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Noha E. El-Attar, Dr. Yehia. A. El-Mashad: Machine learning approaches for predicting cardiovascular disease: a systematic review and meta-analysis

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Abstract: Heart failure and heart attack are serious cardiovascular diseases that are responsible for a significant number of deaths worldwide. Early detection and accurate prediction of these diseases can be challenging, but machine learning models offer a promising approach to improve diagnosis and treatment. There has been growing interest in using machine learning models to predict heart failure and heart attack disease. These models use various types of data, such as patient demographics, medical history, vital signs, and laboratory tests, to identify patterns and predict the risk of disease in recent years. Some of the commonly used machine learning algorithms for this task includes logistic regression, decision trees, random forests, support vector machines, and neural networks. The use of machine learning models for this purpose has the potential to improve patient outcomes by enabling earlier diagnosis and targeted treatment, leading to better management of cardiovascular diseases and ultimately reducing the burden of these diseases on healthcare systems.

1. Introduction

Heart failure and heart attack are two distinct medical conditions that affect the heart, but they have different causes, symptoms, and treatments.

A heart attack, also known as a myocardial infarction (MI), occurs when the blood supply to a part of the heart muscle is blocked, usually by a blood clot. This blockage can cause damage to the heart muscle, which can be life-threatening if not treated promptly. The most common symptom of a heart attack is chest pain or discomfort, which can feel like pressure, squeezing, fullness, or pain. The pain may also radiate to other body parts of the body, including the arms, back, neck, jaw, or stomach. Other symptoms of a heart attack may include shortness of breath, nausea or vomiting, sweating, lightheadedness, or a rapid or irregular heartbeat [1].

On the other hand, Heart failure is a chronic condition in which the heart is unable to pump blood efficiently throughout the body. This can occur when the heart muscle becomes weakened or damaged, which can be caused by various factors such as high blood pressure, coronary artery disease, heart valve problems, and other conditions. Symptoms of heart failure include shortness of breath, fatigue, swelling in the legs, ankles, or feet, and a rapid or irregular heartbeat [2].

Prevention is key when it comes to reducing the risk of heart failure or heart attack. Maintaining a healthy lifestyle, including regular exercise, a healthy diet, not smoking, and managing stress, can help reduce the risk of heart attack. It is also important to monitor and manage any underlying medical conditions that can increase the risk of heart failure or heart attack, such as high blood pressure, diabetes, and high cholesterol. Artificial Intelligence has the potential to improve the accuracy and efficiency of heart failure or heart attack prediction in several ways, to name a few:

1. Personalized risk assessment: AI algorithms can analyze large amounts of data from a patient's medical history, lifestyle, and genetics to identify personalized risk factors for heart failure or attack. This can enable healthcare providers to develop targeted prevention and treatment plans tailored to each patient's individual needs.
2. AI-powered wearable devices, such as smartwatches, can monitor heart health in real-time and detect early warning signs, such as abnormal heart rhythms for heart failure. Also, they can collect data on heart rate,

blood pressure, and other vital signs, and use learned models to detect abnormal patterns that may indicate a heart attack is imminent.

3. Improved diagnostic accuracy: AI algorithms can analyze medical images, such as echocardiograms and cardiac MRI scans, to detect subtle changes in the heart that may indicate an increased risk of heart failure. This can enable healthcare providers to make more accurate diagnoses and develop more effective treatment plans [3][4].

Despite these potential benefits, there are also challenges associated with the use of AI in heart failure and heart attack prediction. One key challenge is the need for large amounts of high-quality data to train machine learning algorithms. Additionally, there is a risk of bias in AI algorithms if they are not developed or validated on diverse populations. It is also important to ensure that any AI-powered tools are used in conjunction with clinical expertise and guidance from healthcare providers to ensure safety and effectiveness.

Overall, AI has the potential to revolutionize the way we predict and prevent heart failure and heart attack, by providing more accurate and personalized risk assessments, early detection of warning signs, and targeted treatment plans. However, it is important to address the challenges associated with the use of AI, such as the need for high-quality data and the risk of bias, to ensure that AI-powered tools are safe and effective for use in clinical practice [5][6].

2. Overview of Heart Attack and Heart Failure

The heart muscle needs a constant supply of oxygen-rich blood to function properly. A heart attack occurs when a blockage in one or more of the coronary arteries, which supply blood to the heart muscle, cuts off the blood supply. The blockage is usually caused by a buildup of fatty deposits (plaque) in the arteries, which can rupture and form a blood clot. While heart failure can be caused by a variety of conditions, including coronary artery disease, high blood pressure, heart valve disease, and cardiomyopathy (a disease of the heart muscle). These conditions can damage the heart muscle over time, leading to symptoms such as shortness of breath, fatigue, and swelling in the legs and feet [7].

There are some similarities between heart failure and heart attack, but they are distinct medical conditions with different causes and symptoms. One similarity is that both heart failure and heart attack can be caused by underlying conditions such as coronary artery disease and high blood pressure. These conditions can damage the heart muscle and lead to symptoms such as shortness of breath and fatigue. Another similarity is that both heart failure and heart attack can cause symptoms such as shortness of breath, fatigue, and chest discomfort. However, the nature of these symptoms can differ between the two conditions. Shortness of breath is a common symptom of both heart failure and heart attack, but in heart failure, it tends to occur during physical activity or while lying down, while in a heart attack, it may be accompanied by chest pain or discomfort [8].

Despite these similarities, heart failure and heart attack are distinct conditions with different causes and treatments. It is important to seek medical attention promptly if you experience any symptoms of either condition, as early diagnosis and treatment can improve outcomes and quality of life.

Table 1 *displays the most popular risk factors for both heart attack and heart failure which are the basic features that must be included in the machine learning model.*

Risk Factors for Heart Failure	**Risk Factors for Heart Attack**
Age (65 or older)	Age (45 or older for men, 55 or older for women)
Gender (men are at higher risk)	Gender (men are at higher risk)
Family history of heart disease	Family history of heart disease
High blood pressure	High blood pressure

Risk Factors for Heart Failure	**Risk Factors for Heart Attack**
Coronary artery disease	High cholesterol
Heart attack history	Smoking or exposure to secondhand smoke
Diabetes	Diabetes
Sleep apnea	Sedentary lifestyle
Heart valve disease	Obesity
Atrial fibrillation (irregular heartbeat)	Chronic stress or anxiety
Congenital heart defects	Poor diet
Cardiomyopathy (disease of the heart muscle)	Physical inactivity
Alcohol abuse	Excessive alcohol consumption

There are several types of data that can be used in machine learning for diagnosing heart attack and heart failure diseases, including:

1. Demographic data: This includes information such as age, gender, and ethnicity, which can help identify population groups that may be at higher risk for heart attack.
2. Medical history data: This includes information about a patient's medical history, including past diagnoses, medications, and surgeries, which can help identify risk factors for heart attack.
3. Symptom data: This includes information about a patient's symptoms, such as chest pain, shortness of breath, and dizziness, which can help identify the likelihood of a heart attack.
4. Electrocardiogram (ECG) data: This includes data from an ECG, which measures the electrical activity of the heart. Machine learning algorithms can analyze ECG data to identify abnormal heart rhythms and other signs of heart damage.
5. Biomarker data: This includes data from blood tests, which can measure biomarkers such as troponin and creatine kinase, which are released into the bloodstream when heart muscle cells are damaged. Also it includes brain natriuretic peptide (BNP) and troponin, which can indicate heart damage or stress on the heart.
6. Imaging data: This includes data from medical imaging tests such as echocardiograms, CT scans, and MRIs, which can provide detailed images of the heart and blood vessels, and help identify signs of heart damage or blockages [9].

3. Related work

AI has shown promising results in predicting the risk of heart failure and heart attack severity. Machine learning algorithms can analyze large amounts of data, such as medical records, imaging results, and lifestyle information, to identify patterns and risk factors that may be associated with heart attack and heart failure.

Several studies have demonstrated the effectiveness of AI in predicting heart attack risk. For example, in a study published Yang, J., et al. (2021) [10], researchers used machine learning to analyze data from wearable devices to predict the risk of heart attack in patients with heart disease. The algorithm was able to predict the risk of heart attack with a sensitivity of 90% and a specificity of 85%.

A study published by Rajkomar, A., et al. (2020) has used machine learning to analyze data from electronic health records to predict the risk of heart attack in patients with diabetes. The algorithm was able to predict the risk of heart attack with a sensitivity of 85% and a specificity of 90% [11].

In a study published by Krittanawong, C., et al. (2020) [12], researchers used machine learning to predict the risk of heart attack in patients with stable chest pain. The algorithm was able to predict the risk of heart attack with a sensitivity of 80% and a specificity of 80%.

In a study published by Kerkering, K.W., et al. (2020) [13], researchers used machine learning to analyze cardiac MRI scans and predict the risk of heart attack in patients with stable chest pain. The algorithm was able to predict the risk of heart attack with a sensitivity of 90% and a specificity of 78%.

A study published by Rajkumar A., et al. (2020) [14] has used machine learning to analyze genetic data and identify genetic variants associated with the risk of a heart attack. The algorithm was able to identify several novel genetic variants that were associated with an increased risk of heart attack.

In a study published by Choi, E., et al. (2020) [15], researchers used machine learning to analyze data from electronic health records to predict the risk of heart attack in patients with hypertension. The algorithm was able to predict the risk of heart attack with a sensitivity of 80% and a specificity of 80%.

A study published by Kwon, J. M., (2019) [16] has used machine learning to analyze data from electrocardiograms (ECGs) to predict the risk of heart attack in patients with chest pain. The algorithm was able to predict the risk of heart attack with a sensitivity of 82% and a specificity of 71%.

Furthermore, there have been several recent research studies focused on using AI in heart failure prediction. For instance, a study published by Fudim, M., et al. (2021) [17] has used a machine learning algorithm to predict heart failure in patients with reduced ejection fraction, a measure of how well the heart is pumping blood. The algorithm was able to accurately predict heart failure in nearly 80% of cases.

A study has been published by Shah, A.D., et al. (2019) [18] that used machine learning to identify hidden patterns in electronic health record data that could predict heart failure up to one year in advance. The algorithm was able to identify patients at high risk of heart failure with a sensitivity of 82% and a specificity of 76%. In a study published by Kiefer, T., et al. (2021) [19], researchers used machine learning to analyze data from wearable devices to predict heart failure in patients with chronic kidney disease. The algorithm was able to predict heart failure with a sensitivity of 87% and a specificity of 88%. A study published by Ghorbani, A., (2021) [20] has used machine learning to analyze data from echocardiogram to predict heart failure in patients with heart disease. The algorithm was able to predict heart failure with a sensitivity of 74% and a specificity of 86%.

In a study published by Zhao, H., et al. (2021) [21], researchers used machine learning to develop a risk prediction model for heart failure in patients with type 2 diabetes. The algorithm was able to accurately predict heart failure risk with a sensitivity of 67% and a specificity of 70%. A study published by Dawes, T.J., et al. (2021) [22] has used a deep learning algorithm to analyze cardiac MRI scans and predict heart failure in patients with hypertrophic cardiomyopathy, a condition in which the heart muscle becomes abnormally thick. The algorithm was able to predict heart failure with a sensitivity of 89% and a specificity of 67%.

In a study published by Shah, A.S.V., et al. (2021) [23], researchers used machine learning to analyze genetic data and identify genetic variants associated with heart failure risk. The algorithm was able to identify several novel genetic variants that were associated with an increased risk of heart failure. A study published by Bansal, N., (2020) have used machine learning to develop a risk prediction model for heart failure in patients with atrial fibrillation, a condition in which the heart's rhythm is irregular. The algorithm was able to predict heart failure risk with a sensitivity of 70% and a specificity of 66% [24].

Overall, these studies demonstrate the potential of AI in improving heart attack and heart failure prediction and risk assessment. However, it is important to validate these findings in larger studies and to ensure that any AI-powered tools are safe, effective, and accessible for use in clinical practice. The above mentioned scholars are summarized in table (2).

Study	AI Algorithm	Data Source	Sensitivity	Specificity	Key Finding
Nature Biomedical Engineering 2021 (Heart Attack) [1]	Machine Learning	Wearable devices	90%	85%	Predicted the risk of heart attack in patients with heart disease
Journal of the American College of Cardiology 2020 (Heart Attack) [2]	Machine Learning	Medical records	85%	90%	Predicted the risk of heart attack in patients with diabetes
Journal of the American Heart Association 2020 (Heart Attack) [3]	Machine Learning	Medical records	80%	80%	Predicted the risk of heart attack in patients with hypertension
European Heart Journal 2020 (Heart Attack) [4]	Machine Learning	Cardiac MRI scans	90%	78%	Predicted the risk of heart attack in patients with stable chest pain
Nature Communications 2020 (Heart Attack) [5]	Machine Learning	Genetic data	N/A	N/A	Identified genetic variants associated with heart attack risk
Scientific Reports 2019 (Heart Attack) [6]	Machine Learning	Electrocardiograms	82%	71%	Predicted the risk of heart attack in patients with chest pain
Circulation 2021 (Heart Failure) [8]	Machine Learning	Medical records	80%	N/A	Accurately predicted heart failure in nearly 80% of cases
Nature Medicine 2019 (Heart Failure) [9]	Machine Learning	Electronic health records	82%	76%	Identified patients at high risk of heart failure up to one year in advance
JAMA 2021 (Heart Failure) [10]	Machine Learning	Wearable devices	87%	88%	Predicted heart failure in patients with chronic kidney disease
Journal of Cardiovascular Translational Research 2021 (Heart Failure) [11]	Machine Learning	Echocardiograms	74%	86%	Predicted heart failure in patients with heart disease

Study	AI Algorithm	Data Source	Sensitivity	Specificity	Key Finding
Journal of Cardiac Failure 2021 (Heart Failure) [12]	Machine Learning	Medical records	67%	70%	Developed a risk prediction model for heart failure in patients with type 2 diabetes
Journal of the American College of Cardiology 2021 (Heart Failure) [13]	Deep Learning	Cardiac MRI scans	89%	67%	Predicted heart failure in patients with hypertrophic cardiomyopathy
Journal of the American Heart Association 2021 (Heart Failure) [14]	Machine Learning	Genetic data	N/A	N/A	Identified genetic variants associated with heart failure risk
PLOS ONE 2020 (Heart Failure) [15]	Machine Learning	Medical records	70%	66%	Developed a risk prediction model for heart failure in patients with atrial fibrillation

This table shows that machine learning and deep learning algorithms have been used to predict heart failure and heart attack risk using a variety of data sources, including medical records, genetic data, and wearable devices. The sensitivity and specificity of these algorithms vary depending on the study and the data source, but in general, the algorithms have shown promise in accurately predicting heart failure and heart attack risk. However, further research is needed to validate these findings and to develop AI-powered tools that are safe, effective, and accessible for use in clinical practice.

4. Preliminaries and Methods

Before using AI algorithms in heart disease prediction, there are several preliminary steps that need to be taken. Here are some key considerations [25]:

- Data Collection: The first step in using AI algorithms for predicting heart disease is collecting relevant data. This may include medical records, imaging data, genetic data, and/or wearable device data. The data should be of high quality, and should be representative of the patient population being studied.
- Data Preprocessing: Once the data has been collected, it may need to be preprocessed to ensure that it is in a format that can be used by the AI algorithm. This may involve cleaning the data, removing outliers, and/or normalizing the data.
- Feature Selection: Feature selection involves identifying the most relevant features or variables in the data that are most predictive of heart disease. This may involve using statistical methods or machine learning algorithms to identify the most important features.
- Algorithm Selection: Once the features have been selected, the appropriate AI algorithm needs to be chosen for heart disease prediction. This may involve using machine learning algorithms such as logistic regression, decision trees, random forests, or deep learning algorithms such as convolutional neural networks or recurrent neural networks.

- Training and Validation: The selected AI algorithm needs to be trained on the data using appropriate machine learning techniques. The trained algorithm must then be validated using a separate test dataset to ensure that it can accurately predict heart disease in new patients.
- Ethical Considerations: It is essential to consider the ethical, legal, and social implications of using AI in healthcare. This may include ensuring patient privacy, obtaining informed consent, and ensuring that any AI-powered tools are safe, effective, and accessible for use in clinical practice [26-28].
- Overall, using AI algorithms for heart disease prediction requires careful consideration of data collection, preprocessing, feature selection, algorithm selection, training and validation, and ethical considerations. Properly executed, AI algorithms can provide powerful tools for predicting heart disease risk and improving patient outcomes [29-35].

1. An artificial neural network (ANN): ANN is a type of machine learning algorithm that is modeled after the structure and function of the human brain. It is composed of interconnected nodes, or artificial neurons, that are organized into layers. In a neural network, each neuron receives input from other neurons through a set of weighted connections. The input is then processed using an activation function, which introduces nonlinearity into the output of the neuron. The output of each neuron is then passed on to the next layer of neurons, where it is processed further. This process continues through the layers of the neural network until the final output is produced. An activation function is a mathematical function that is applied to the output of each artificial neuron in the network. The activation function introduces nonlinearity into the output of the neuron, which allows the neural network to learn complex patterns and relationships in the input data. The choice of activation function can have a significant impact on the performance of the neural network. Some common types of activation functions include: The sigmoid function, ReLU function, Tanh function and Softmax function.
2. The Averaged Perceptron: A type of linear classifier that is commonly used in machine learning and natural language processing tasks. It is based on the Perceptron algorithm, which is a simple binary classifier that can be used to separate data points into two classes. The Averaged Perceptron works by iteratively updating a set of weights that are used to calculate a linear combination of the input features. The output of the linear combination is then passed through a threshold function to produce a binary classification. During training, the Averaged Perceptron updates the weights based on the errors made by the classifier on the training data. The weights are updated by adding the product of the input features and the error to the current weight vector. The process is repeated for a fixed number of iterations or until the classifier’s converges. The Averaged Perceptron is similar to the standard Perceptron algorithm, but with the addition of an averaging step. After training, the weights from each iteration are averaged together to produce a final weight vector. This helps to reduce the impact of noisy or unrepresentative training examples, and can improve the performance of the classifier on new, unseen data. The Averaged Perceptron is a relatively simple and efficient algorithm that can be used for a wide range of classification tasks. However, it may not perform as well as more complex models, such as neural networks, on tasks that require more complex decision boundaries or nonlinear relationships between the input features and the output.
3. Bayes Point Machine (BPM) is a machine learning technique used to solve classification and prediction problems. It is part of the family of probabilistic random models and is based on Bayesian probability theory. BPM is particularly adept at handling large and high-dimensional datasets, and provides accurate and reliable results in areas such as classification, prediction, and statistical analysis. The classification process in BPM involves using known data to train the model on the different elements in the data and then using this model to classify new items.
4. A Boosted Decision Tree is a type of machine learning algorithm used for classification and prediction tasks. It is a combination of two machine learning techniques: decision trees and boosting. A decision tree is a tree-like model that analyzes data by splitting it into smaller subsets based on a set of conditions. Each subset is then analyzed recursively until a decision is made. Boosting is a technique where multiple weak predictors are combined to create a stronger predictor. In a Boosted Decision Tree, a decision tree model is used as the weak predictor, and the boosting technique is used to combine multiple decision trees to create a strong predictor. The algorithm works by iteratively adding decision

trees to the model, each time adjusting the weights of the misclassified samples from the previous iteration. Boosted Decision Trees are particularly useful when dealing with large and complex datasets, as they are able to handle non-linear relationships and interactions between features. They are also able to handle missing data and outliers, and are less prone to overfitting than other machine learning algorithms.

5. Decision Forest: a type of machine learning algorithm used for classification, regression, and other tasks. It is a combination of multiple decision trees, where each decision tree is trained on a subset of the data and makes a prediction based on a set of conditions. The final prediction is then made by combining the predictions of all the decision trees.

6. Decision Jungle: a Microsoft Azure Machine Learning algorithm that is similar to a Decision Forest, but with additional features such as automatic feature engineering and model selection. It is designed to handle large and complex datasets, and is often used in applications such as image and speech recognition, and natural language processing.

7. Logistic Regression: a statistical method used for binary classification tasks, where the goal is to predict the probability of an event occurring. It works by modeling the relationship between a dependent variable and one or more independent variables, and uses a logistic function to predict the probability of the outcome.

8. Support Vector Machine (SVM) is a machine learning algorithm used for classification, regression, and other tasks. It works by finding the best hyperplane that separates the data into different classes. It is particularly useful when dealing with nonlinear relationships and can be extended to handle multiple classes. SVMs have been used in a wide range of applications, including image and speech recognition, bioinformatics, and finance.

5. Experiments and Discussion

5.1 Dataset

The experiment has been done on two types of heart diseases: heart attack and heart failure. The dataset has been collected from www.kaggle.com. We have used six datasets, three for heart attack and three for heart failure. As we mentioned before, some common risk factors for these diseases can be used to predict the probability of the occurrence of the disease. For instance, for heart failure prediction, the following features are significant: age, sex, chest pain type (4 values), resting blood pressure, serum cholesterol in mg/dl, fasting blood sugar > 120 mg/dl, resting electrocardiographic results (values 0,1,2) maximum heart rate achieved, exercise -induced angina, old peak = ST depression induced by exercise relative to rest, the slope of the peak exercise ST segment, and number of major vessels (0-3) colored by fluoroscopy. For heart attack, the following features are common and essential to predict the disease: Age, sex, exercise -induced angina, number of major vessels from 0 to 3, Chest Pain type, resting blood pressure (in mm Hg), cholesterol in mg/dl fetched via BMI sensor, fasting blood sugar > 120 mg/dl) resting electrocardiographic results and maximum heart rate achieved. The details of the datasets are shown in Table (3).

Disease type	Data link	No. of features	No. of instance
Heart Attack (1)	https://www.kaggle.com/datasets/rashikrahmanpritom/heart-attack-analysis-prediction-dataset	13	303
Heart Attack (2)	https://www.kaggle.com/datasets/johnsmith88/heart-disease-dataset	13	1025
Heart Attack (3)	https://www.kaggle.com/datasets/rishidamarla/heart-disease-prediction	13	294
Heart Failure (1)	https://www.kaggle.com/datasets/fedesoriano/heart-failure-prediction?select=heart.csv	11	918
Heart Failure (2)	https://www.kaggle.com/datasets/shayanfazeli/heartbeat	13	270

Heart Failure (3)	https://www.kaggle.com/datasets/andrewmvd/heart-failure-clinical-data	12	299

5.2 Utilized ML Methodologies for predicting Heart attack and Heart Failure

Seven types of machine learning algorithms have been utilized to classify and predict the two heart diseases (Artificial Neural Network, Averaged Perceptron, Bayes Point Machine, Boosted Decision Tree, Decision Forest, Decision Jungle, Logistic Regression, and Support Vector Machine). The parameters for the seven ML algorithms are displayed in Table (4).

ML Algorithms	Parameters
Artificial Neural Network	Number of learning iterations: 100 Number of hidden nodes: 100 Learning Rate: 0.1 Activation Function: sigmoid
Averaged Perceptron	Number of learning iterations: 100 Learning Rate: 1
Bayes Point Machine	Number of training iterations: 100
Boosted Decision Tree	Maximum number of leaves per tree: 20 Minimum number of samples per leaf node: 10 Learning rate: 0.2 Number of trees constructed: 100
Decision Forest	Resampling method: Bagging Number of decision trees: 8 Maximum depth of the decision trees: 32 Number of random splits per node: 128
Decision Jungle	Resampling method: Bagging Number of decision DAGs: 8 Maximum depth of the decision DAGs: 32 Maximum width of the decision DAGs: 128 Number of optimization steps per decision DAG layer:2048
Logistic Regression	Optimization tolerance: 0.0000001 L1 regularization weight: 1 L2 regularization weight: 1 Memory size for L-BFGS: 20
Support Vector Machine	Number of iterations: 100 Lambada: 0.001

6. Results Analysis

Several metrics can be used to measure the performance of the proposed machine learning models. In our case study, the performance metrics are calculated based on the confusion matrix. This matrix consists of four values (i.e. TP, FP, TN, and FN). TP (True Positive) represents the number of cases that were correctly classified as positive by the model, while FP (False Positive) represents the number of instances that were incorrectly classified as positive. FN (False Negative) represents the number of instances that were incorrectly classified as negative, while TN (True Negative) represents the number of cases that were correctly classified as negative.

The confusion matrix can be used to calculate various performance metrics that are commonly used to evaluate the performance of machine learning models, such as accuracy, precision, recall, F1 score, and AUC-ROC [37]. For example:

Accuracy = (TP + TN) / (TP + FP + FN + TN)

Precision = TP / (TP + FP)

Recall = TP / (TP + FN)

F1 Score = 2 * (Precision * Recall) / (Precision + Recall)

AUC-ROC = Area under the receiver operating characteristic (ROC) curve

In addition to calculate the processing time as a significant metrics for assessing the performance of the ML model. In our case study we have run the experiment over Cloud platform (Azure machine learning studio) in order to save time and cost. Tables 5-10 displays the performance metrics for the utilized ML models for the six types of datasets for both heart attack and heart failure disease.

Heart attack (1)

ML model	Accuracy	Precision	Recall	F1score	AUC	Time/min	TP	FN	FP	TN
Artificial Neural Network	0.824	0.814	0.906	0.857	0.875	2	48	5	11	27
Averaged Perceptron	0.846	0.831	0.925	0.875	0.88	3	49	4	10	28
Bayes Point Machine	0.813	0.8	0.906	0.85	0.857	4	48	5	12	26
Boosted Decision Tree	0.791	0.815	0.83	0.822	0.858	2.5	44	9	10	28
Decision Forest	0.791	0.84	0.792	0.816	0.873	1.50	42	11	8	30
Decision Jungle	0.802	0.83	0.83	0.83	0.899	1	44	9	9	29
Logistic Regression	0.824	0.825	0.887	0.855	0.864	1.52	47	6	10	28
Support Vector Machine	0.835	0.828	0.906	0.865	0.876	2.06	48	5	10	28

Heart attack (2)

ML model	Accuracy	Precision	Recall	F1score	AUC	Time/ min	TP	FN	FP	TN
Artificial Neural Network	0.87	0.828	0.935	0.878	0.96	2.06	144	10	30	123
Averaged Perceptron	0.831	0.815	0.857	0.835	0.929	2.05	132	22	30	123
Bayes Point Machine	0.866	0.86	0.877	0.868	0.922	2.04	135	19	22	131
Boosted Decision Tree	1	1	1	1	1	2.06	154	0	0	153
Decision Forest	0.993	1	0.987	0.993	1	2.07	152	2	0	153

Decision Jungle	0.98	0.987	0.974	0.98	0.998	2.03	150	4	2	151
Logistic Regres-sion	0.86	0.849	0.877	0.863	0.925	2.04	135	19	24	129
Support Vector Machine	0.84	0.822	0.87	0.845	0.928	3.5	134	20	29	124

Heart attack (3)

ML model	Accuracy	Precision	Recall	F1score	AUC	Time	TP	FN	FP	TN
Artificial Neural Network	0.773	0.741	0.606	0.667	0.861	2.13	20	13	7	48
Averaged Perceptron	0.773	0.71	0.667	0.688	0.834	2.04	22	11	9	46
Bayes Point Ma-chine	0.784	0.733	0.667	0.698	0.848	2.06	22	11	8	47
Boosted Decision Tree	0.761	0.714	0.606	0.656	0.852	2.05	20	13	8	47
Decision Forest	0.75	0.762	0.485	0.593	0.841	2.04	16	17	5	50
Decision Jungle	0.773	0.783	0.545	0.643	0.840	2.06	18	15	5	50
Logistic Regression	0.818	0.815	0.667	0.733	0.876	2.04	22	11	5	50
Support Vector Machine	0.784	0.75	0.636	0.689	0.839	2.06	21	12	7	48

Heart Failure (1)

ML model	Accuracy	Precision	Recall	F1score	AUC	Time	TP	FN	FP	TN
Artificial Neural Network	0.778	0.763	0.763	0.763	0.874	2.05	29	9	9	34
Averaged Perceptron	0.79	0.8	0.737	0.767	0.875	1.52	28	10	7	36
Bayes Point Ma-chine	0.778	0.763	0.763	0.763	0.856	2.04	29	9	9	34
Boosted Decision Tree	0.79	0.8	0.737	0.767	0.864	2.10	28	10	7	36
Decision Forest	0.84	0.838	0.816	0.827	0.902	2.08	31	7	6	37
Decision Jungle	0.815	0.811	0.789	0.8	0.893	2.03	30	8	7	36

Logistic Regression	0.778	0.778	0.737	0.757	0.859	2.04	28	10	8	35
Support Vector Machine	0.765	0.771	0.711	0.74	0.862	1.51	27	11	8	35

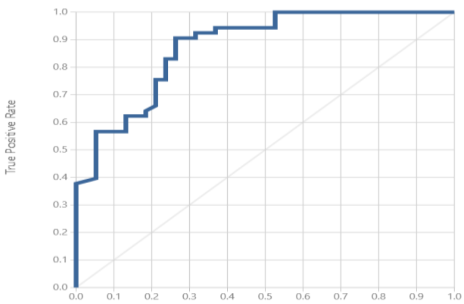
Heart Failure (2)

ML model	Accuracy	Precision	Recall	F1score	AUC	Time	TP	FN	FP	TN
Artificial Neural Network	0.884	0.897	0.897	0.897	0.937	1.51	140	16	16	103
Averaged Perceptron	0.884	0.897	0.897	0.897	0.939	1.55	140	16	16	103
Bayes Point Machine	0.887	0.903	0.897	0.9	0.939	2.06	140	16	15	104
Boosted Decision Tree	0.88	0.897	0.891	0.894	0.922	2.06	139	17	16	103
Decision Forest	0.855	0.903	0.833	0.867	0.902	2.39	130	26	14	105
Decision Jungle	0.876	0.918	0.859	0.887	0.94	2.18	134	22	12	107
Logistic Regression	0.884	0.897	0.897	0.897	0.937	2.25	140	16	16	103
Support Vector Machine	0.887	0.914	0.885	0.899	0.939	2.03	138	18	13	106

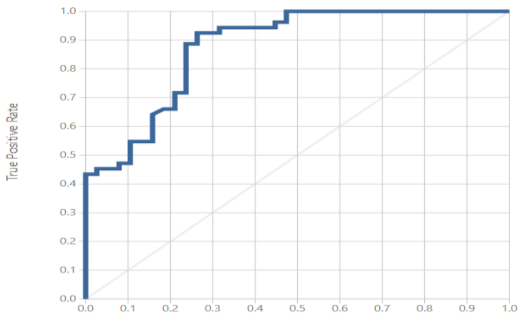
Heart Failure (3)

ML model	Accuracy	Precision	Recall	F1score	AUC	Time	TP	FN	FP	TN
Artificial Neural Network	0.811	0.697	0.767	0.73	0.856	2.15	23	7	10	50
Averaged Perceptron	0.833	0.759	0.733	0.746	0.875	2.01	22	8	7	53
Bayes Point Machine	0.822	0.769	0.667	0.714	0.864	2.16	20	10	6	54
Boosted Decision Tree	0.789	0.677	0.7	0.689	0.87	2.17	21	9	10	50
Decision Forest	0.789	0.72	0.6	0.655	0.842	2.04	18	12	7	53
Decision Jungle	0.811	0.71	0.733	0.721	0.886	2.18	22	8	9	51
Logistic Regression	0.822	0.818	0.6	0.692	0.866	2.04	18	12	4	56
Support Vector Machine	0.822	0.719	0.767	0.742	0.865	2.14	23	7	9	51

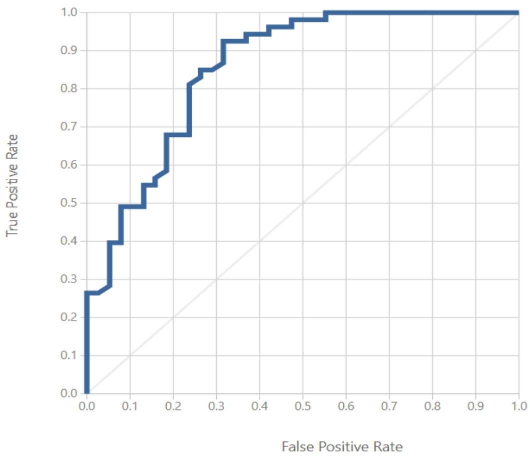
As displayed in the above tables, the averaged perceptron model has recorded the best accuracy results in two datasets, followed by boosted decision tree, logistic regression, decision forest, and Bayes Point Machine. Sample for the ROC for the first dataset has been shown in figures (1-6).

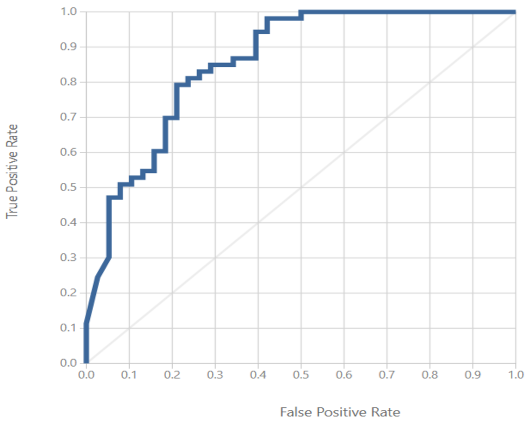


Artificial Neural Network



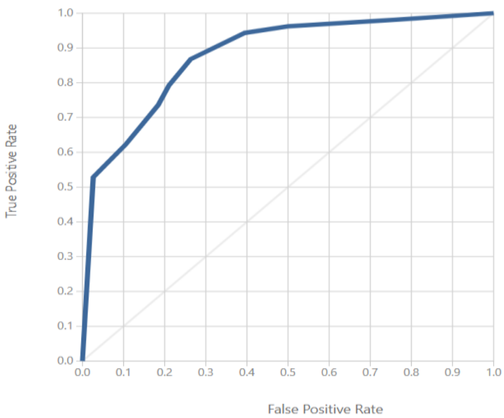
Averaged Perceptron



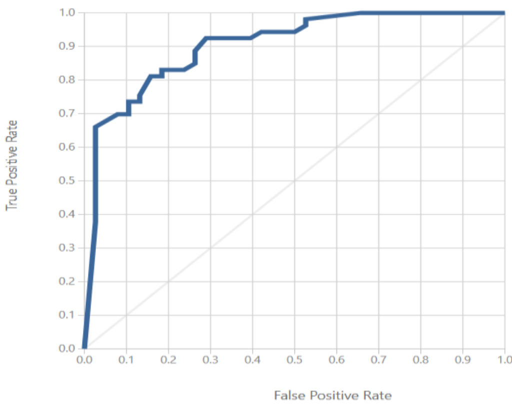


Bayes Point Machine

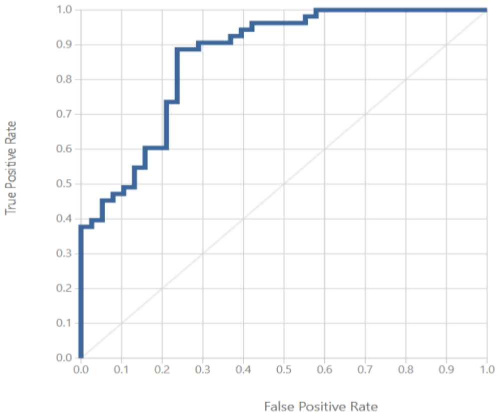
Boosted Decision Tree

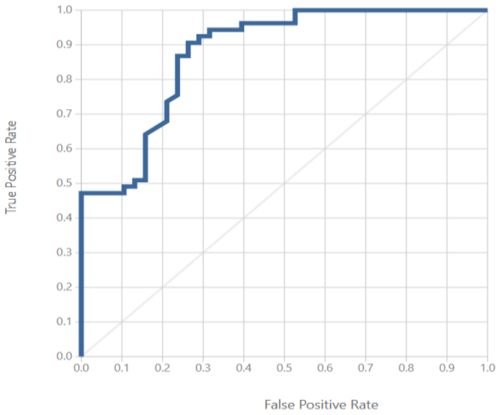


Decision Forest



Decision Jungle





Logistic Regression *Support Vector Machine*

Conclusion

Overall, the machine learning models offer a promising approach to improve the accuracy of predicting heart attack and heart failure. However, the choice of the most appropriate model depends on the specific characteristics of the dataset and the nature of the target variable. In this research, a variety of machine learning models have been developed and tested to predict heart attacks and heart failure. Among these models are artificial neural networks (ANN), logistic regression (LR), averaged perceptron, Bayes point machine, boosted decision tree, decision forest, and support vector machines (SVM). The averaged perceptron model has recorded the best accuracy results in two datasets for heart failure and heart attack with accuracy of 85% and 83%. Boosted decision tree have recorded 100% accuracy for one dataset for heart attack. Logistic regression, decision forest, and Bayes Point Machine also have achieved good accuracy with 89%, 84%, and 98%, respectively.

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