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Artificial Intelligence in Cardiology: Precision Detection and Prognosis of Coronary Artery Disease

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Abstract

Coronary Artery Disease stands as a leading cause of mortality worldwide. Early diagnosis and prompt medical intervention for cardiovascular patients hold the potential to significantly curtail mortality rates and lessen the financial burden associated with coronary artery disease treatments. Addressing the roots of cardiovascular risk factors is imperative, and Artificial Intelligence coupled with Machine Learning has emerged as a promising avenue for exploration. This study delved into the utilization of open-source Python code employing machine learning algorithms on various health parameters to predict coronary artery disease outcomes. The suggested model diagnosed coronary artery disease relying on clinical data, circumventing the need for invasive procedures. This research examined the potential of artificial intelligence machine learning algorithms leveraging an open-source comma separated values dataset from Kaggle involved in coronary artery disease prediction, assessing their efficacy, visual clarity, accuracy, and range of data. It aimed to ascertain whether the integration of these technologies will enforce a beneficial or detrimental impact on the healthcare and patient care sector. The aforementioned technologies demonstrated an accuracy level of 84.50%, with the visual clarity derived from artificial intelligence and comma separated values data being comprehensible not only for researchers and physicians to analyze, but also for patients. Artificial Intelligence driven predictive models hold promise in medical decision support systems and in addressing certain limitations that impede the effectiveness of classic regression models or traditional methods presently utilized. Subsequently, this study explored avenues for future research, where this knowledge can be used to efficiently predict coronary artery diseases.

Keywords: Artificial Intelligence, Machine Learning, Cardiovascular Disease, Coronary Artery Disease, CAD

1. Introduction

Cardiovascular diseases (CVDs) remain the leading cause of morbidity and mortality worldwide, despite the impressive advancements in patient prognosis achieved in the last decades through several innovations in the diagnosis and management of a broad spectrum of CVDs (Virani et al., 2020). The cost of heart diseases in the United States alone is more than $200 billion annually and it has been predicted to increase twofold by 2030 (Benjamin et al., 2018). Cardiovascular diseases are heart conditions that include diseased blood vessels, structural problems, and blood clots, and the most common types are shown in Figure 1. Coronary Artery Disease (CAD) is the most common type of Ischemic Heart Disease (IHD), which occurs when at least one of the coronary arteries has more than 50% stenosis (narrowing of blood vessels or heart valves, which can restrict the flow of blood) (Cardiovascular Disability: Updating the Social Security Listings, 2010).

Artificial intelligence (AI) has emerged as an increasingly useful and reliable tool for various applications, particularly in healthcare. Starting from the field's inception in the 1960s to present-day innovative applications in areas such as precision medicine, robotic surgery, and drug development, AI has the potential to enhance the practice

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of physicians by facilitating improved efficiency and organization, thus improving patient care and outcomes (Hirani et al., 2024). AI is the ability of machines or computers to perform tasks that require human intelligence based on which machines are designed to think, learn, and act like humans. Machine Learning (ML) is the ability of a machine to learn something without having to be programmed for that specific thing. It is the field of study where computers use a massive set of data and apply algorithms for 'training' themselves and making predictions. In today's world, AI along with ML offers the wide range of technologies we use every day like smartphone apps which help to improve photo and video quality, provide voice assistance, image search, and targeted advertising based on interest to chatbots that provide customer support in real time.

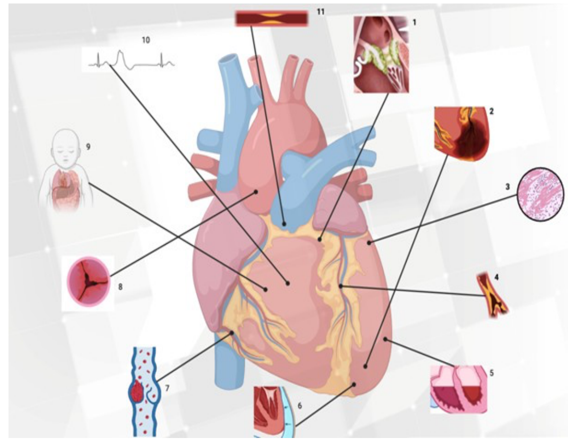

Figure 1. Major heart diseases of significance labeled 1- 11. 1. Endocarditis (Infection caused by bacteria which enters the blood and takes root in the heart), 2. Rheumatic heart disease (Condition developed when heart muscles and valves are damaged by Rheumatic fever, which is linked to Strep Throat and Scarlet Fever), 3. Heart Failure (Heart doesn't pump blood as well as it should to meet the body's needs), 4. Heart Valve Disease (When valves are unable to open or close correctly), 5. Pericardial Disease (Disease of Pericardium, sac surrounding the heart), 6. Cardiomyopathy (Heart muscle disease, the muscle gets stretched, thickened, or stiff), 7. Myocardial Infarction (Heart attack), 8. Atherosclerosis (Hardening of the arteries), 9. Congenital Heart Disease (Something goes wrong when the heart is forming in a baby while still in the womb, including septal abnormality, pulmonary stenosis, ductus arteriosus), 10. Heart Arrhythmia (Irregular heartbeat pattern), 11. Coronary Artery Disease (Blockage in Coronary Artery). Created using BioRender.com.

1.1 Cardiology Current Scenario

1 in 5 Americans die from the conditions listed in Figure 1, which is a startling 695 thousand deaths in 2021 only. Diseases of the heart are a major public health problem and are the leading cause of death for men, women, and people of most racial and ethnic groups in the United States. This cost the United States about $239.9 billion each year from 2018 to 2019, and includes the cost of healthcare services, medicines, and lost productivity due to death (National Center for Health Statistics, 2023). By 2030, it's anticipated that CAD will result in over 23 million fatalities, affecting roughly 30.50% of the global populace (Sarrafzadegan et al., 2019).

The early diagnosis and timely medical intervention for cardiovascular patients can significantly avert sudden fatalities and alleviate the substantial financial burden associated with surgeries and other treatments (Aydin et al., 2016). CAD diagnosis is a complex clinical process that requires expertise and experience from physicians, substantial time and financial resources, utilization of diverse equipment, and meticulous investigation into various risk factors including laboratory tests and physical examinations to achieve accurate results (Verma et al., 2016). Invasive coronary angiography (medical imaging technique used to visualize the inside of arteries, veins, and the heart chambers) remains the benchmark for diagnosing CAD (Alizadehsani et al., 2018). Due to its expense and associated complications, researchers are persistently seeking non-invasive, cost-effective, rapid, and reliable techniques for the early diagnosis of CAD (Li et al., 2019).

CDC's Data Modernization Initiative supports artificial intelligence, machine learning (ML), and other powerful solutions for large or complex data. These solutions can help us maximize insights from our data and systems and use those insights to drive public health action. Machine learning allows a computer to analyze data to do a task without being explicitly programmed. The main kinds of machine learning are (1) to find patterns, like groupings of similar items and (2) to forecast an output based on a given set of inputs (Sung et al., 2020). Fairly new concerning its involvement in the medical field, AI integration in predicting heart disease can help make the delivery of healthcare more efficient and revolutionize medical practices. Powered by breakthroughs in machine learning algorithms, enhanced computing capabilities, and expanding data volume and storage capacities, AI has achieved significant progress. Experts predict AI-based medical devices and algorithms will play a major role in the delivery of preventive,

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diagnostic, and therapeutic interventions (Matheny et al., 2020).

The current scenario in cardiology emphasizes the importance of understanding the morphology of the heart, as changes in heart anatomy are often key factors in the development of cardiovascular diseases, influencing both diagnosis and treatment strategies.

1.2 Morphology of the Heart

General Structure of the Heart: The heart is a four-chambered, muscular organ roughly the size of a fist that helps with the circulation of blood, nutrients, and oxygen around the body. It comprises three main layers: the tough, muscular wall known as the myocardium, a thin, soft tissue layer called the pericardium that covers the outside, and the endocardium which lines the inside of the heart. Heart walls divide the organ's cavity into 4 chambers. The top two chambers are called atrium, while the bottom two are called ventricles, and each chamber is further divided into the right and left sides. The divisions between the 4 chambers are punctuated by valves, body parts that control one-way blood flow. Connected to the heart are several blood vessels such as the pulmonary vein, pulmonary artery, aorta, and the superior and inferior vena cavas. Generally, veins carry deoxygenated blood except for the pulmonary vein which carries oxygenated blood. Similarly, arteries carry oxygenated blood except for the pulmonary artery which transports deoxygenated blood. The blood flow pathway is shown in Figure 2.

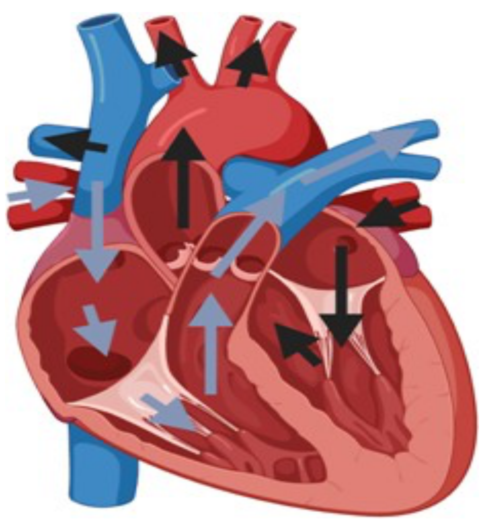

Figure 2. This figure demonstrates the path of blood through the different cavities, valves, and blood vessels in the heart that are transported to the lungs to be oxygenated, and to the body, to distribute oxygen and oxygenate different body parts. The black arrows demonstrate oxygenated blood as it enters the lungs and circulates the body. The grey arrows demonstrate deoxygenated blood as it enters the heart from the body and is sent to the lungs to get oxygenated. Created using BioRender.com.

Pumping of the Heart: The heart is a muscle that pumps blood around the body due to alternating relaxations and contractions of the myocardium. These movements are triggered by electrical impulses from a natural pacemaker called the sinoatrial (SA) node located in the right atrium. An impulse from the SA node causes the atria to contract, pushing blood down into the ventricles. During relaxation, the pressure formed in the ventricle decreases, allowing blood to flow back into the atria where the process, also called the cardiac cycle, restarts. Blood pressure refers to the amount of pressure exerted onto the blood vessels during contraction and relaxation. The period of relaxation refers to the diastole or diastolic pressure. The period of contractions refers to the systole or systolic pressure (WebMD, 2023).

Metabolism of the Heart: Because the heart must constantly be pumping blood, the organ has a great metabolic capability for energy production and homeostasis. Adenosine triphosphate (ATP) is the main energy source of the body and heart, with 60-70% of it being used to contract the heart muscles. ATP is a very energy-concentrated molecule due to the presence of high-energy phosphate bonds. However, the heart contains small pools of ATP, which is why cardiac function is highly dependent on the continuous production of the molecule. In the case of heart failure, cardiac metabolism may have gotten impaired, where the influx of ATP is insufficient to power the heart. Changes in cardiac metabolic processes can negatively affect metabolic processes in the entire body, such as those affecting growth, homeostasis, and autophagy. Treatments targeting cardiac metabolic processes can give a good insight into the prevention and cure of CVDs (Lopaschuk et al., 2021).

Acknowledging the necessity for innovative approaches to predict CAD risk factors at their core, AI has emerged as a promising avenue for exploration. This study seeks to assess the effectiveness of integrating these technologies—an approach that holds promise for favorable outcomes in CAD research.

1.3 Artificial Intelligence and Cardiology

AI encompasses computational systems capable of undertaking tasks typically requiring human intelligence and decision-making (Lam et al., 2022). Unlike traditional computer algorithms, ML, a subset of AI, enables algorithms to enhance themselves through experience (Javaid et al., 2022). Deep learning, a specific form of ML, constructs intricate feature representations by connecting simple mathematical functions into a neural network structure (LeCun et al., 2015). Cardiology, being data-driven and evidence-based, has swiftly embraced ML; demonstrating enhanced performance compared to conventional risk assessments (Attia et al., 2019; Madani et al., 2018). ML applications in cardiology span various areas including ECG analysis, echocardiogram interpretation, and risk prediction (Kakadiaris et al., 2018; Alaa et al., 2019).

Currently, 64 AI-powered medical devices and algorithms have received FDA approval in the U.S., reflecting AI's expanding role in reshaping biomedical research and clinical practice. Moreover, AI has become pivotal in cardiovascular medicine, with several applications transitioning into mainstream clinical practice (Benjamens et al., 2020). Wearable devices with optical sensors, like smartwatches, have facilitated the detection of cardiovascular irregularities, such as atrial fibrillation and flutter, showcasing AI's potential for remote monitoring and diagnosis (Strain et al., 2019; Tison et al., 2018). In cardiology, AI offers manifold benefits, including aiding in daily decision-making processes, enhancing heart imaging, improving surgical precision, reducing risks, advancing knowledge, and elevating patient care (Madani et al., 2018). AI's integration in cardiology aims to bolster clinical effectiveness and performance, allowing clinicians to focus on core competencies like empathy and physician-patient interaction. Despite AI's potential, challenges remain in understanding its complex algorithms and ensuring transparency in decision-making processes (Petch et al., 2022). Ethical considerations are necessary to ensure safe and acceptable implantation of AI within the healthcare space. The use of AI deployment demands robust regulation, transparent algorithms, and safeguarding of patient privacy along with addressing challenges such as data privacy, consent, sustainability, and cybersecurity (Lewin et al., 2024).

Artificial intelligence and machine learning are poised to revolutionize various aspects of cardiology, offering enhanced efficiency, personalization, and effectiveness in patient care (Johnson et al., 2018). Physicians stand to benefit from AI-driven support tools, freeing them from routine tasks and empowering them to focus on crucial aspects of patient care.

2. Materials and Methods

The study utilized foundational open-source Python code along with four machine learning algorithms. Additionally, a set of metadata Comma Separated Value (CSV) files were used, containing information on a total of 920 participants, with various columns of information which included different health and demographic parameters that affect heart health. Specifically, for this study, the Python code and CSV data pertain to coronary artery disease.

2.1 CSV Data

The CSV datasets accessible on Kaggle contained comprehensive information about the varied health parameters of 920 patients which were extensively utilized for this research. For each of the patients, the datasets contained 14 attributes as shown in Table 1.

Table 1. One of the CSV datasets found on Kaggle and used for this research. The code draws trends based on the numbers present in the table for the likelihood of developing CAD.

age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
57	0	0	120	354	0	1	163	1	0.6	2	0	2	1

The 14 attributes containing information about patients in integer value (as applicable) included age in years, sex,

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chest pain (cp) also known as Angina (4 types - typical angina, atypical angina, non-anginal pain, asymptomatic), resting blood pressure (trestbps) in mmHg, serum cholesterol (chol) in mg/dL, fasting blood sugar (fbs) >120 mg/dL (likely to be diabetic), resting electrocardiogram (restecg- normal/having ST-T wave abnormality/ showing probable or definite left ventricular hypertrophy), maximum heart rate achieved per minute (thalach), exercise induced angina (exang), ST depression induced by exercise relative to rest (oldpeak) in mm, the slope of the peak exercise ST segment (slope), number of major vessels (ca) colored by fluoroscopy - Major cardiac vessels are: aorta, superior vena cava, inferior vena cava, pulmonary artery (oxygen-poor blood --> lungs), pulmonary veins (oxygen-rich blood --> heart), and coronary arteries (supplies blood to heart tissue), thal: fixed defect (heart tissue can't absorb thallium both under stress and in rest)/ reversible defect (heart tissue is unable to absorb thallium only under the exercise portion of the test) and target (referring to the presence or absence of heart disease in the patient).

2.2 Machine Learning Algorithms

There were 4 machine learning methods utilized - logistic regression (supervised machine learning algorithm widely used for binary classification tasks to determine the presence or absence of CAD), naïve bayes (probabilistic machine learning algorithm which calculates the probability of an event occurring given the probability of another event that has already occurred), decision trees (flowchart-like structure used to make predictions based on data) and random forest (machine learning algorithm that combines multiple decision trees to improve prediction accuracy).

For implementing the machine learning algorithms, the dataset was first loaded and cleaned by removing any blank or incomplete values of the 14 attributes for all the 920 participants. The number of unique records per attribute was reviewed to ensure completeness. All the machine learning models were imported using the Scikit-learn open-source library for Python. Naive bayes logistic regression model was trained without any transformations and data was analyzed. After analyzing categorical data, to make the final training decision on what variables to drop, Decision Trees and Random Forests ML techniques were used. Each of the machine learning models were trained using a training set with 70.00% of instances from the CSV dataset and performance was evaluated through a test set with the rest 30.00% of the instances.

The naive bayes regression model was set without any initial assumptions about the data.The model parameter for Decision Tree was set to make sure that each decision point has enough data to be reliable, and it used a random seed number 1 to ensure consistent results each time. The Random Forest model was set to look at 25% of the data at each decision point, use 1000 decision trees, and make decisions based on the "Gini index," which is a method of measuring how pure each decision is. It also used a random seed number 0 to keep results consistent.

2.3 Python Code

Multiple open source Python codes as shown in Figure 3 and Figure 4 from Kaggle aimed at predicting CAD using the four machine learning methods were taken into account in the development of this research. It provided diverse inputs regarding symptoms that could be utilized for predicting CAD. The code took into consideration patients' inputs over all the 14 attributes.

```
sns.countplot(df['cp'],
            alpha = 0.9,
            hue = df['class'],
            ax = ax2,
            palette = 'rocket',
            order=df['cp'].value_counts().index)
ax2.legend()
plt.xticks( fontsize = 14)

ax3 = fig.add_subplot(grid[1, :2])
ax3.set_title('Resting Electrographic Results Distribution')
sns.countplot(df['restecg'],
            alpha = 0.9,
            hue = df['class'],
            ax = ax3,
            palette = 'rocket',
            order=df['restecg'].value_counts().index)
ax3.legend()
plt.xticks(fontsize = 14)

ax4 = fig.add_subplot(grid[1, 2:])
ax4.set_title('Defect Type Distribution')
sns.countplot(df['thal'],
            alpha = 0.9,
            hue = df['class'],
            ax = ax4,
            palette = 'rocket',
            order=df['thal'].value_counts().index)
ax4.legend()
plt.xticks(fontsize = 14)
plt.show()
```

Figure 3. This figure is an example of one Python code analyzed for research. This particular example shows the code gathering data from a Resting Electrographic Exam and generating a tree diagram using a decision tree machine learning algorithm that will categorize symptoms and results from the exam and assign a risk value that will let researchers and doctors know when a patient is likely to develop CAD. Sourced from Kaggle.

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```
import os
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from IPython.display import display_html
import statsmodels.formula.api as smf
import statsmodels.api as sm
import matplotlib.gridspec as gridspec
from sklearn import model_selection
from sklearn import metrics
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, accuracy_score

import matplotlib.gridspec as gridspec

blue_red = ['#74a09e','#86c1b2','#98e2c6','#f3c969','#f2a553', '#d96548', '#c14953']
sns.palplot(sns.color_palette(blue_red))

# Set Style
sns.set_style("whitegrid")
sns.despine(left=True, bottom=True)
```

Figure 4. The aforementioned characteristics were developed into a code that created a flow chart, with each box in the flow chart depicting statistics about the prevalence of the factors. Sourced from Kaggle.

3. Results

All CSV datasets included input regarding the age of multiple patients. The average age was 60 years old, with most participants falling into the older age category (defined as over 40 years old). There were considerably more male participants in the data compared to females. In terms of demographics, males aged over 60 showed higher susceptibility to CAD compared to women of the same age. Chest pain is one of the most common indicators of coronary artery disease. The majority of CSV datasets also collected information on the prominence of chest pain among participants, with some further categorizing it into specific types (such as asymptomatic or nonanginal pain). Unhealthy cholesterol levels have long been linked to heart diseases, such as coronary artery disease, where fats accumulate and block arteries, posing significant risks to individuals. Most of the cholesterol levels in the CSV datasets fall within the healthier, lower range. High blood sugar levels can harm blood vessels and the walls of the heart, thereby increasing the risk of developing coronary artery disease. Some CSV datasets collected information on general blood sugar levels, while others included data on resting and fasting blood sugar as well as on resting blood pressure. An unusually high or low heart rate is indicative of coronary artery disease and potentially the presence of other cardiovascular health-related issues. In many of the CSV datasets, a higher-than-average heart rate was observed. Additional factors considered in the CSV datasets included the patient's electrocardiogram results, exercise habits, stress levels, depression, and the presence of underlying conditions like cardiovascular problems related to major blood vessels and heart disease.

Utilizing AI along with machine learning methods on a dataset of 920 patients, a predicted CAD outcome was measured. In addition, the AI-generated analysis identified the six most significant attributes—Sex, Type of chest pain, Maximum heart rate, Angina, Depression, and Major blood vessels—to consider for CAD outcomes. A confusion matrix (which summarizes the performance of a machine learning model on a set of test data and is used for displaying the number of accurate and inaccurate instances based on the model's predictions) was generated as shown in Figure 5 where it compared the actual CAD condition (represented as True label) with the AI predicted CAD outcome (represented as Predicted label) and had accuracy of 84.50% using the equation specified in section 3.1.

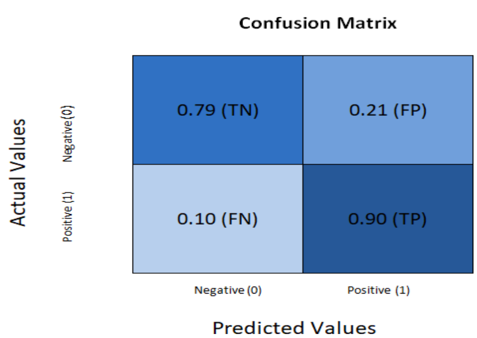

Figure 5. Accuracy analysis representing the accuracy of the AI generated CAD outcome. The rows represent the actual outcome, while the columns represent the AI predictions of CAD.

3.1 Equation

Accuracy is defined as total correct predictions (AI-based CAD outcome matches actual CAD condition) divided by total predictions (includes all predictions, regardless of whether the AI-based CAD outcome matches the actual CAD condition).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

Where
TP (True Positive): AI-based outcome for CAD is Positive and Actual CAD condition is Positive
TN (True Negative): AI-based outcome for CAD is Negative and Actual CAD condition is Negative
FP (False Positive): AI-based outcome for CAD is Positive and Actual CAD condition is Negative
FN (False Negative): AI-based outcome for CAD is Negative and Actual CAD condition is Positive

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4. Discussion

The observed AI/ML method focused on predicting CAD in patients by analyzing trends of various parameters. The dataset predominantly featured demographic and medical data.

The model is accurate enough to capture the directly proportional relationship between attributes Major blood vessels, Depression, Angina, Chest pain type, Sex (in order of strength of association) and the inversely proportional relationship between Maximum heart rate and the outcome of confirmed coronary artery disease. This is a positive outcome, indicating that the model, when applied to the validation dataset, successfully captured the underlying signals in the data.

The AI predicted CAD outcome had accuracy of 84.50%. Consequently, it can be inferred that the model demonstrates good generalization and that its accuracy is adequate for utilization based on the captured features.

One of the primary limitations of AI in the study was its ability to make decisions based on limited information. Additionally, AI systems can only learn from data provided to them. This means that if there are biases or gaps in the data like more males and elderly participants in this study, the AI system may make decisions based on these biases. Machine learning algorithms are only as good as the data they are trained on. However, their performance can degrade significantly when presented with data substantially different from the data on which they were trained.

5. Conclusion

Coronary Artery Disease is a prominent cause of death for millions of people around the world, with no established long-term cure. However, with the use of AI, doctors can analyze a patient's medical history, lifestyle, and other relevant data to identify CAD earlier, before the condition becomes too severe to treat. This research demonstrates how AI algorithms, combined with CSV data, can predict CAD with high levels of accuracy, often detecting symptoms months before they become life-threatening. By implementing these AI-driven tools, healthcare providers can make earlier, more informed decisions, potentially saving lives, improving patient outcomes, and reducing healthcare costs by intervening at the right time. This approach has the potential to transform the way CAD is diagnosed and managed, leading to better overall care for patients.

It is important to acknowledge some limitations inherent in this dataset. This specific technology cannot study and analyze data with 100% accuracy as it relies on a regression model, thus introducing a margin of error. This margin of error has the potential to skew some data, particularly when certain inputs lack a substantial sample size like gender or age skewness. Regression techniques are founded on assumptions and may consequently limit their accuracy in certain settings. Additionally, different forms of AI possess distinct defining characteristics that may redefine specific results. It is crucial to understand that while AI is a universal concept, its implementation will vary depending on the type of AI system, the models/codes being utilized, and the analysis techniques employed. AI and ML are at the forefront of decreasing the presence of CAD in communities globally, and further research in artificial intelligence intervention and machine learning in this field can revolutionize the future of cardiovascular disease diagnosis.

6. Future Research Recommendations

The accuracy value of 84.50% represents the percentage of correct positive diagnoses (true positives) made by the methods used in this research. For future study, it is recommended to compare this to the precision of traditional diagnostic methods used for Coronary Artery Disease (CAD), such as angiography or stress tests, to highlight the effectiveness of this method and to help gauge its relative importance in clinical decision-making.

The use of technology such as codes and graphics is rapidly becoming a more integral part of the medical field. The current research aims to observe one perspective of this. For deeper investigation, given the complexity of the Python code under scrutiny, a greater comprehension of the code could be attained by someone with a more advanced proficiency of the programming language. Furthermore, there are a vast number of other coding languages besides Python (such as JavaScript and C++) that could also be used to create such models. In-depth investigations could involve exploring alternative programming languages, diverse methods of data collection and analysis (such as various regression techniques, statistical analysis, etc.), and graphical visualization methods.

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