# EXPLAINABLE ARTIFICIAL INTELLIGENCE TO PREDICT CARDIOVASCULAR DISEASES

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***Abstract* :** *The increase in health issues made people to look at the trending technologies like Internet of Things, cloud computing, big data, and artificial intelligence, together with modern biotechnology [14] to deal with them. So, people started investing in hospitals where they can get good treatment. With the technologies growth, the healthcare results are promising and that led to the reduction in healthcare costs. In this paper, author uses Explainable Artificial Intelligence (XAI) which is an extension of artificial intelligence that extends the capability of ai by explaining why it has given that prediction whether we can rely on its decision or not. In this paper, the author aims to predict the health care records of Cardiovascular disease patients using Explainable Artificial Intelligence (XAI) with What-if tool for getting better accuracy. It compares models and predicts the best model and justifies why it has chosen that model based on what features will also be mentioned. The author uses methods like Random Forest, Decision Tree and XGBoost. The author uses the dataset that is downloaded from the Kaggle website which consists of 70000 datapoints. Each datapoint consists of 13 features. Based on those features, model is designed and it predict the model that gives better accuracy. Based on the results, Random Forest gives an accuracy of 75% which is best compared to other models.*

**Keywords: Cardiovascular disease, Decision Trees, Explainable Artificial Intelligence, Random Forest, XGBoost**

## 1. Introduction

Now-a-days, most of the people are suffering with several cardiovascular diseases such as coronary, cerebrovascular, congenital, peripheral arterial diseases and some other. The main causes of cardiovascular diseases are high blood pressure, high cholesterol, smoking, overweight, age, alcohol consumption and inactivity. When a patient visits a hospital regarding cardiovascular disease they mainly checks for the above symptoms and those details are stored in the form of records called electronic healthcare record. This data is used for predicting the whether the person has cardiovascular disease or not.

There are many prediction algorithms like decision tree, random forest, boosted trees which gives us high accuracy but not end-to-end interpretability and algorithms like Naive-Bayes, logistic regression are interpretable but less accurate. Though they are interpretable they lack the relationship within the characteristic attributes present within the healthcare records [15]. So, the prediction models accuracy is compromised. As, many people cannot understand these algorithms it is important to design a model which is understandable by layman. So, interpretability helps the clinicians with explanations that builds trust towards machine learning models.

The Explainable Artificial Intelligence (XAI), provides a very high-level interaction with user. Transparency, Explainability, Justification and Uncertainty estimation are the main objectives of XAI [8]. Sometimes, AI models can provide incorrect prediction which may have grave consequences. Even though machine learning models are mostly used everywhere they have remained mostly as black boxes. To understand the reasons for these leads to trust issues which is important if one wants to take decision based on the prediction and these predictions sometimes leads towards trustworthy one [12]. Clinicians must be ready to understand the underlying reasoning of AI models in order that they can trust the predictions and be ready to identify individual cases during which an AI model potentially gives incorrect predictions. An explanation that's too hard to perceive and comprehend will presumably not have any practical effect.

To implement Explainable Artificial Intelligence What-If tool from Google is used. It basically questions like "based on what features the outcome is effected and what-if a change in datapoint, will it effect?". It is a visual interface tool which helps in understanding the dataset and also helpful for comparing two models and their predictions [2]. And the features of What-if tool is to visualize outcomes, arranging data based on similarity, comparing multiple machines learning models and modifying datapoints to see changes in model.

In this paper, the author uses these tools and methods like Decision Tree, Random Forest and Extreme Gradient Boosting to design an end-to-end interpretability Explainable Artificial Intelligence System for Cardiovascular disease to get accurate results.

## 2. Literature Survey

Many authors and researchers have explained and experimented on different kinds of datasets to predict cardiovascular and other diseases. They have used different methods Explainable AI methods and tools. Some of them are explained as follows:

J. W. Benjamins, T. Hendriks, et al (2019) proposed a paper “A primer in artificial intelligence in cardiovascular medicine”. The main objective of this paper is to introduce the broad cardiovascular community to the fundamentals of recent ML-based AI and explain several commonly used algorithms and summarizes future applications relevant to the cardiovascular field. Also explained about Future implementations of AI which will provide clinicians with diagnostic tools, clinical decision systems and greatly enhanced workflows in electronic health records, reducing costs in healthcare, which improves the extent of patient care and enabling doctors to focus more on their actual responsibility, treating patients.

Jose Jimenez-Luna, Francesca Grisoni and Gisbert Schneider (2020) proposed a paper [8]. This paper summarizes the foremost prominent algorithmic concepts of explainable AI, and forecasts future opportunities, potential applications also as several remaining challenges. Also, it encourages additional efforts towards the event and acceptance of explainable AI techniques. And it's crucial to carefully devise a group of control 10 experiments to validate the machine-driven hypotheses and increase their reliability and objectivity.

Juarez-Orozco, L.E. Knol, R.J. Sanchez-Catasus, C.A. et al. (2020) proposed a paper [9]. The main objective of this paper is to obtain the features that leads to myocardial ischemia or major risk at Major Adverse Cardiovascular Events (MACE). So, based on that decision future therapeutic decision are taken. Based on their work, they have classified as any myocardial ischemia if regional Myocardial perfusion reserve (MPR) $< 2.0$ and an elevated risk of MACE if global Myocardial perfusion reserve (MPR)$< 2.0$. They have used ROC curves to evaluate ML performance.

M. Shamim Hossain, Ghulam Muhammad, and Nadra Guizani (2020) proposed a paper [11]. The main objective of this paper is to implement a hierarchical edge computer system provides many advantages, like low latency, scalability, and therefore the protection of application and model training data, enabling COVID-19 to be evaluated by a local server. In this paper, they proposed a framework i.e., B5G that utilizes the 5G network’s low-latency, high-bandwidth functionality to detect COVID-19 using chest X-ray or CT scan images, and to develop a mass closed-circuit television to watch social distancing and wearing mask.

Marco Tulio Ribeiro, Sameer Singh, Carlos Guestrin (2016) proposed a paper [12]. The main objective of this papers to understand the machine learning models and the reasons on the output predicted and whether we can trust those outcomes or not is discussed. They proposed LIME, a technique used for interpretability. Based on this technique they explained the reasons for trusting or not trusting a model.

Mads Kristensen, Simon Meyer Lauritsen, et al (2020) proposed a paper [13]. The main objective of this paper is to predict the acute critical illness from patient’s electronic health records. They explained about explainable AI early warning score (xAI-EWS) which is used for detecting critical illness and also provides visual explanation. They used method like Temporal Convolutional Network (TCN) and Deep Taylor Decomposition (DTD). Five-fold cross validation is used for evaluating model’s performance.

Urja Pawar, Donna O’Shea, et al (2020) proposed a paper [14]. In this paper, the author discussed about the main objective Explainable Artificial Intelligence (XAI), a technique that is used in the analysis and diagnosis of health data by Artificial Intelligence based systems and a proposed approach presented with the aim of achieving accountability, transparency, result tracing, and model improvement within the domain of healthcare.

## 3. Proposed System

The figure-3 shows the system architecture of this paper which is an explainable artificial intelligence model that involves five major steps. They are:

3.1 Data Acquisition
3.2 Data Pre-processing
3.3 Feature Selection
3.4 Training Classification Methods
3.5 Testing Data

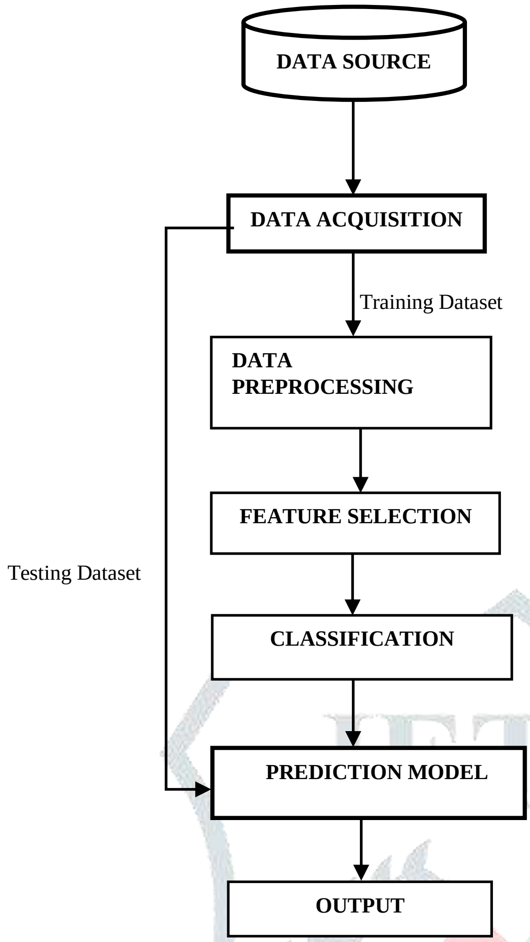


Fig-3 System Architecture

*3.1 Data Acquisition:*

The aim of this step is to spot and acquire all data-related problems. During this step, author would like to spot the various data sources, as data are often collected from various sources like files and database. The size and quality of the collected data will determine the efficiency of the output. The more the number of datapoints, the more accurate will be the prediction. From Kaggle website, the dataset for cardiovascular disease is collected.

*3.2 Data Pre-Processing:*

The aim of this step is to understand the nature of the data that author used to work with. Also, to know the characteristics, format, and quality of data. The data needs cleaning and converting it into a useable format. It's the method of cleaning the datapoints, selecting the variable to use, and converting the data into a proper format that is suitable for analysis within the next step. It's one among the foremost important steps of the entire process. Cleaning of datapoints is required to deal with the quality issues.

Here in the pre-processing step, usually checks for null values and replace them with the mean of the feature. And also, to identity the duplicate datapoints and drop them from the dataset.

*3.3 Feature Selection:*

The aim of this step is to identify the best features that gives high efficiency. To get the best features one should find the outliers that are present in the dataset and have to adjust them using interquartile range. And after identifying outliers one has to scale the features. Feature scaling is the final step of data pre-processing. It is a way to standardize the independent variables of the dataset into a specific range. In feature scaling, put our variables within the same range and within the same scale so that no variable dominates the other variable. For feature

scaling, we'll use StandardScaler class of sklearn.preprocessing library. And author also used What-If tool which is an Explainable AI tool from Google. The What-If Tool, a visual interface designed to assist you understand your data sets. It helps in editing data points to see how the model reacts to changes and also useful for comparing multiple machine learning models. The features that are identified are age, height, weight, systolic pressure, diastolic pressure and cholesterol.

*3.4 Training Classification Methods:*

*3.4.1 Decision Tree:*

Decision Tree is a Supervised learning technique i.e., preferred for solving Classification problems as our main motto is to classify whether the person is having cardiovascular disease or not. Decision Tree is a tree-structured classification algorithm, where internal nodes represent the columns or features of a dataset, branches represent the decisions that has to be made and each leaf node represents the output. And the features are selected based on Attribute Selection Measure (ASM) such as Entropy and Gini index. They are calculated using the below formulas,

$$\text{Entropy} = -\sum_{i=1}^{n} p_i * \log(p_i) \qquad \text{------equation (1)}$$

$$\text{Gini index} = 1 - \sum_{i=1}^{n} p_i^2 \qquad \text{-------equation (2)}$$

Where ‘i’ is the number of classes and $p_i$ is the probabilities of each class respectively.

The basic idea behind decision tree algorithm is as follows:

Step-1: Select the best attribute using Attribute Selection Measures (ASM) to split the records using equation (1) and equation (2).
Step-2: The selected attribute is made a decision node and then split the dataset into smaller subsets.
Step-3: After step2, begins tree building by repeating step-1 and step-2 recursively for each child either all the tuples belong to the same attribute value or there are no more remaining attributes.

*3.4.2 Random Forest:*

Random forest is a Supervised learning technique based on ensemble learning. Ensemble learning is a type of learning where you join different decision tree algorithms multiple times to form a more accurate prediction model. As a combination of multiple decision trees, resulting in a forest of trees, hence they have given the name "Random Forest". The random forest algorithm is not biased as it depends on majority voting and based on that voting it produces the final prediction. Random Forest also uses the same formulas equation (1) and equation (2) as of Decision Tree.

The basic idea Random Forest algorithm is as follows:

Step 1 : Firstly, start the selection of random samples from a given training dataset.
Step 2 : Next, this algorithm will construct a decision tree for every sample using decision tree algorithm. Then for each decision tree an outcome is resulted.
Step 3 : In this step, voting will be performed for every outcome that is resulted.
Step 4 : At last, select the most voted outcome result as the final prediction result.

*3.4.3* Extreme Gradient Boosting*:*

Extreme Gradient Boosting also referred to as XGBoost. XGBoost is an optimized gradient boosting library which has many benefits which makes the model highly efficient, flexible and portable. The implementation of the algorithm was done so that it meets the efficiency of computing time and memory resources. The design goal of XGBoost is to make the best use of available resources to train the model.

Some key algorithm implementation features include:

1. Spare Aware implementation with automatic handling of missing data values.
2. Block Structure to support the parallelization of tree construction.
3. Continued Training so that you can further boost an already fitted model on new data.

*3.5 Testing Data:*

Once Cardiovascular Disease Prediction model has been trained on cardiovascular dataset, then the model is tested using different datapoint. In this step, model is checked for the correctness and accuracy by providing a test dataset to it. Then it is to be verified whether the model is improving its performance using available datapoints or not.

## 4. Performance Analysis and Results

As, the model is built for Prediction the next step is to measure the performance of the model. In this section, measures that have been used in the paper are described. To evaluate the model, some of the standard measures such as precision and recall are used. Accuracy is the measure of total correct predictions to that of total predictions. The precision is the measure of patients that we correctly identified having cardiovascular disease out of all the patients actually having it. The Recall is the measure of, out of all the patients who actually have cardiovascular disease, how many patients were correctly identified having a cardiovascular disease. The F-measure is a Harmonic mean or weighted mean of precision and recall, it is also known as balanced F-score.

$$\text{Precision (P)} = \frac{\text{No of patients identified correctly having cardiovascular disease}}{\text{No. of patients having cardiovascular disease}} \quad \text{-----equation (3)}$$

$$\text{Recall (R)} = \frac{\text{No. of patients identified correctly having cardiovascular disease}}{\text{No.of patients identified with cardiovascular disease}} \quad \text{------equation (4)}$$

$$\text{F – measure} = \frac{2PR}{P+R} \quad \text{------equation (5)}$$

The datapoints are partitioned into four sets namely yes or no and having cardiovascular disease or not having cardiovascular disease. It is aimed to find the efficiency of the system. By calculating the accuracy, precision, recall and f-measure the results we can compare our trained model.

Table-1: Classified as yes or no and having cardiovascular disease or not

| Predict<br>Actual | Having Cardiovascular disease | Not having cardiovascular disease |
|---|---|---|
| Having Cardiovascular disease | $T_p$ | $F_p$ |
| Not having Cardiovascular disease | $F_n$ | $T_n$ |

Where, Tp, Fp, Fn and Tn are true positives, false positives, false negatives and true negatives respectively.

In the dataset, 70000 datapoints are maintained and for these patients with cardiovascular disease are identified. Now the manual calculations are compared to the predicted model calculations. For 10 datapoints, the manual calculations were shown in Table-2.

Table-2: Sample datapoints

| Id | Having Cardiovascular disease |
|---|---|
| 1 | yes |
| 2 | yes |
| 3 | no |
| 4 | yes |
| 5 | no |
| 6 | yes |
| 7 | no |
| 8 | no |
| 9 | yes |
| 10 | no |

Table-3 shows the performance of the system for the first 10 datapoints and for the same datapoints system generated results were compared.

Table-3: Comparing manual and system generated outputs

| Id | Having Cardiovascular disease (manual) | Having Cardiovascular disease (System generated) |
|---|---|---|
| 1 | yes | yes |
| 2 | yes | no |
| 3 | no | no |
| 4 | yes | yes |
| 5 | no | no |
| 6 | yes | yes |
| 7 | no | yes |
| 8 | no | no |
| 9 | yes | yes |
| 10 | no | no |

When compared with manual evaluation, results are promising. Random Forest has 0.75 precision which is a higher value when compared to other two models. XGBoost has a high recall value of 0.70 where random forest has 0.68 and decision forest has 0.59. If precision reaches 1 it shows that the system is more efficient. Coming to accuracy, the decision tree model is giving an accuracy of 0.68 in prediction whereas XGBoost is giving an accuracy of 0.72. Random Forest is giving an accuracy of 0.75 which is greater than the other two models. From the results, it is very clear that Random Forest performs well and gives minimum accuracy of 75%.

## 5. Conclusion

In this paper, the author has predicted the health care records of Cardiovascular disease patients using Explainable Artificial Intelligence (XAI) with What-if tool for getting better accuracy. It compares models and predicts the best model and justifies why it has chosen that model based on what features will also be mentioned. The author used the dataset that is downloaded from the Kaggle website which consists of 70000 datapoints. Each datapoint consists of 13 features. Based on those features the author designed a model that gives better accuracy of 75%. The author used methods like Random Forest, Decision Tree and XGBoost and based on those methods a prediction model is generated. To evaluate the performance of the model author used performance measures like accuracy, precision, recall and f-1score. And at last author have compared the system generated and manually obtained results to determine the efficiency. In future, author will compare those methods using performance measures and explainability can also be extended by using other explainable AI tools.

## References


[1] J. London “Artificial Intelligence and Black-Box Medical Decisions: Accuracy versus Explainability”. Hastings Cent Rep, 49(1):15–21, January 2019.

[2] Amal Nair “https://analyticsindiamag.com/explainable-ai-with-what-if-tool/”, India Magazine, November 2019.

[3] A. Holzinger, C. Biemann, C. S. Pattichis, and D. B. Kell, “What do we need to build explainable AI systems for the medical domain?,” no. Ml, pp. 1–28, 2017.

[4] D. Wang, Q. Yang, A. Abdul , and B. Y. Lim, “Designing Theory-Driven User-Centric Explainable AI”, Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems – CHI’19, pp.1-15, 2019.

[5] Erico Tjoa, and Cuntai Guan “A Survey on Explainable Artificial Intelligence (XAI): towards Medical XAI”, Journal of Latex Class Files, vol. 14, no. 8, August 2015.

[6] Feiyu Xu, Hans Uszkoreit “Explainable AI: A Brief Survey on History, Research Areas, Approaches and Challenges”, Natural Language Processing and Chinese Computing. NLPCC, vol. 11839, ISBN no. 978-3-030-32235-9, September 2019.

[7] J.W.Benjamins, T.Hendriks , et al “A primer in artificial intelligence in cardiovascular medicine” Netherlands Heart Journal, vol. 27, pp. 392–402, 20 May 2019.

[8] Jose Jimenez-Luna, Francesca Grisoni, Gisbert Schneider “Drug discovery with explainable artificial intelligence” Nature Machine Intelligence, vol. 2, pp. 573–584, October 2020.

[9] Juarez-Orozco, L.E. Knol, R.J. Sanchez-Catasus, C.A. et al. “Machine learning in the integration of simple variables for identifying patients with myocardial ischemia”, Journal of Nuclear Cardiology, no. 27, pp. 147–155 (2020)

[10] Kristin P. Bennett, “Artificial Intelligence for Public Health” IEEE International Conference on Bioinformatics and Biomedicine (BIBM), ISBN no. 978-1-7281-1867-3/19, March-2019.

[11] M. S. Hossain, G. Muhammad and N. Guizani, "Explainable AI and Mass Surveillance System-Based Healthcare Framework to Combat COVID-I9 Like Pandemics”, in *IEEE* Network, vol. 34, no. 4, pp. 126-132, July/August 2020.

[12] M. T. Riberio and C. Guestrin ““Why Should I Trust You?” Explaining the Predictions of Any Classifier”, pp. 1135-1144, 2016.

[13] Mads Kristensen, Simon Meyer Lauritsen, et al “Explainable artificial intelligence model to predict acute critical illness from electronic health records”, Nature Communications 11, Article number: 3852, July 2020.

[14] Shuo Tian, Wenbo Yang, et al “Smart healthcare: making medical care more intelligent”, Global Health Journal, vol. 3, no. 3, pp. 62-65, 2019.

[15] Urja Pawar, Donna O’Shea, Et al “Explainable AI in Healthcare”, International Conference on Cyber Situational Awareness, Data Analytics and Assessment (CyberSA) ISBN no. 978-1-7281-6691-9, June 2020.