half at each node. The node with the highest success rate and the data is entered into the algorithm for branching by assessing the feature vectors affecting the dividend data characteristics. After branching, the algorithm continues to run indefinitely until it classifies all the data (31). Decision trees are generated from trained data from general to specific and downward. The tree begins with a root node that contains all the data in the sample. When the structure of decision trees is considered, they consist of roots, branches, and leaves. Its structure resembles a tree. Decision trees, which begin with the root node, divide a large number of data set into small groups and branches as they go downward. Starting from this root and extending to the branches, each node in the tree structure is called a node; different types of nodes in these trees generated at the same time are referred to as child nodes, and those of the same type are referred to as terminal nodes. Each node is divided into two or more branches, and the branching stops if there are no new questions after the node. Thus, a leaf representing a class is created. In decision trees, there are two steps to data classification. These are the learning and categorization. To develop a model, the training data collected prior to the learning step is analyzed using a classification approach. This learned model is stated in the form of classification rules. The test data is utilized in the second stage, the categorization step, to determine whether the decision tree is correct (28).

MATERIAL AND METHODS

In our study, a total of 600 patients, 300 female and 300 male, who were diagnosed with IHD as a result of the findings obtained from the reports of the patients who underwent CAG in the Fırat University Hospital were included in our study. To determine this 25 - 69 in the range of age, male and female patients according to gender; 25 - 39, 40 - 54, 55 - 69 were divided in to age groups. The 300 female and 300 male patients were subdivided into 150 smokers and 150 non-smokers. IHD grouping if left artery descending (LAD) and circumflex artery (CxA) which are main branches of left coronary artery (LCA) and rigth coronary artery (RCA) and classified as artificial intelligence-based in two classes as ‘there is a gap’ and ‘there is no gap’ in the relevant areas. In classification processes, algorithms from machine learning algorithms K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Naive Bayes (NB) and Decision Tree (Tree) were used.

RESULTS

Accuracy, precision, sensitivity, specificity, and F1-score performance values were obtained by the classification. To better present these data, scatter plots and ROC (Receiver Operating Characteristic) curves were used. Performance measurements were calculated using the complexity matrix shown in Table 1.

Table 1: Confusion Matrix

Predicted Class	Actual Class	
	Positive	Negative
True	True Positive (TP)	True Negative (TN)
False	False Positive(FP)	False Negative (FN)

Equations 1, 2, 3, 4, and 5 demonstrate the mathematical equations for the performance metrics employed in the study.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (1)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (2)$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \quad (3)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \quad (4)$$

$$\text{F1}-\text{score} = \frac{2*\text{TP}}{2*\text{TP+FP+FN}} \quad (5)$$

Figure 1: Confusion matrix.

Figure 1: depicts the complexity matrix developed as a result of the study. This matrix shows how many of the 'there is a gap' and 'there is no gap' groups are correctly identified and how many are wrongly labeled as a result of each algorithm.

When the numerical values obtained from the complexity matrix given in Figure 1 were substituted in equations 1, 2, 3, 4, and 5, the performance results of the Right coronary artery in Table 2, the Left circumflex artery in Table 3, and Left artery descending data in Table 4 were calculated.

Table 2: Right coronary artery performance results of the three-class system

Classifier	Accuracy	Precision	Sensitivity	Specificity	F1-score
NB	0.660550	0.950704	0.668317	0.562500	0.784884
SVM	0.756881	0.908451	0.763314	0.734694	0.829582
KNN	0.830275	0.943662	0.822086	0.854545	0.878689
Tree	0.743119	0.859155	0.772152	0.666667	0.813333

Table 3: Left circumflex artery performance results of the three-class system

Classifier	Accuracy	Precision	Sensitivity	Specificity	F1-score
NB	0.577982	0.486239	0.595506	0.565891	0.535354
SVM	0.683486	0.623853	0.708333	0.663934	0.663415
KNN	0.766055	0.706422	0.802083	0.737705	0.751220
Tree	0.674312	0.633028	0.690000	0.661017	0.660287

Table 4: Left artery descending performance results of the three-class system

Classifier	Accuracy	Precision	Sensitivity	Specificity	F1-score
NB	0.573394	0.361111	0.619048	0.554839	0.456140
SVM	0.711009	0.666667	0.727273	0.697479	0.695652
KNN	0.733945	0.750000	0.723214	0.745283	0.736364
Tree	0.655963	0.666667	0.648649	0.663551	0.657534

Figures 2, 3, and 4 demonstrate the Right Coronary Artery scatter plot, the Left Circumflex Artery, the Left Artery Descending scatter plot, respectively. On these graphs, each data classified as true and false by the classification algorithms was presented clearly.

Among the algorithms we have used, KNN had the highest success rate. It was followed by SVM in the second success rate. The success rate of RCA was 83% in KNN, and it was 75% in SVM. While the success rate of LCx in KNN was 76%, it was 68% in SVM. Similarly, the success rate of LAD in KNN was 73%, and it was 71% in SVM.

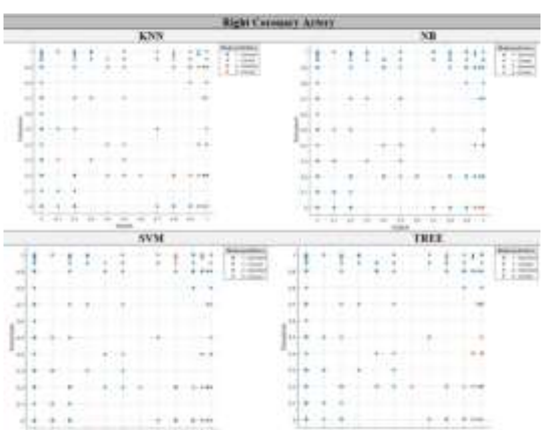

Figure 2: Right Coronary Artery Scatter Plot graph

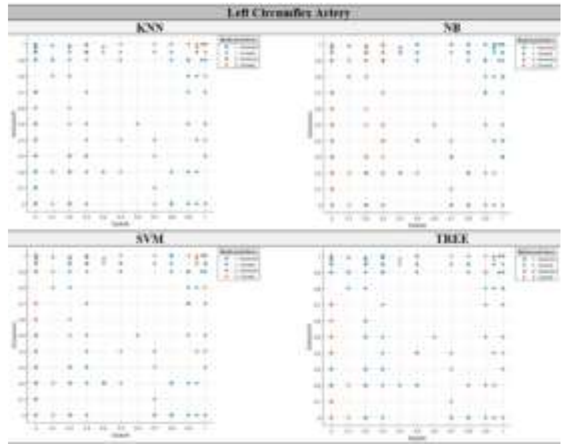

Figure 3: Left Circumflex Artery Scatter Plot graph

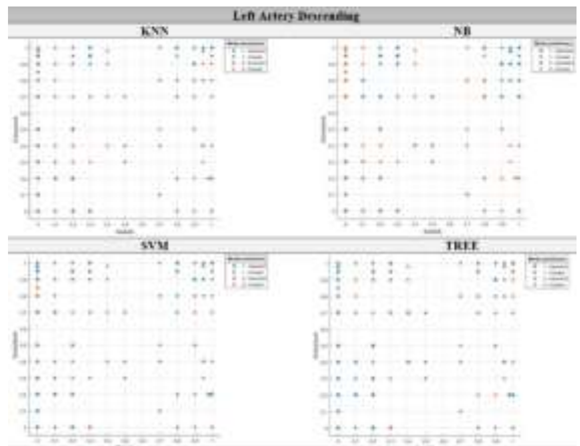

Figure 4: Left Artery Descending Scatter Plot graph

In addition, the Right Coronary Artery ROC curve graph, the Left Circumflex Artery ROC curve graph, and the Left Artery Descending ROC curve graph were given in Figures 5, 6, and 7, respectively. The data classification performances of classification algorithms are depicted clearly on this graph.

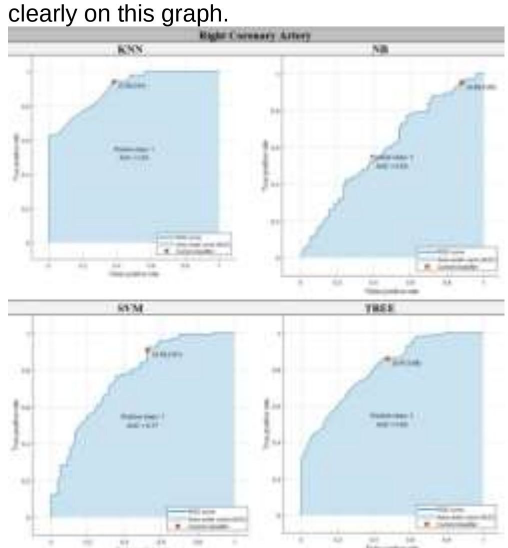

Figure 5: Right Coronary Artery ROC curve graph.

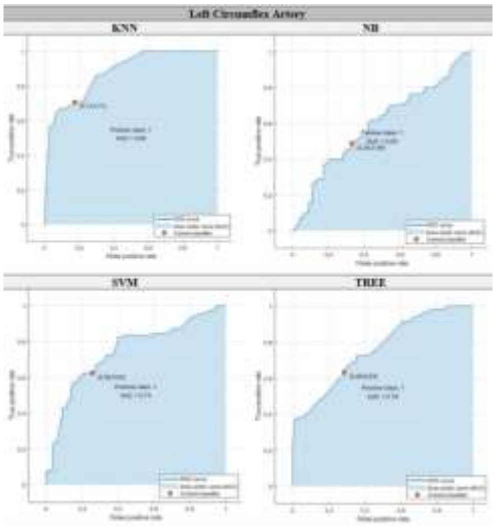
Figure 6: Left Circumflex Artery ROC curve graph.

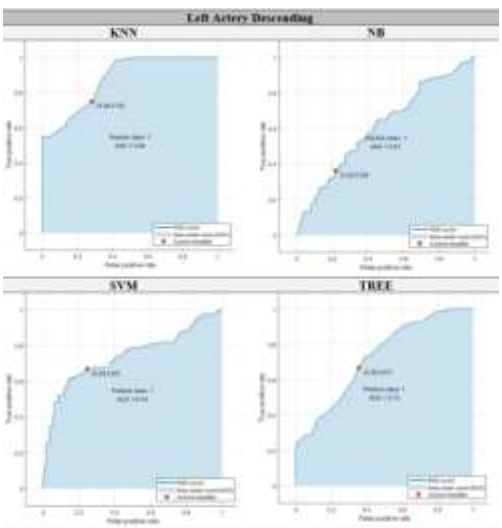
Figure 7: Left Artery Descending ROC curve graph.

DISCUSSION

Cardiovascular imaging has long been considered one of the most significant standards for the diagnosis of CVD. In the future, deep learning will make imaging diagnostics more reliable, easier, and faster. In addition, the utilization of minimally invasive surgery technologies such as AI and the Da Vinci Surgical Robot could make automated surgery more realistic, reduce patient trauma, improve surgical safety, and shorten hospital stays. Furthermore, with such a combination, AI, instead of clinicians, may undertake cardiac interventional procedures in patients such as percutaneous coronary intervention (PCI) operations and catheter ablations of atrial fibrillation; thus, it will reduce radiation exposure for clinicians arisen from the use of digital angiography (2).

Although Turing asserted the idea of AI in 1950, the definition of AI is still unclear. Yet, no one can fully explain the concept of AI; it is known that AI is a kind of computer science, multidisciplinary in theory and practice, and may improve our quality of life (2).

Human interpretation is still tiring, despite their experience. In addition, the current medical system still has many shortcomings, such as career education requiring several years of experience, shortage of specialist physicians in underdeveloped areas, and high medical costs for patients. (2, 19).

In early 2018, scientists from Verily (Research Organization of Alphabet Inc. – Google Life Sciences) used machine learning to assess the risk of a patient with cardiovascular disease. They developed an effective algorithm to analyze the scanned image of the patient’s eye and then accurately extract various data types, including the age of the patient, blood pressure, and smoking status. As a result, this data allowed scientists to estimate the patient’s risk of cardiovascular disease. To train the program, they employed machine learning to evaluate the medical data of over 300,000 patients (32).

Kang et al. developed an artificial intelligence technique to measure CAD stenosis based on a two-step algorithm with a vector machine. They stated that the algorithm was able to estimate the degree of stenosis in one second in patients collected using dual-source CT of 42 populations, with a sensitivity, specificity, and accuracy of 93%, 95%, and 94% in the proximal and mid segments, respectively (33).

When hybrid images are used, Yoneyama et al. detected CAD in the observer A Right Coronary Artery (RCA), Left Artery Descending (LAD), and Left Circumflex Artery (LCX) coronary arteries with an accuracy of 83.6%, 89.3%, and 94.4%, respectively; however, observer B detected %72,9, %84,2, and %89,3 accuracy, respectively. Artificial neural network (ANN) was with the accuracy of 79.1%, 89.8%, and 89.3% for each coronary artery (34).

The results of cardiac magnetic resonance imaging (MRI) scans and blood tests of 256 heart disease patients were recorded in Dawes TJW’s artificial intelligence software study. With each heartbeat, the software tracked the movement of 30,000 points on cardiac structures. This information was paired with the patients’ 8-year health records to predict abnormal conditions that would lead to the patient’s death. The research suggested that AI could predict presumable times of death for heart disease patients (35).

Compared to traditional risk scores, most ML models include a similar set of independent demographic variables (E.g., age, gender, smoking status) and laboratory values. Although these variables are not individually well-validated in clinical trials, they may have predictive value in some cases. There is a need for research that compares machine learning algorithms to traditional risk models head-to-head. Although general machine learning algorithms demonstrate promising results, there are significant restrictions that must be overcome before ML techniques might be used in clinical applications. In cardiovascular medicine, SVM and magnification algorithms are utilized commonly with favorable results. However, study interpretation in the original clinical setting is essential for selecting relevant algorithms for appropriate research topics, comparison with human experts, validation groups, and reporting all potential assessment matrices are vital for study interpretation in the exact clinical context. Most critically, prudential research comparing machine learning algorithms to traditional risk models is required. Once validated in this way, ML algorithms can be integrated with electronic health record systems and applied in clinical practice, particularly in high resource areas. (23,37,38).

In the Multi-Ethnic Study of Atherosclerosis, Bharath AV et al. used baseline measurements to predict cardiovascular results over the 12-year follow-up period (MESA). MESA included a total of 6814 individuals, ranging between age from 45 to 84 years old, from four ethnic origins, and from six different locations around the United States. The 735 variables were acquired from imaging and non-invasive testing, questionnaires, and biomarker panels. Using the random forest algorithm, effective cardiovascular risk estimate has been established in a large phenotypic population without CVD at baseline, including death, stroke, cardiovascular events, heart failure, and atrial fibrillation. Inflammation, subclinical atherosclerosis, myocardial damage, and heart chamber stress were among the most significant factor of all results. In an initially asymptomatic population, machine learning combined with deep phenotyping has been demonstrated to improve prediction accuracy in predicting cardiovascular events (36).

CONCLUSION

Among the AL algorithms used in our study, KNN was determined to be the most successful algorithm. The success rate in calculating the stenosis rate was 83% in RCA, 76% in LCX, and 73% in LAD, respectively.

The demand for CAG will be rising in the coming years, owing to an increase in HR. Therefore, new strategies will be sought to reduce the duration of CAG. We consider the application of AI in routine clinical practice.

REFERENCES

1. Romiti S, Vinciguerra M, Saade W, Cortajarena IA, Greco E. Artificial Intelligence (AI) and Cardiovascular Diseases: An Unexpected Alliance. Cardiology Research and Practice. Published 27 June 2020 doi: 10.1155/2020/4972346.
2. Yan Y, Zhang JW, Zang GY, Pu J. The primary use of artificial intelligence in cardiovascular diseases: what kind of potential role does artificial intelligence play in future medicine? J Geriatr Cardiol 2019 doi:10.11909/j.issn.1671-5411.2019.08.010.
3. Williams PL, Bannister LH, Berry MM, Collins P, Dyson M, Dussek JE et al. Gray's Anatomy. 38 th edition. London: Pearson Professional Limited, 1995.
4. Hatice Dülek H, Tuzcular Vural Z, Gönenç I. Risk Factors in Cardiovascular Diseases. Jour Turk Fam Phy. 2018;09 (2):53-58. doi: 10.15511/tjtfp.18.00253.
5. Drouet L. Atherothrombosis as a systemic disease. Cerebrovasc Dis. 2002;13:1-6. doi: 10.1159/000047782.
6. Durusoy E, Yıldırım T, Altun A. Koroner arter hastalığı poliklinik takibi. Trakya Üniversitesi Tıp Fakültesi Dergisi 2010; 1:13-18.
7. Binder CJ, Chang M, Shaw PX, Yury IM, Hartvigsen K, Dewan A, et al. Innate and acquired immunity in atherogenesis. Nature Medicine. 2002;8:1218-1226. doi: 10.1038/nm1102-1218.
8. Jha P. The hazards of smoking and the benefits of cessation: A critical summation of the epidemiological evidence in high-income countries. eLife. 2020;9:e49979. doi: 10.7554/eLife.49979.
9. Ece c. The relations between the family nutrition and physical activity levels and prevalence of obesity of their children in turkey. progress in Nutrition. 2021;(23)1:e2021172. doi: 10.23751/pn.v23iS1.1161.
10. Manfrini O, Yoon J, Scahaar MVD, Kedev S, Vavlukis M, Stankovic G, Sex Differences in Modifiable Risk Factors and Severity of Coronary Artery Disease. Journal of the American Heart Association. 2020;9:e017235. doi: 10.1161/JAHA.120.017235.
11. Yıldız B. Menemen İlçesinde 35 - 64 Yaş Grubunda Koroner Kalp Hastalıkları Risk Faktörleri Sıklığının Araştırılması. Doktora Tezi, İzmir, Ege Üniversitesi Sağlık Bilimleri Enstitüsü, Halk Sağlığı Anabilim Dalı, 2002.
12. Castelli WP, Garrison RJ, Dawber TR, McNamara PM, Feinleib F, Kannel WB. The filter cigarette and coronary heart disease: The framingham study. Lancet. 1981;2:109-113. doi: 10.1016/s0140-6736(81)90297-x.
13. Thygesen K, Alpert JS, Jaffe AS, Başkan BR, Bax JJ, Sabah DB, et al. Fourth universal definition of myocardial infarction. Circulation. 2018;138(20):e618–e651. doi: 10.1161/CIR.0000000000000617.
14. Braunwald E. Unstable angina: A classification. Circulation, 1989;80:410-414.
15. Ertaş FS, Oral D, Candan İ. Koroner Anjiyografi. Türk Kardiyol Dern Arş - Arch Turk Soc Cardiol. 2002;2:229-261.
16. Tüysüz ME. Koroner anjiografik olarak görüntülenemeyen sol ön inen arter (LAD) hastalıklarında cerrahi ile medikal tedavinin kısa ve uzun dönem sonuçlarının karşılaştırılması. Uzmanlık Tezi, İstanbul: Dr. Siyami Ersek Göğüs Kalp ve Damar Cerrahisi Eğitim ve Araştırma Hastanesi, 2005.
17. Van Assen M, Muscogiuri G, Caruso D, Lee SJ, Laghi A. De Cecco CN. Artificial intelligence in cardiac radiology. La Radiologia Medica. 2020;125:1186–1199. doi: 10.1007/s11547-020-01277w.
18. Lim LJ, Tison GH, Delling FN. Artificial Intelligence in Cardiovascular Imaging. Methodist Debakey Cardiovasc J. 2020;16(2):138-145. doi: 10.14797/mdcj-16-2-138.
19. Muscogiuri G, Van Assen M, Tesche C, De Cecco CN, Chiesa M, Scafuri S, et al. Artificial Intelligence in Coronary Computed Tomography Angiography: From Anatomy to Prognosis. BioMed Research International. Volume 2020, Article ID 6649410, 10 pages. doi:10.1155/2020/6649410.
20. Tesche C, Gray HN. Machine learning and deep neural networks applications in coronary flow assessment: the case of computed tomography fractional flow reserve. Journal of Thoracic Imaging. 2020;1:66-71. doi: 10.1097/RTI.0000000000000483.
21. Madani A, Arnaout R, Mofrad M, Arnaout R. Fast and accurate view classification of echocardiograms using deep learning. NPJ Digital Medicine. 2018;1:6. doi:10.1038/s41746-017-0013-1.
22. Görgün M. Makine öğrenmesi yöntemleri ile kalp hastalığının teşhis edilmesi. Yükseklisans Tezi, İstanbul Aydın Üniversitesi Lisansüstü Eğitim Enstitüsü, 2020.
23. Krittanawong C, Virk HUH, Bangalore S, Wang Z, Johnson KW, Pinotti R, et al. Machine learning prediction in cardiovascular diseases: a meta analysis. Scientific Reports. 2020;10:16057. doi:10.1038/s41598-020-72685-1.
24. Bishop, CM. Pattern Recognition and Machine Learning, 2006.
25. Topal Ç. Alan Turing'in Toplumbilimsel Düşünü: Toplumsal Bir Düş Olarak Yapay Zekâ, DTCF Dergisi. 2017:1340-1364. doi: 10.1501/Dtcfder_0000001565.
26. Seetharam K, Kagiyama N, Sengupta PP. Application of mobile health, telemedicine and artificial intelligence to echocardiography. Echo Research and Practice. 2019;(6)2:41–52. doi: 10.1530/ERP-18-0081.
27. Cramer JS. The Orijins of Logistic Regression. Faculty of Economics and Econometrics, University of Amsterdam, and Tinbergen Institute. 2002;2:119-4.
28. Demirel ŞY, Giray S. Karar Ağacı Algoritmaları ve Çocuk

İşçiliği Üzerine Bir Uygulama. Social Sciences Research Journal. 2019;8(4):52-65.
29. Johnson ED, Tubau E. Comprehension and computation in Bayesian problem solving. Front. Psychol. 2015;6:938. doi: 10.3389/fpsyg.2015.00938.
30. Aksu MÇ, Karaman E. Karar Ağaçları ile Bir Web Sitesinde Link Analizi ve Tespiti. Acta infologica. 2017;1(2):2602-3563. doi: 10.3389/fpsyg.2015.00938.
31. Breiman L. Random forests. Machine learning. 2001;45(1):5-32.
32. Poplin R, V. Varadarajan A, Blumer K, Liu Y, V McConnell M, et al. Predicting cardiovascular risk factors from retinal fundus photographs using deep learning. Nat Biomed Eng. 2018;2:158-164. doi: 10.1038/s41551-018-0195-0.
33. D. Kang, Dey D, J. Slomka P, Arsanjani J, Nakazato R, Ko H, et al. Structured learning algorithm for detection of nonobstructive and obstructive coronary plaque lesions from computed tomography angiography. Journal of Medical Imaging. 2015;2(1):014003. doi: 10.1117/1.JMI.2.1.014003.
34. Yoneyama H, Nakajima K, Taki J, Wakabayashi H, Matsuo S, Konishi T, et al., “Ability of artificial intelligence to diagnose coronary artery stenosis using hybrid images of coronary computed tomography angiography and myocardial perfusion SPECT,” European Journal of Hybrid Imaging. 2019;3(1):4. doi:10.1186/s41824-019-0052-8.
35. Dawes TJW, Marvao A, Shi W, Fletcher T, Watson GMJ, Wharton J, et al. Machine learning of three-dimensional right ventricular motion enables outcome prediction in pulmonary hypertension: a cardiac MR imaging study. Radiology. 2017;283:381–390. doi: 10.1148/radiol.2016161315.
36. Ambale-Venkatesh B, Yang X, Wu CO, Liu K, Hundley G, McClelland R, et al. Cardiovascular Event Prediction by Machine Learning: The Multi-Ethnic Study of Atherosclerosis. Circ Res. Author manuscript. 2017;121(9):1092–1101. doi: 10.1161/CIRCRESAHA.117.311312.
37. Özdemir M.,Tanır H., Ilkim M.Özmaden M.(2017). The effects of 8 week exercise program on reaction time performance of hearing impaired students at 11-14 years of age, SHS Web of Conferences, Volume 37
38. Özsarı A.,Ilkım M.(2021) Investigation of the spiritual intelligence features of physically handicapped badminton players in terms of various variables, International Journal Of Life Science And Pharma Research , Pp.29-35