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Enhanced Machine Learning-Assisted Convolutional Neural Network for Heart Disease Prediction

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Abstract: The accurate and timely diagnosis of heart disease remains a critical challenge in modern healthcare. Recent advancements in deep learning have paved the way for intelligent diagnostic systems that enhance medical decision-making. This study introduces an Enhanced Deep Learning-Assisted Convolutional Neural Network (EDCNN) for heart disease prediction, leveraging the Internet of Medical Things (IoMT) to enable real-time and remote diagnostics. The proposed model integrates a multi-layer perceptron (MLP) framework with optimized regularization techniques, ensuring robust feature extraction and classification. The system's performance is evaluated using both comprehensive and reduced feature sets to analyze the trade-off between computational efficiency and diagnostic accuracy. Experimental results demonstrate that EDCNN outperforms traditional models such as Artificial Neural Networks (ANN), Deep Neural Networks (DNN), and Recurrent Neural Networks (RNN) in terms of precision, recall, and overall predictive accuracy. Implemented on a cloud-based IoMT platform, the model facilitates seamless access to diagnostic insights, supporting healthcare professionals worldwide. Comparative analysis indicates that fine-tuning EDCNN's hyperparameters enables it to achieve a remarkable precision rate of **99.1%**, reinforcing its potential as a reliable and efficient tool for heart disease prognosis.

Indexing terms: Convolutional Neural Network (CNN) , Enhanced Deep Learning-Assisted CNN (EDCNN) ,Internet of Medical Things (IoMT) , Multi-Layer Perceptron (MLP) Hyperparameter Optimization , Cloud-Based Healthcare

1. Introduction

Heart disease is one of the leading causes of death worldwide, accounting for millions of fatalities annually. The early and accurate detection of cardiovascular conditions is crucial for reducing mortality rates and improving patient outcomes. However, traditional diagnostic methods, such as electrocardiograms (ECG), echocardiograms, and clinical assessments, often require expert interpretation and may not always be available in remote or underdeveloped areas. Furthermore, manual analysis of medical data is prone to subjectivity and human error, which can lead to misdiagnosis or delayed treatment.

In recent years, artificial intelligence (AI) and deep learning have gained significant attention in the medical field for their ability to enhance diagnostic accuracy and automate complex tasks. Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown remarkable success in medical imaging and classification tasks. These models can learn intricate patterns from large datasets, making them well-suited for disease prediction. The integration of Internet of Medical Things (IoMT) with AI-based models further enhances diagnostic capabilities by enabling real-time monitoring and remote access to patient data. IoMT allows healthcare professionals to analyze patient information from cloud-based platforms, providing timely insights for early detection and intervention. Despite these advancements, the efficiency and accuracy of deep learning-based diagnostic systems depend on several factors, including feature selection, network architecture, and computational complexity. Traditional AI models such as Artificial Neural Networks (ANN), Deep Neural Networks (DNN), and Recurrent Neural Networks (RNN) have been used for heart disease prediction, but they often struggle with overfitting, high computational costs, and suboptimal performance in real-time applications. To overcome these limitations, there is a need for an optimized and robust deep learning model that ensures precise classification while maintaining computational efficiency.

To address this challenge, this study introduces an Enhanced Deep Learning-Assisted Convolutional Neural Network (EDCNN) for heart disease prediction. The EDCNN model is designed with a deeper architecture that integrates a multi-layer perceptron (MLP) framework and optimized regularization techniques to enhance learning efficiency. The proposed model is trained and validated on both full and reduced feature sets to analyze the impact of dimensionality reduction on accuracy and processing time. The system is implemented on an IoMT platform, allowing seamless integration with cloud-based healthcare services for real-time decision support.

1.1. Contribution of work:

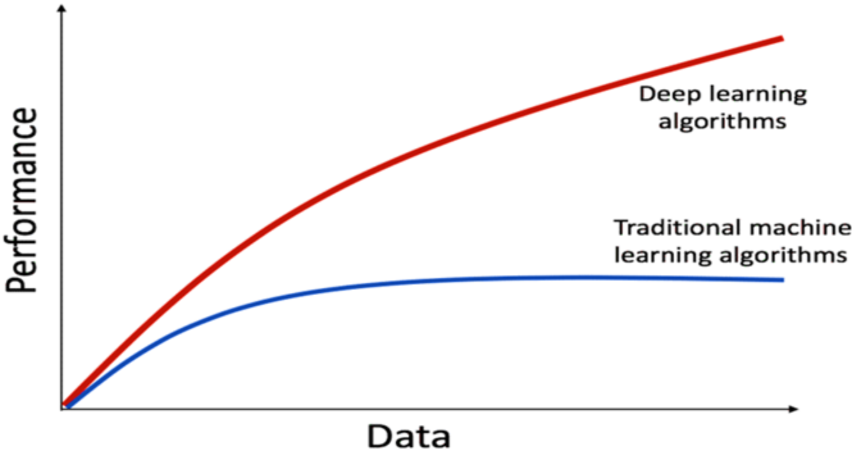


Fig 1.Survey on Various Deep learning assistance with traditional algorithm

Experimental results show that the **EDCNN model achieves a precision of 99.1%**, outperforming conventional AI models in heart disease detection. By leveraging deep learning and IoMT technologies, this system has the potential to significantly improve early diagnosis and reduce the burden on healthcare professionals. The primary contributions of this study are as follows:

- Development of an optimized deep learning model (EDCNN) with enhanced feature extraction and classification capabilities for heart disease diagnosis.
- Integration of IoMT to enable real-time and remote monitoring of patient data, improving accessibility and timely intervention.

- Comparative analysis with traditional models such as ANN, DNN, and RNN, demonstrating superior performance in terms of accuracy, precision, and computational efficiency.
- Hyperparameter tuning and feature selection techniques to balance model complexity and processing speed while maintaining high predictive accuracy.

Tomov and Tomov [23] introduced the Deep Neural Net- work (DNN) for detecting heart disease, and the results have discovered in the process of the five-level DNN architecture for Algorithmic Risk-reduction and Optimization for the best prediction accuracy as shown in Figure.1.

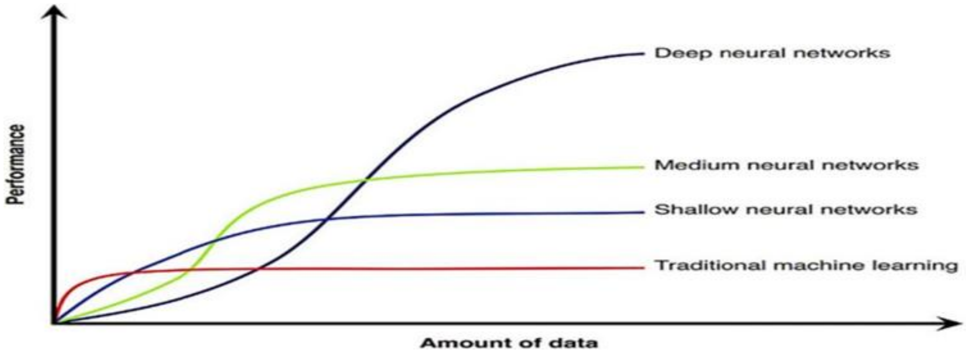


Fig 2. Survey on Various neural network and its importance

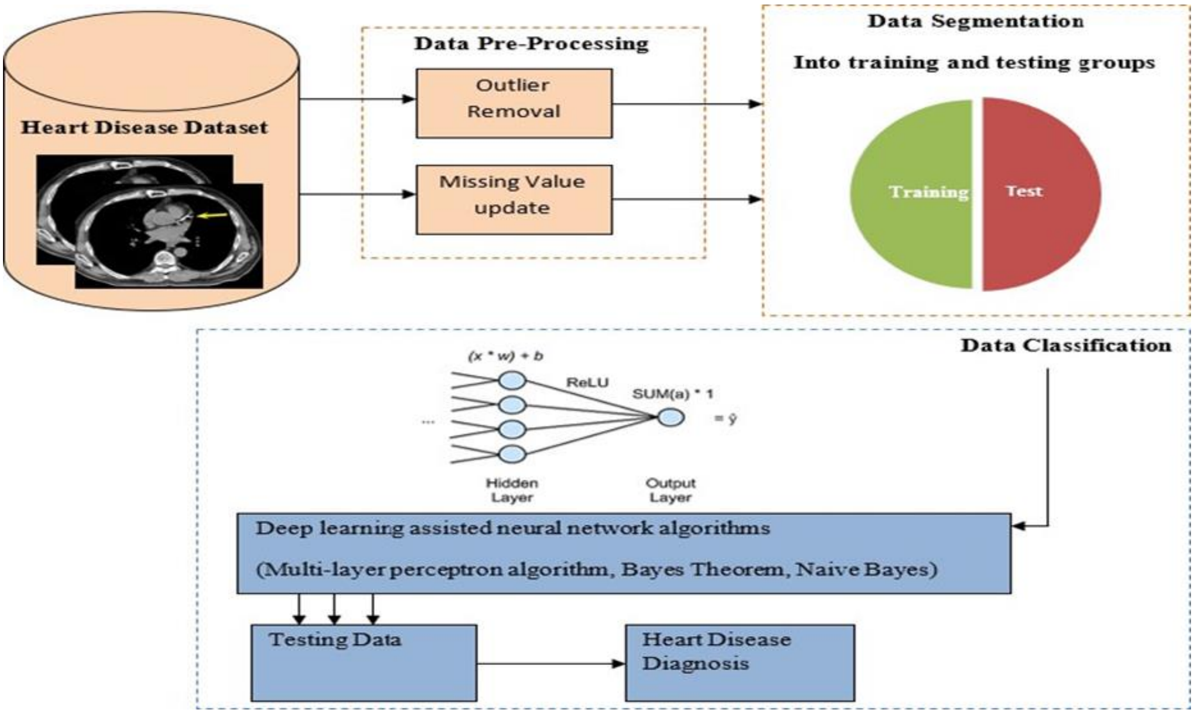


Fig 3.EDCNN method architecture.

The remainder of this paper is structured as follows: **Section 2** reviews related work and existing methodologies for heart disease diagnosis. **Section 3** presents the proposed EDCNN framework and its implementation. **Section 4** discusses the experimental results and performance analysis. Finally, **Section 5** concludes the study and highlights future research directions.

Fig 4. Medical Diagnostic interface

In Fig 4 presents a high-tech, medical diagnostics interface, likely representing a futuristic healthcare system that integrates big data, and predictive analytics to improve disease detection and patient monitoring. In Fig 5 illustrates that the internet of Medical things for heart diseases analysis. It describes through the internet sensor, IoMT, visualize, deep learning and health description.

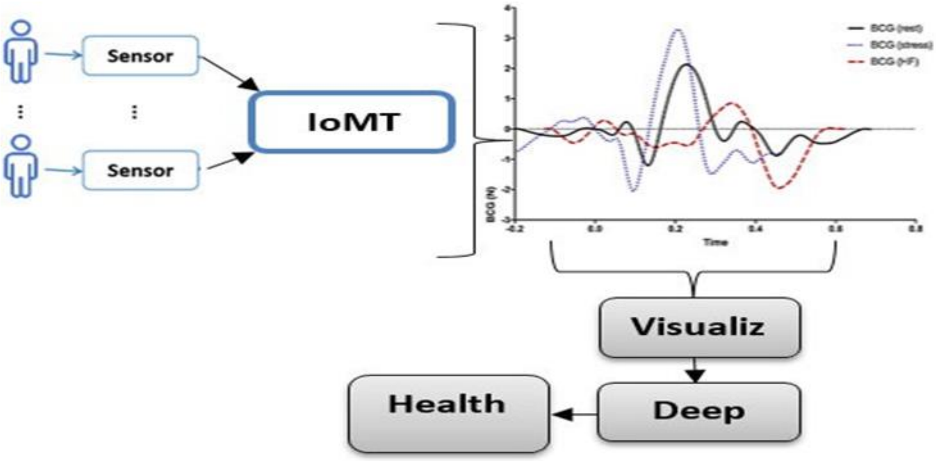


Fig 5. The Internet of Medical Things for Heart disease analysis

1.2. Medical Analysis

The image contains multiple interconnected circular elements, suggesting a neural network-inspired data processing approach. The use of brain scans, organ images, and DNA structures hints at advanced biomedical for disease detection. The labels "Disease Index," "Observation Range," and "Prediction" indicate a system that analyzes health metrics to identify potential risks.. Various charts and graphs display trend analysis over time, likely for tracking patient conditions. The use of circular infographics, bar charts, and interactive dashboards suggests real-time processing of health data.AI-driven feature analysis and statistical models likely provide insights into disease progression, treatment effectiveness, and risk assessments.

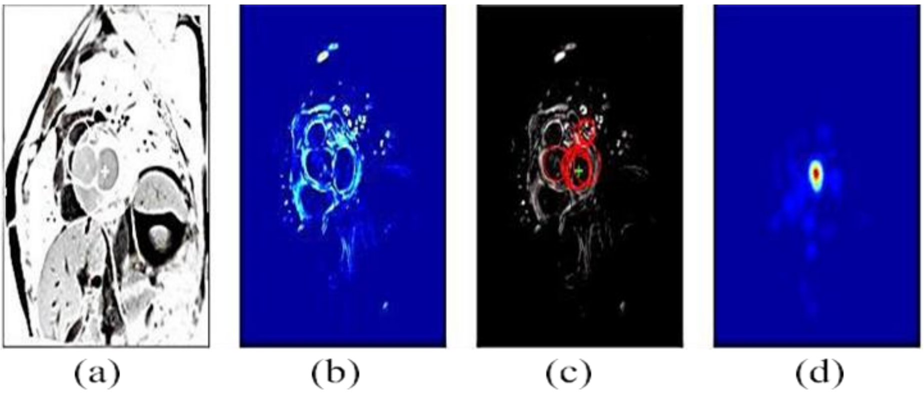


Fig 6. ROI extraction of Heart disease images: a) one slice image with ROI (b)Fourier image (c) circle for slice (d) probability surface across all slices.

Fig. 7 Health Risk Assessment

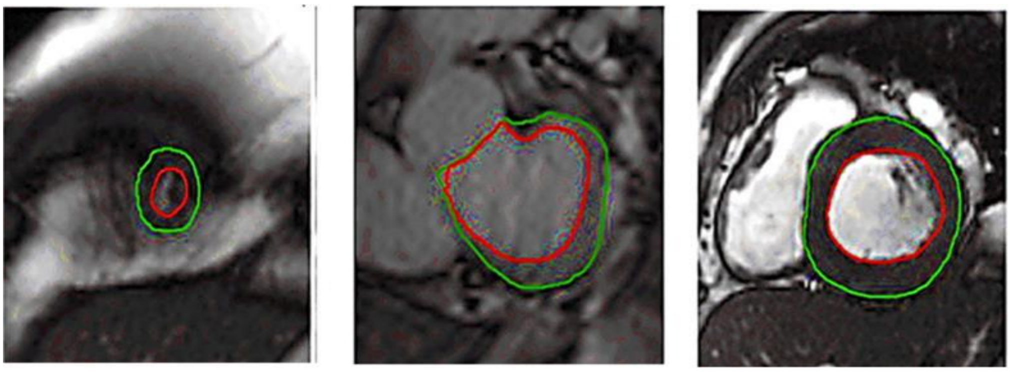


Fig 8. Prediction probability of heart disease analysis.

Fig-7, appears to be an infographic related to **Health Risk Assessment**, displaying various risk factors, health problems, and outcomes

1. Title: "Health Risk Assessment" – The overall theme focuses on evaluating risks related to health.

2. Risk Factors – The top section likely contains internal and external factors influencing health risks, such as:

- Age
- Genetics
- Lifestyle choices
- Environmental exposure

3. Health Problems – The center of the graph seems to illustrate common health issues like:

- Cardiovascular diseases (Heart conditions)
- Lung diseases
- Diabetes
- Obesity
- Other chronic illnesses

4. Pathways & Steps – The flowchart or network visually represents how risk factors contribute to diseases, which in turn lead to different health outcomes.

5. Outcomes – The bottom section appears to show possible health results:

- Positive outcomes (recovery, improved lifestyle)
- Negative outcomes (chronic illness, hospitalization, severe health complications)

This visualization helps in understanding how various factors contribute to health risks, emphasizing prevention, early detection, and management of diseases. Fig-3, illustrates a data-driven workflow for heart disease prediction using artificial intelligence. Heart Disease Detection: The process begins with gathering heart health data. Outlier Detection & Removal: Any extreme or erroneous values are identified and removed to improve data quality. Handling Missing Values: Missing values in the dataset are managed through imputation techniques. Categorizing Data: The AI system organizes relevant features (e.g., heart rate, blood pressure).

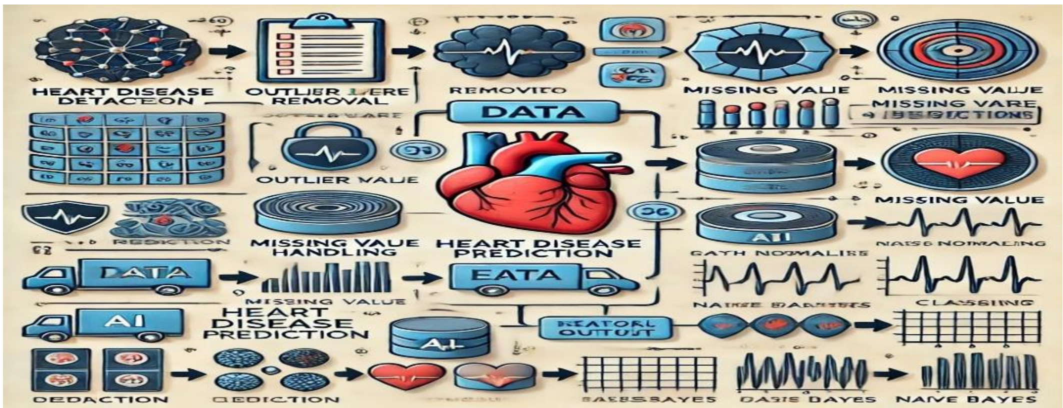


Fig 9. Data-driven workflow for heart disease prediction using artificial intelligence

Normalization: Data normalization techniques such as Gaussian (Normal) distribution adjustments help improve model performance. identify the most significant predictors of heart disease. Machine learning models analyze the processed data- Classification Techniques: Approaches like Naïve Bayes are used to categorize patients based on their risk levels. Prediction Output: The final AI-based system provides predictions regarding heart disease risks.

II. Medical visualization of the human heart

In Fig 10 seems to represent an medical visualization of the human heart, likely showcasing different imaging modalities or computational simulations. Here's a breakdown of the key elements: Structural Representation (Top Row - Grayscale)

- The images in the top row appear to be high-contrast, X-ray-like or MRI-style depictions of the heart.
- The fine lines and mesh patterns suggest that these reconstructions, possibly generated using deep learning techniques in medical imaging.
- The progression from left to right could indicate different levels of detail, imaging techniques, or stages .

2.1. Functional Analysis (Bottom Row - Colorized)

The second row introduces **red and green colors**, which may indicate, Blood flow visualization: Red for oxygenated blood, green for deoxygenated blood. Tissue activity levels: Red areas may represent higher activity or stress, while green could indicate normal function or AI-detected anomalies. These could be representations from **cardiac imaging software** used in-Disease detection (e.g., coronary artery disease, arrhythmias). Blood flow simulation (e.g., assessing blockages or valve function). Predictive modelling of heart conditions. The presence of mesh grids and wireframe-like structures suggests computational modelling. Simulate heart function based on patient data. Assist in diagnosing conditions like heart failure or arrhythmias. Enhance image quality and interpretation for doctors.

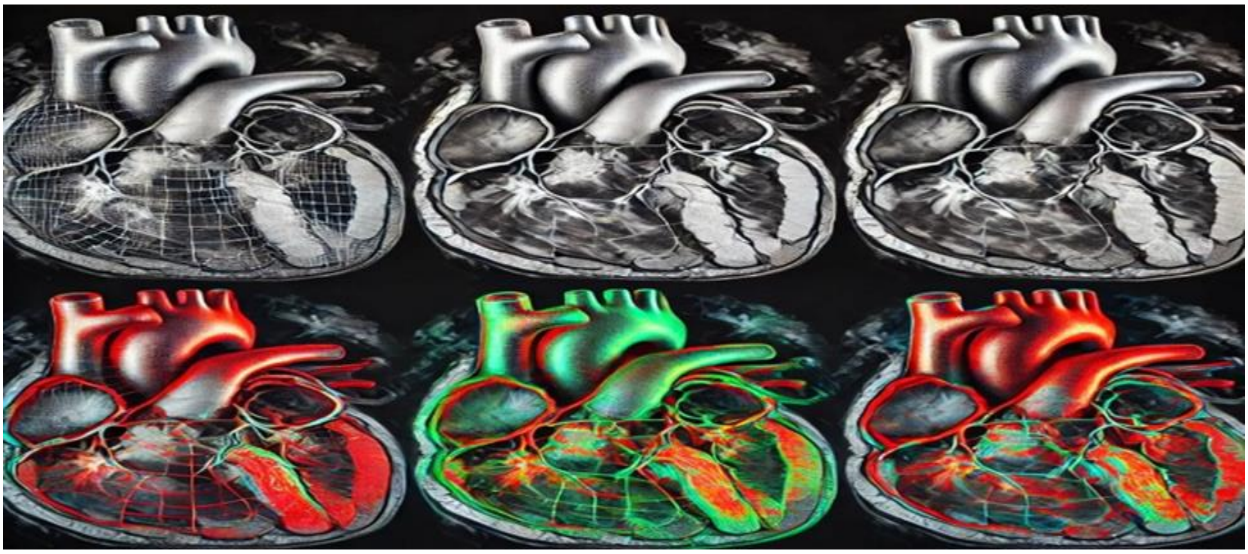


Fig 10. Medical visualization of the human heart

Medical imaging : Used in hospitals to assist radiologists and cardiologists. Augmented reality (AR) for surgery: Surgeons might use similar models for preoperative planning. Cardiac research & predictive healthcare: models could predict heart diseases based on imaging and patient data.

2.2. Flowchart of heart disease prediction.

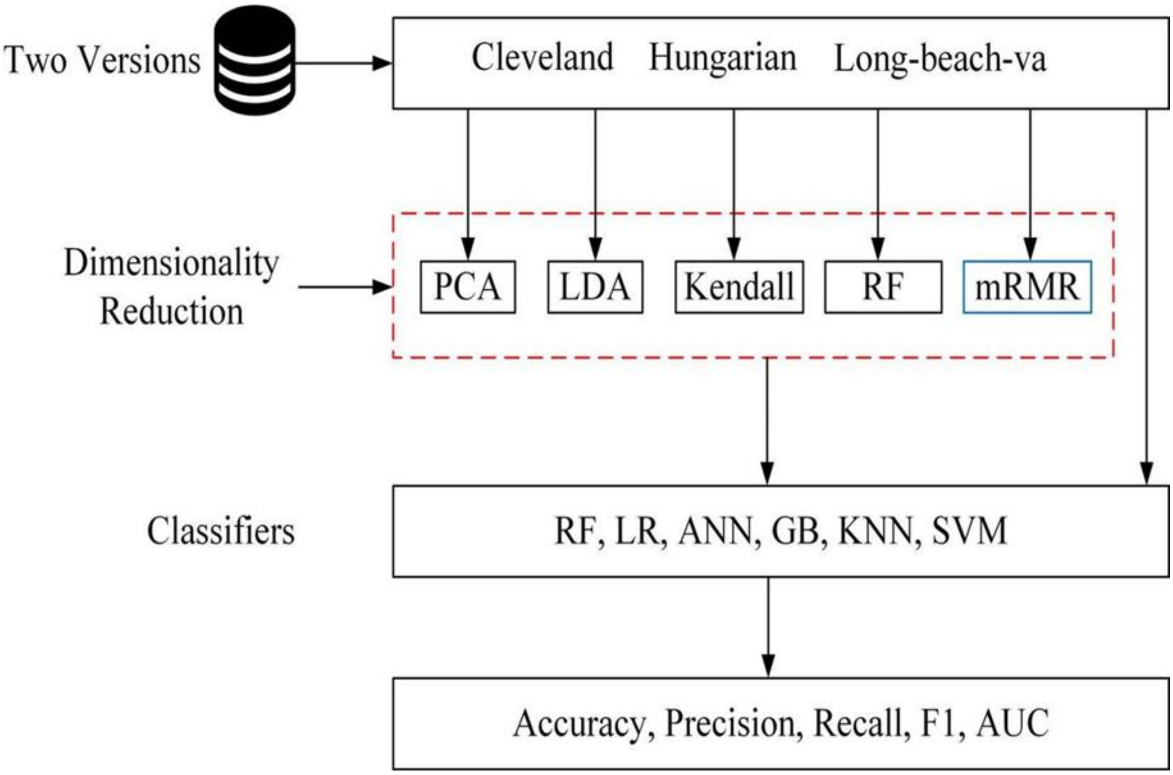


Fig 11. Flowchart of heart disease prediction.

III. Proposed Algorithm:

Our Predictor (Y, Positive or Negative diagnosis of Heart Disease) is determined by 13 features (X):

predict whether a patient should be diagnosed with Heart Disease. This is a binary outcome.
Positive (+) = 1, patient diagnosed with Heart Disease
Negative (-) = 0, patient not diagnosed with Heart Disease

-To experiment with various Classification Models & see which yields greatest accuracy.
- Examine trends & correlations within our data
- determine which features are important in determing Positive/Negative Heart Disease

3.1.Algorithm for heart diseases:

1. age (#)
2. sex : 1= Male, 0= Female (Binary)

3. (cp)chest pain type (4 values -Ordinal):Value 1: typical angina ,Value 2: atypical angina, Value 3: non-anginal pain , Value 4: asymptomatic (

4. (trestbps) resting blood pressure (#)

5. (chol) serum cholestoral in mg/dl (#)

6. (fbs)fasting blood sugar > 120 mg/dl(Binary)(1 = true; 0 = false)

7. (restecg) resting electrocardiographic results(values 0,1,2)

8. (thalach) maximum heart rate achieved (#)

9. (exang) exercise induced angina (binary) (1 = yes; 0 = no)

10. (oldpeak) = ST depression induced by exercise relative to rest (#)

11. (slope) of the peak exercise ST segment (Ordinal) (Value 1: upsloping , Value 2: flat , Value 3: downsloping)

12. (ca) number of major vessels (0-3, Ordinal) colored by fluoroscopy

13. (thal) maximum heart rate achieved - (Ordinal): 3 = normal; 6 = fixed defect; 7 = reversable defect

IV. Simulation Results:

4.1. Dataset commonly used for heart disease prediction

Table-1 dataset commonly used for heart disease prediction

index	**age**	**sex**	**cp**	**trestbps**	**chol**	**fbs**	**restecg**	**thalach**	**exang**	**oldpeak**	**slope**	**ca**	**thal**	**target**
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1
5	57	1	0	140	192	0	1	148	0	0.4	1	0	1	1
6	56	0	1	140	294	0	0	153	0	1.3	1	0	2	1
7	44	1	1	120	263	0	1	173	0	0.0	2	0	3	1
8	52	1	2	172	199	1	1	162	0	0.5	2	0	3	1

index	**age**	**sex**	**cp**	**trestbps**	**chol**	**fbs**	**restecg**	**thalach**	**exang**	**oldpeak**	**slope**	**ca**	**thal**	**target**
9	57	1	2	150	168	0	1	174	0	1.6	2	0	2	1
10	54	1	0	140	239	0	1	160	0	1.2	2	0	2	1
11	48	0	2	130	275	0	1	139	0	0.2	2	0	2	1
12	49	1	1	130	266	0	1	171	0	0.6	2	0	2	1
13	64	1	3	110	211	0	0	144	1	1.8	1	0	2	1
14	58	0	3	150	283	1	0	162	0	1.0	2	0	2	1

This table 1 represents a dataset commonly used for heart disease prediction. Each row corresponds to a patient, and each column represents a specific medical attribute or characteristic. Here’s what each column means:

Column Descriptions:

1. **index** – The row index (not a feature, just an identifier).
2. **age** – Age of the patient (in years).
3. **sex** – Gender of the patient (1 = male, 0 = female).
4. **cp (Chest Pain Type)** – Type of chest pain experienced:
   - 0: Typical angina
   - 1: Atypical angina
   - 2: Non-anginal pain
   - 3: Asymptomatic
5. **trestbps (Resting Blood Pressure)** – Blood pressure (in mm Hg) at rest.
6. **chol (Serum Cholesterol)** – Cholesterol level (in mg/dL).
7. **fbs (Fasting Blood Sugar > 120 mg/dL)** – Whether fasting blood sugar is high:
   - 1 = Yes
   - 0 = No
8. **restecg (Resting Electrocardiographic Results)** – Results of ECG test:
   - 0: Normal
   - 1: ST-T wave abnormality
   - 2: Left ventricular hypertrophy

9. **thalach (Maximum Heart Rate Achieved)** – The highest heart rate recorded during the test.

10. **exang (Exercise-Induced Angina)** – Chest pain caused by exercise:

- ➢ 1 = Yes
- ➢ 0 = No

11. **oldpeak (ST Depression Induced by Exercise)** – Deviation in ST segment measured in ECG (higher values suggest ischemia).

12. **slope (Slope of the Peak Exercise ST Segment)** –

- ➢ 0: Upsloping
- ➢ 1: Flat
- ➢ 2: Downsloping

13. **ca (Number of Major Vessels Colored by Fluoroscopy)** – Number of vessels (0–3). Higher values indicate more severe narrowing.

14. **thal (Thalassemia Type)** –

- ➢ 1: Normal
- ➢ 2: Fixed defect (blood flow issue)
- ➢ 3: Reversible defect (temporary blood flow issue)

15. **target (Heart Disease Presence)** –

- ➢ 1: Heart disease present
- ➢ 0: No heart disease

Possible Uses of the Dataset:

- Predicting heart disease using machine learning models.
- Identifying risk factors that contribute most to heart disease.
- Visualizing trends (e.g., cholesterol levels vs. heart disease presence).

```
(Rows, columns): (303, 14)
Index(['age', 'sex', 'cp', 'trestbps', 'chol', 'fbs', 'restecg', 'thalach',
       'exang', 'oldpeak', 'slope', 'ca', 'thal', 'target'],
•            dtype='object')
```

4.2. Statistics for a dataset heart disease prediction

Table-2 summary statistics for a dataset heart disease prediction

index	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
count	303.0	303.0	303.0	303.0	303.0	303.0	303.0	303.0	303.0	303.0	303.0	303.0	303.0	303.0
mean	54.366336633663366	0.6831683168316832	0.966996699669967	131.62376237623764	246.26402640264027	0.1485148514851485	0.528052805280528	149.64686468646866	0.32673267326732675	1.0396039603960396	1.3993399339933994	0.7293729372937293	2.3135313531353137	0.5445544554455446
std	9.082100989837	0.4660108233396251	1.0320524894832992	17.53814281351709	51.830750987930045	0.35619787492797594	0.525859596359298	22.905161114914087	0.46979446452231716	1.1610750220686343	0.6162261453459631	1.0226063649693276	0.6122765072781412	0.4988347841643926

index	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
	858													
min	29.0	0.0	0.0	94.0	126.0	0.0	0.0	71.0	0.0	0.0	0.0	0.0	0.0	0.0
25%	47.5	0.0	0.0	120.0	211.0	0.0	0.0	133.5	0.0	0.0	1.0	0.0	2.0	0.0
50%	55.0	1.0	1.0	130.0	240.0	0.0	1.0	153.0	0.0	0.8	1.0	0.0	2.0	1.0
75%	61.0	1.0	2.0	140.0	274.5	0.0	1.0	166.0	1.0	1.6	2.0	1.0	3.0	1.0
max	77.0	1.0	3.0	200.0	564.0	1.0	2.0	202.0	1.0	6.2	2.0	4.0	3.0	1.0

Table-2 summary statistics for a dataset heart disease prediction

This table provides summary statistics for a dataset, likely related to heart disease prediction. Here's a breakdown of each part:

Columns (Features) Explained:

1. **index** – Just an index for records (not relevant for analysis).
2. **age** – Age of the patient.
3. **sex** – Gender (0 = Female, 1 = Male).
4. **cp (Chest Pain Type)**

➢ 0: Typical angina

➢ 1: Atypical angina

➢ 2: Non-anginal pain

- 3: Asymptomatic

5. **trestbps (Resting Blood Pressure)** – Blood pressure in mm Hg when at rest.
6. **chol (Serum Cholesterol)** – Cholesterol level in mg/dL.
7. **fbs (Fasting Blood Sugar > 120 mg/dL)**
   - 0: False
   - 1: True
8. **restecg (Resting Electrocardiographic Results)**
   - 0: Normal
   - 1: ST-T wave abnormality
   - 2: Left ventricular hypertrophy
9. **thalach (Maximum Heart Rate Achieved)** – The highest heart rate during exercise.
10. **exang (Exercise-Induced Angina)**
    - 0: No
    - 1: Yes
11. **oldpeak (ST Depression Induced by Exercise)** – A measure of heart stress.
12. **slope (Slope of the Peak Exercise ST Segment)**
    - 0: Upsloping
    - 1: Flat
    - 2: Downsloping
13. **ca (Number of Major Vessels Colored by Fluoroscopy)** – Ranges from 0 to 4.
14. **thal (Thalassemia Type)**
    - 1: Normal
    - 2: Fixed defect
    - 3: Reversible defect
15. **target (Heart Disease Presence)**
    - 0: No disease
    - 1: Disease present

Rows (Statistical Summary) Explained:

- count – Number of records (303 patients).
- mean – The average value for each column.

- std (Standard Deviation) – A measure of data spread.
- min – The minimum value observed.
- 25% (First Quartile) – 25% of the data falls below this value.
- 50% (Median) – The middle value in the dataset.
- 75% (Third Quartile) – 75% of the data falls below this value.
- max – The highest observed value.

Sharp Decline: The graph starts at a very high value at age 0 and drops steeply by age

- Low Point: The lowest value occurs around age 2.
- Gradual Increase: After age 2, the values increase steadily until age 7
- If this represents population distribution, it might indicate a high initial count at birth, a sharp decrease due to infant mortality or some other factor, followed by a gradual stabilization.
- If it represents a different dataset (such as users of a service or product adoption), it could indicate a peak at the start, followed by a dip and a later resurgence.
- If the y-axis represents population count, this could be a demographic distribution where birth rates are high but decrease rapidly due to infant mortality or other factors.
- If the y-axis represents sales, engagement, or user adoption, this could suggest an initial surge followed by a decline and then a gradual resurgence.
- If it's related to health data (e.g., disease occurrence by age), it might indicate that a particular condition is very common at birth, declines in early years, and then becomes more frequent as people
- The steep drop at the beginning suggests that the highest rate of change happens early (age 0 to 1).
- The gradual increase from age 2 onward suggests a more stable but rising trend over time.

4.3. Correlation Matrix

In Fig-12,The table in the image is a correlation matrix represented as a heatmap. It shows the correlation coefficients between different variables in a dataset

- **Diagonal Elements (1.0):** Each variable is perfectly correlated with itself.
- **Colour Coding:**
  - ➢ Red shades indicate positive correlations.

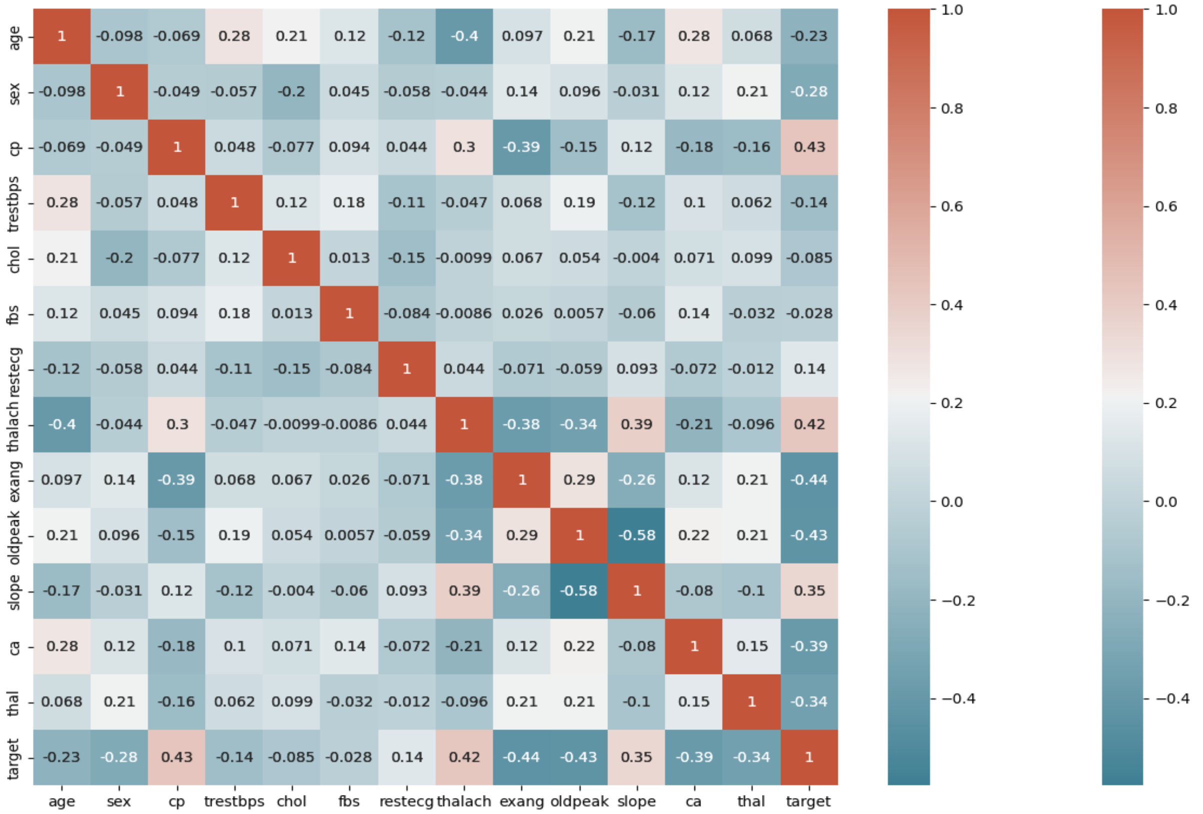
➢ Blue shades indicate negative correlations.

➢ White represents weak or no correlation.

- **Target Column:** The last column represents correlations with the target variable, which might be the presence of a condition (e.g., heart disease).

➢ Strongest positive correlations: cp (chest pain), thalach (max heart rate).

➢ Strongest negative correlations: oldpeak (ST depression), ca (number of major vessels), thal.



	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
age	1	-0.098	-0.069	0.28	0.21	0.12	-0.12	-0.4	0.097	0.21	-0.17	0.28	0.068	-0.23
sex	-0.098	1	-0.049	-0.057	-0.2	0.045	-0.058	-0.044	0.14	0.096	-0.031	0.12	0.21	-0.28
cp	-0.069	-0.049	1	0.048	-0.077	0.094	0.044	0.3	-0.39	-0.15	0.12	-0.18	-0.16	0.43
trestbps	0.28	-0.057	0.048	1	0.12	0.18	-0.11	-0.047	0.068	0.19	-0.12	0.1	0.062	-0.14
chol	0.21	-0.2	-0.077	0.12	1	0.013	-0.15	-0.0099	0.067	0.054	-0.004	0.071	0.099	-0.085
fbs	0.12	0.045	0.094	0.18	0.013	1	-0.084	-0.0086	0.026	0.0057	-0.06	0.14	-0.032	-0.028
restecg	-0.12	-0.058	0.044	-0.11	-0.15	-0.084	1	0.044	-0.071	-0.059	0.093	-0.072	-0.012	0.14
thalach	-0.4	-0.044	0.3	-0.047	-0.0099	-0.0086	0.044	1	-0.38	-0.34	0.39	-0.21	-0.096	0.42
exang	0.097	0.14	-0.39	0.068	0.067	0.026	-0.071	-0.38	1	0.29	-0.26	0.12	0.21	-0.44
oldpeak	0.21	0.096	-0.15	0.19	0.054	0.0057	-0.059	-0.34	0.29	1	-0.58	0.22	0.21	-0.43
slope	-0.17	-0.031	0.12	-0.12	-0.004	-0.06	0.093	0.39	-0.26	-0.58	1	-0.08	-0.1	0.35
ca	0.28	0.12	-0.18	0.1	0.071	0.14	-0.072	-0.21	0.12	0.22	-0.08	1	0.15	-0.39
thal	0.068	0.21	-0.16	0.062	0.099	-0.032	-0.012	-0.096	0.21	0.21	-0.1	0.15	1	-0.34
target	-0.23	-0.28	0.43	-0.14	-0.085	-0.028	0.14	0.42	-0.44	-0.43	0.35	-0.39	-0.34	1

Fig-12 correlation matrix

4.4. Histograms representing the distribution of each variable

The **diagonal** contains histograms representing the distribution of each variable. The **off-diagonal** contains scatter plots, showing how two variables relate to each other.

4.5. Variable Descriptions (Likely from a Medical Dataset)

The variables in the pairplot appear to be related to cardiovascular health. Here's what each variable likely represents:

Variable	**Description**
Age	Age of the patient
trestbps	Resting blood pressure (in mm Hg)
Chol	Serum cholesterol level (mg/dL)
Thalach	Maximum heart rate achieved
oldpeak	ST depression induced by exercise (compared to rest)

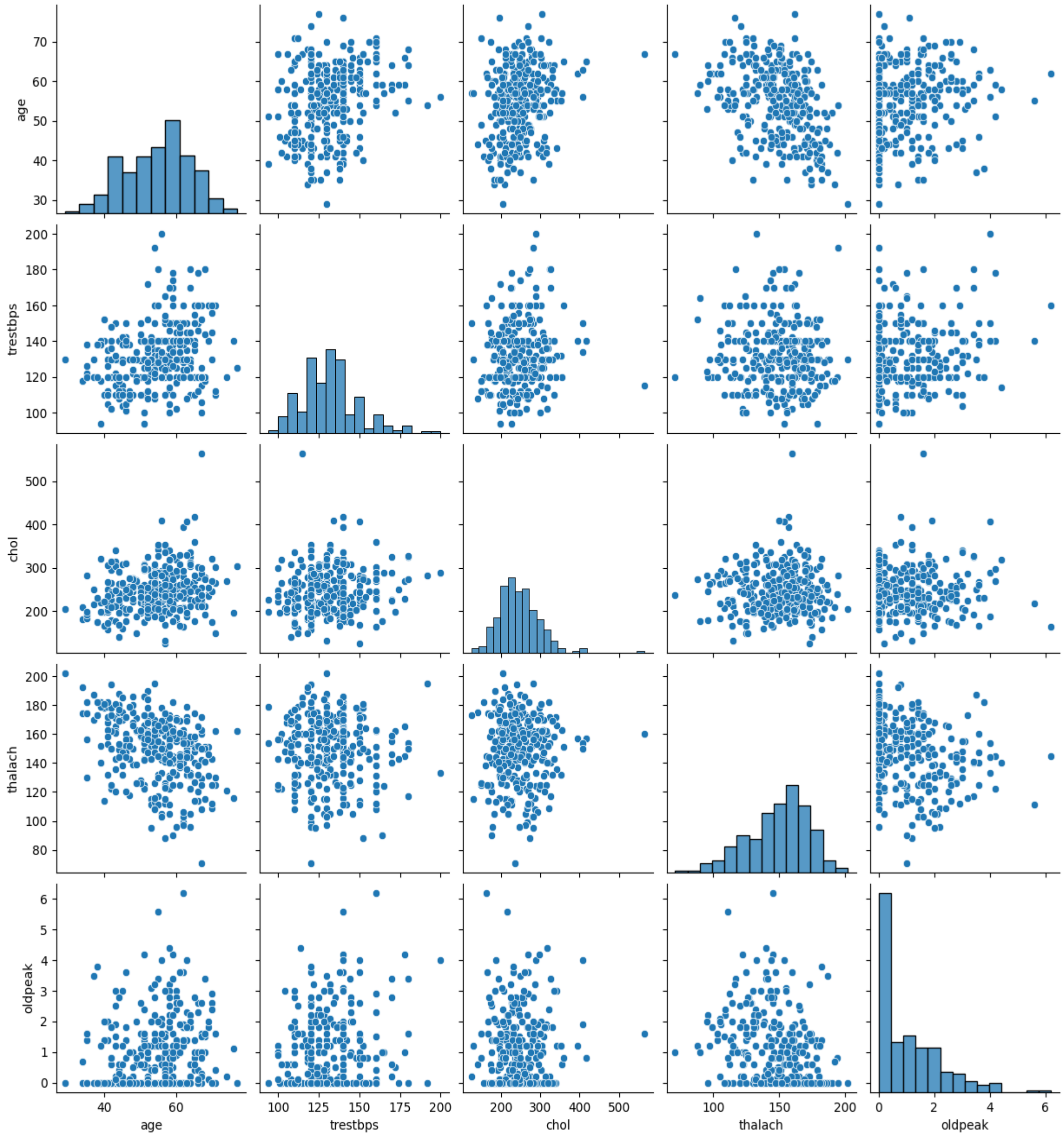


Fig 13. histograms representing the distribution of each variable

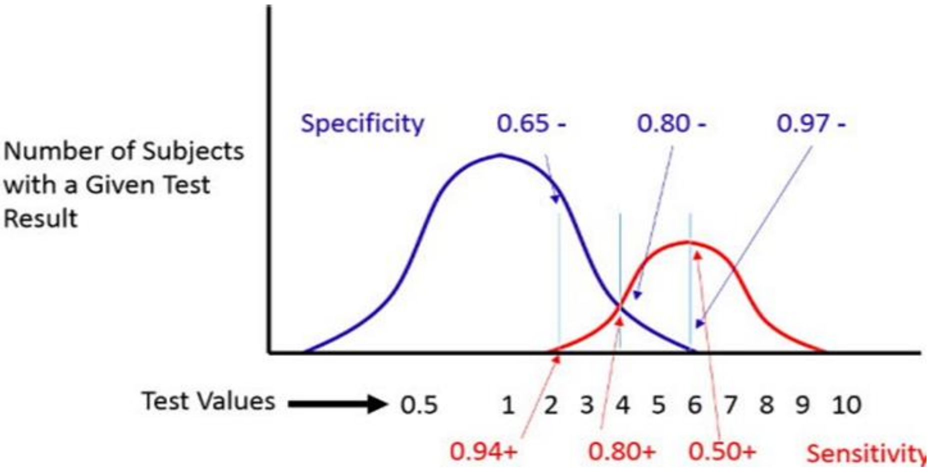


Fig 14. Likelihood Sensitivity

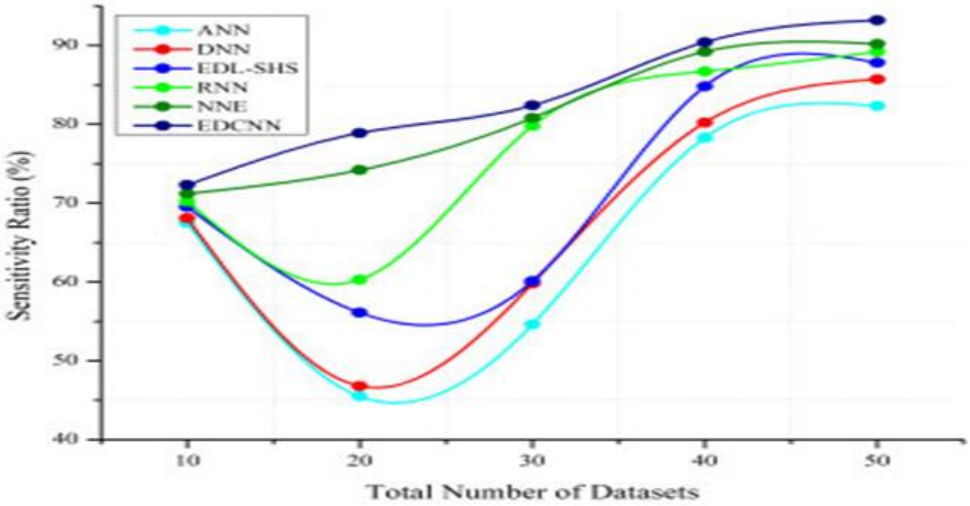


Fig 15. Test analysis.

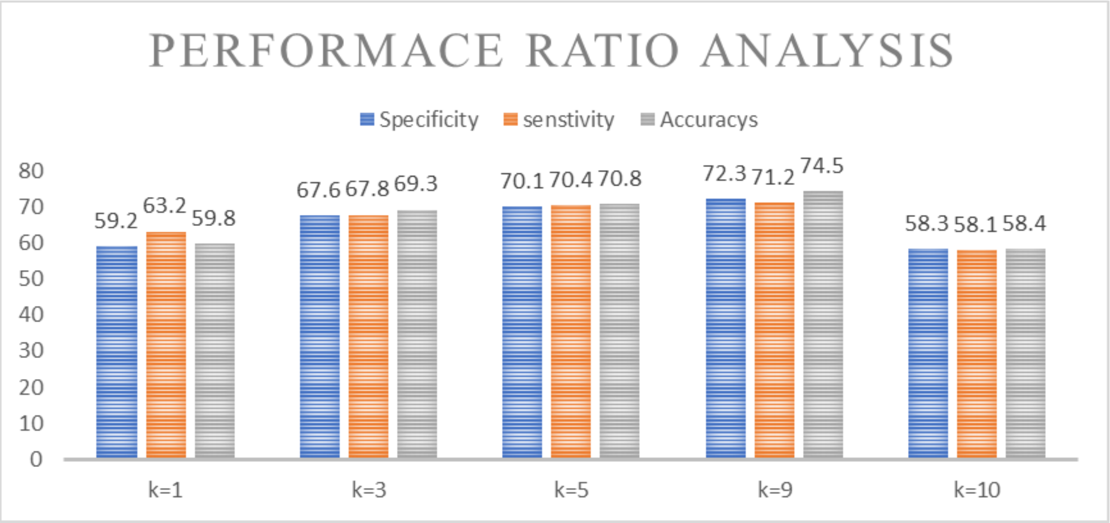


Fig 16.Performance Ratio analysis

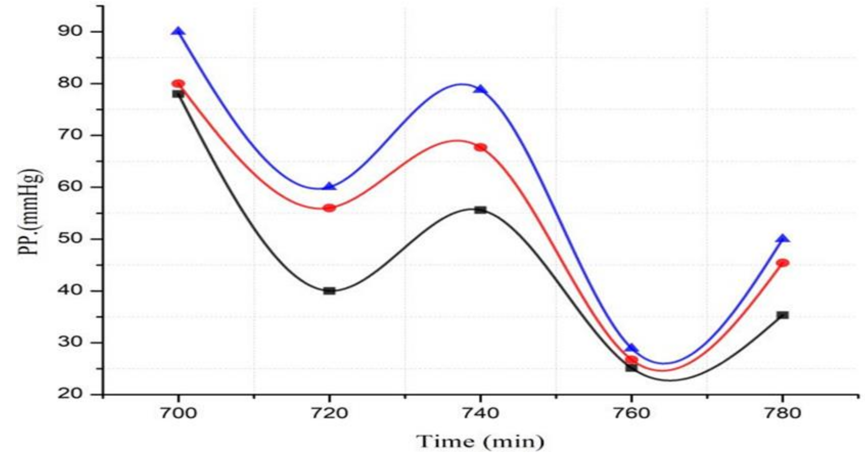


Fig 17. Fourier analysis on PP in mmHG.

Associative classification provides high accuracy and high flexibility, even in the handling of unstructured data, compared to traditional classification. The proposed EDCNN model has proved to be a useful tool in the detection of heart disease in medical professionals. An additional stage of feature selection was proposed to improve accuracy.

Table 1. Likelihood sensitivity ratio numerical analysis

Total number of data sets	ANN	DNN	EDL SHs	RNN	NNE	EDCNN
10	67.5	68.3	69.1	70.8	72.1	73.2
20	45.8	47.2	56.8	60.8	74.8	79.1
30	54.8	59.9	60.3	79.9	80.9	83.5
40	78.9	80.7	84.9	86.8	89.4	91.3
50	82.5	86.8	88.3	89.9	90.7	94.2

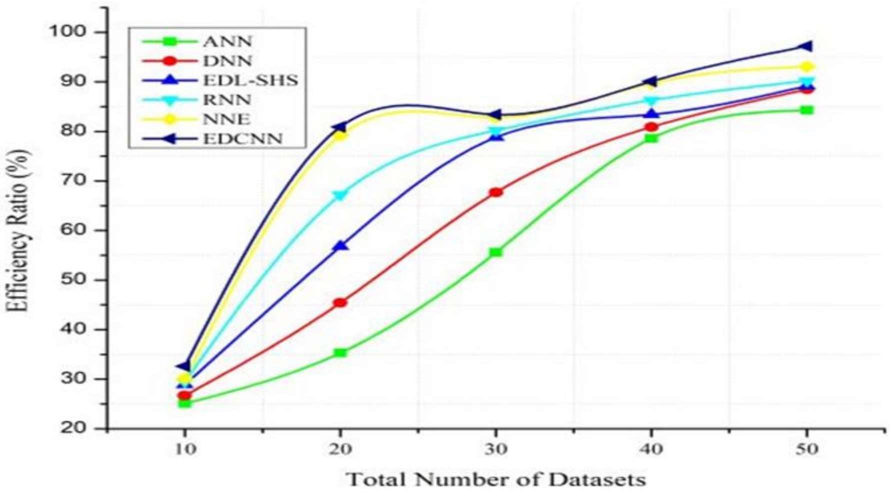


Fig 18.Efficiency ratio analysis.

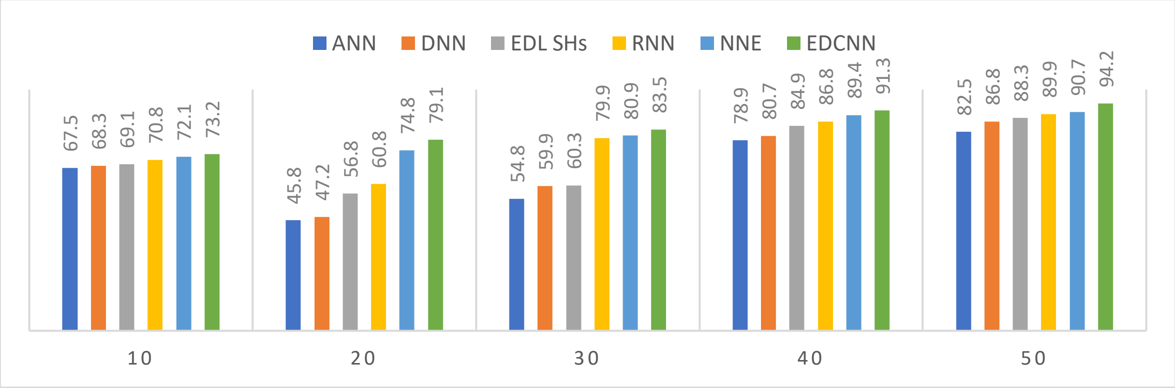


Fig 19. Likelihood sensitivity ratio numerical analysis.

Table Efficiency Evaluation

Total number of data sets	ANN	DNN	EDL SHS	RNN	NNE	EDCNN
10	22.1	24.3	26.1	28.5	30.1	38.6
20	32.2	43.6	53.4	64.2	78.2	79.9
30	53.2	80.1	81.3	81.8	82.8	83.4
40	78.6	82.9	84.4	87.3	89.7	91.1
50	84.3	87.5	89.2	91.2	92.1	98.2

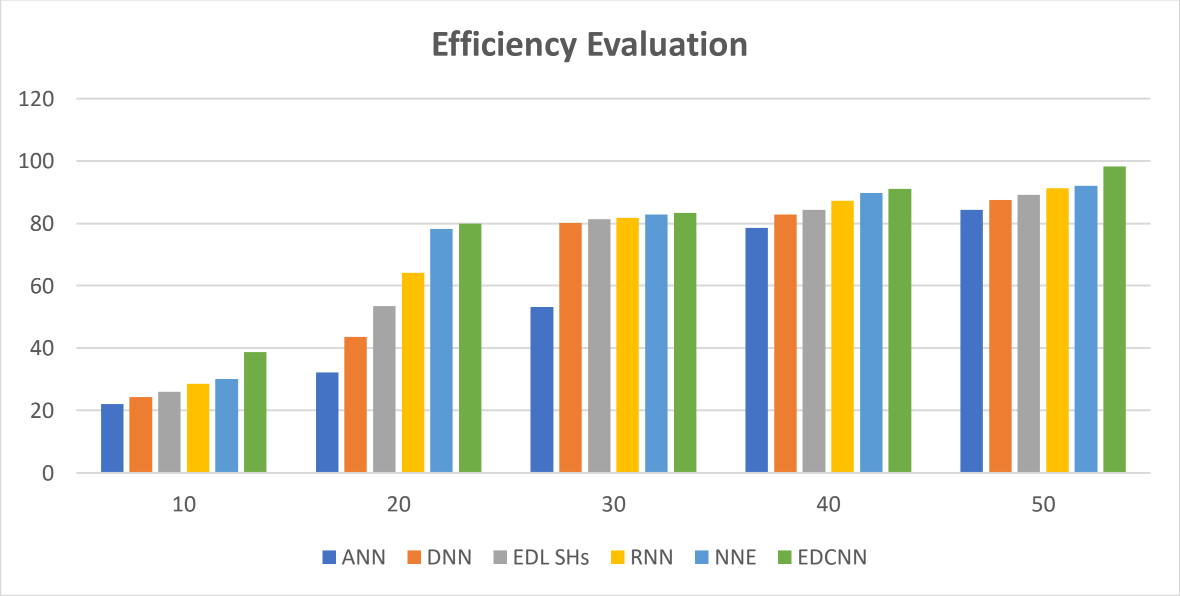


Fig 20. Efficiency Evaluation

4.6. ST segment depression

ST segment depression occurs because when the ventricle is at rest and therefore repolarized. If the trace in the ST segment is abnormally low below the baseline, this can lead to this Heart Disease. This is supports the plot above because low ST Depression yields people at greater risk for heart disease. While a high ST depression is considered normal & healthy. The "slope" hue, refers to the peak exercise ST segment, with values: 0: upsloping , 1: flat , 2: down sloping). Both positive & negative heart disease patients exhibit equal distributions of the 3 slope categories.

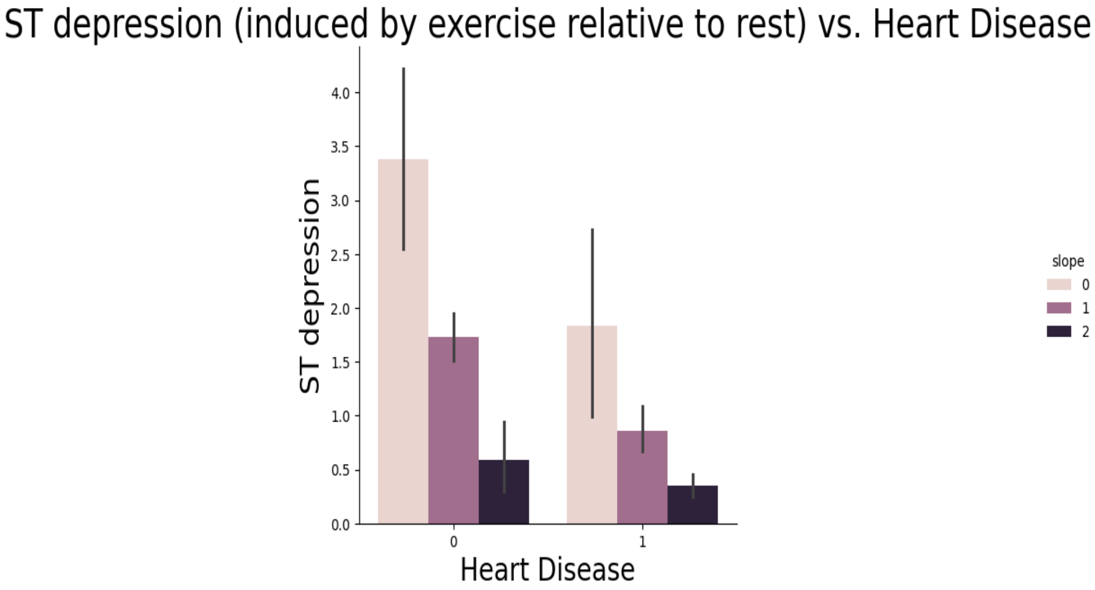


Fig 21. ST segment depression

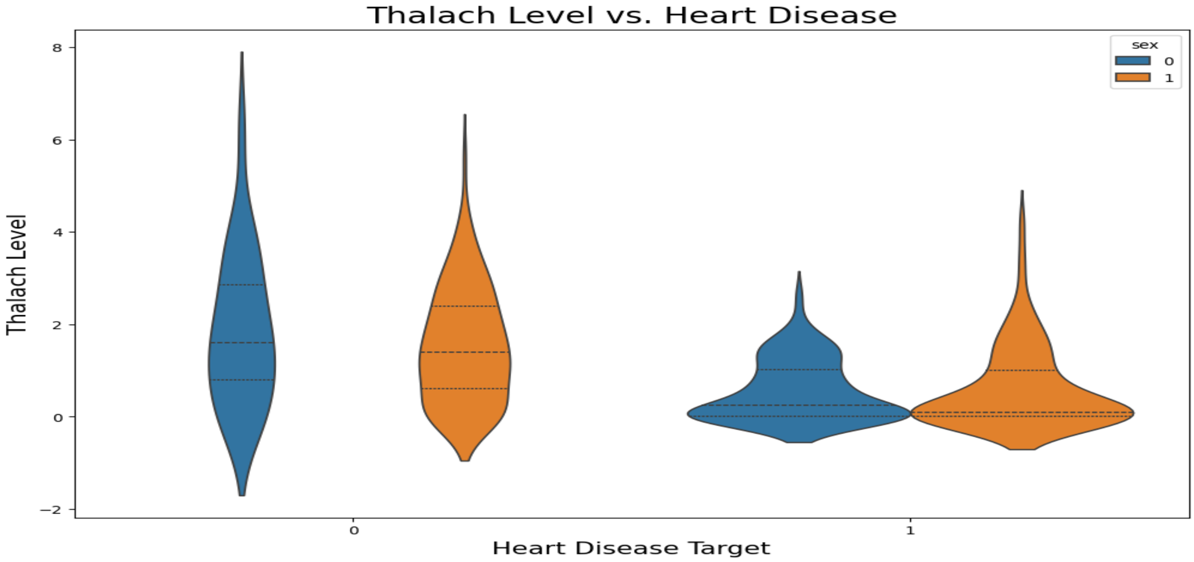


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Fig 22. violin plot that visualizes the distribution of Thalach Level

Fig-17 **violin plot** that visualizes the distribution of Thalach Level (Maximum Heart Rate Achieved) against Heart Disease Target (0 = No Disease, 1 = Disease**)** while distinguishing by Sex (0 = Female, 1 = Male)

- **X-axis (Heart Disease Target)**: Represents whether a person has heart disease (1) or not (0).
- **Y-axis (Thalach Level)**: Represents the normalized or scaled values of maximum heart rate achieved.
- **Violin Plot Interpretation**:
  - ➢ The width of each violin represents the density of data points at different values.
  - ➢ The internal horizontal lines represent quartiles (median, 25th, and 75th percentiles).
  - ➢ A wider section in the violin means more data points are concentrated at that value.
- **Color Representation (Sex)**:
  - ➢ Blue (0) represents females.
  - ➢ Orange (1) represents males.

1. **Thalach Levels Vary by Heart Disease Status**:
   - ➢ People without heart disease (Target = 0) tend to have a wider distribution of thalach values.
   - ➢ People with heart disease (Target = 1) seem to have lower thalach values on average.
2. **Sex-based Differences**:
   - ➢ For both heart disease and non-heart disease groups, the distribution of thalach differs by sex.
   - ➢ Males (orange) and females (blue) have different density patterns.

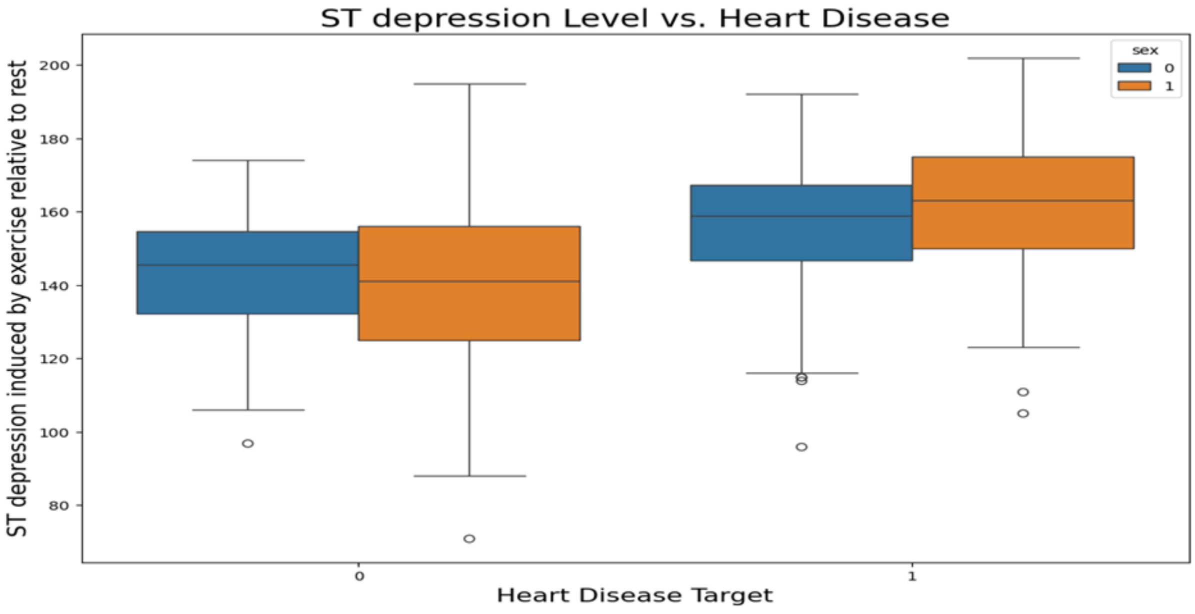

Fig 23. ST depression level vs Heart disease

This is a box plot comparing in Fig 18, ST depression levels induced by exercise relative to rest with the presence or absence of heart disease, categorized by

1. X-axis (Heart Disease Target):
   - 0 represents individuals without heart disease
   - 1 represents individuals with heart disease
2. Y-axis (ST Depression Level):
   - Measures ST depression induced by exercise (a diagnostic indicator for heart conditions).
3. Box Plot Representation:
   - Each box represents the interquartile range (IQR) (middle 50% of data).
   - The horizontal line within the box is the median ST depression level.
   - The whiskers extend to show the range of data (excluding outliers).
   - Small circles outside the whiskers represent outliers.
4. Color Legend (Sex):
   - Blue (0): Likely represents female participants
   - Orange (1): Likely represents male participants
   - Individuals with heart disease (1) tend to have higher ST depression levels compared to those without heart disease (0).
   - Variation in ST depression is seen across both sexes, but males (orange) generally have a wider range of values.
   - Some outliers exist, suggesting a few individuals had significantly different ST depression levels compared to the major.

Higher ST depression levels may indicate greater stress on the heart during exercise, which could be a risk factor for heart disease. This box plot helps visualize differences between those with and without heart disease and highlights potential differences between sexes. Positive patients exhibit a heightened median for ST depression level, while negative patients have lower levels. In addition, we don’t see many differences between male & female target outcomes, expect for the fact that males have slightly larger ranges of ST Depression.

4.7.Filtering data by positive & negative Heart Disease patient

Table-3 Filtering data by positive & negative Heart Disease patient

index	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
count	165.0	165.0	165.0	165.0	165.0	165.0	165.0	165.0	165.0	165.0	165.0	165.0	165.0	165.0

index	**age**	**sex**	**cp**	**trestbps**	**chol**	**fbs**	**restecg**	**thalach**	**exang**	**oldpeak**	**slope**	**ca**	**thal**	**target**
mean	52.4969696969697	0.5636363636363636	1.3757575757575757	129.3030303030303	242.23030303030302	0.139393939393939394	0.593939393939394	158.46666666666667	0.1393939393939394	0.583030303030303	1.593939393939394	0.36363636363636365	2.121212121212121	1.0
std	9.550650751946778	0.49744357555882157	0.9522215049717542	16.16961326687487	53.55287155453835	0.34741150297891643	0.5048178818796776	19.174275619393168	0.3474115029789162	0.7806832719018298	0.5936346262434834	0.848893893588628	0.46575245686060823	0.0
min	29.0	0.0	0.0	94.0	126.0	0.0	0.0	96.0	0.0	0.0	0.0	0.0	0.0	1.0

index	**age**	**sex**	**cp**	**trestbps**	**chol**	**fbs**	**restecg**	**thalach**	**exang**	**oldpeak**	**slope**	**ca**	**thal**	**target**
25%	44.0	0.0	1.0	120.0	208.0	0.0	0.0	149.0	0.0	0.0	1.0	0.0	2.0	1.0
50%	52.0	1.0	2.0	130.0	234.0	0.0	1.0	161.0	0.0	0.2	2.0	0.0	2.0	1.0
75%	59.0	1.0	2.0	140.0	267.0	0.0	1.0	172.0	0.0	1.0	2.0	0.0	2.0	1.0
max	76.0	1.0	3.0	180.0	564.0	1.0	2.0	202.0	1.0	4.2	2.0	4.0	3.0	1.0

It looks like you have a dataset summarizing heart disease patients with various medical attributes. You may want to filter the data based on the **target** column, where:

- **target = 1:** Indicates a **positive** heart disease diagnosis.
- **target = 0**: Indicates a **negative** heart disease diagnosis

4.7.separate positive and negative heart disease cases in Python

```
import pandas as pd
# Load your dataset (assuming it's a CSV file)
df = pd.read_csv("your_dataset.csv")
# Filter Positive and Negative Cases
positive_cases = df[df["target"] == 1]
negative_cases = df[df["target"] == 0]
# Save to new CSV files (optional)
positive_cases.to_csv("positive_cases.csv", index=False)
negative_cases.to_csv("negative_cases.csv", index=False)
# Display the count of each
print(f"Positive Cases: {len(positive_cases)}")
print(f"Negative Cases: {len(negative_cases)}")
```

Table 4. Heart disease data set

index	**age**	**sex**	**cp**	**trestbps**	**Chol**	**fbs**	**Restecg**	**thalach**	**exang**	**oldpeak**	**slope**	**ca**	**thal**	**target**
count	138.0	138.0	138.0	138.0	138.0	138.0	138.0	138.0	138.0	138.0	138.0	138.0	138.0	138.0
mean	56.60144927536232	0.8260869565217391	0.4782608695652174	134.3985507246377	251.08695652173913	0.15942028985507245	0.4492753623188406	139.10144927536233	0.5507246376811594	1.5855072463768116	1.1666666666666667	1.1666666666666667	2.5434782608695654	0.0
std	7.962081537501172	0.38041551386121225	0.9059204401375939	18.72994396158135	49.45461360407158	0.3674011473702363	0.5413212245494148	22.598782298785903	0.49923245858990545	1.3003396931053652	0.5613244677999096	1.0434595276713314	0.6847618288848193	0.0
min	35.0	0.0	0.0	100.0	131.0	0.0	0.0	71.0	0.0	0.0	0.0	0.0	0.0	0.0
25%	52.0	1.0	0.0	120.0	217.25	0.0	0.0	125.0	0.0	0.6	1.0	0.0	2.0	0.0
50%	58.0	1.0	0.0	130.0	249.0	0.0	0.0	142.0	1.0	1.4	1.0	1.0	3.0	0.0
75%	62.0	1.0	0.0	144.75	283.0	0.0	1.0	156.0	1.0	2.5	1.75	2.0	3.0	0.0
max	77.0	1.0	3.0	200.0	409.0	1.0	2.0	195.0	1.0	6.2	2.0	4.0	3.0	0.0

(Positive Patients ST depression): 0.583030303030303

(Negative Patients ST depression): 1.5855072463768116

Positive Patients thalach): 158.46666666666667

(Negative Patients thalach): 139.1014492753623

From comparing positive and negative patients we can see there are vast differenes in means for many of our Features. From examing the details, we can observe that positive patients experience heightened maximum heart rate achieved (thalach) average. In addition, positive patients exhibit about 1/3rd the amount of ST depression induced by exercise relative to rest (oldpeak).

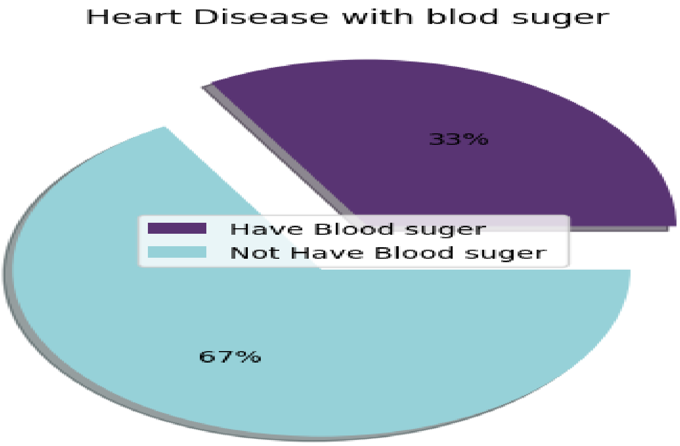

Fig 24. distribution of blood sugar levels

A majority (67%) of people with heart disease do not have high blood sugar. However, **33% of people with heart disease have high blood sugar,** indicating a possible link between blood sugar levels and heart disease. The **3D effect and the separation of one slice** (exploded pie chart) are likely used to emphasize the **Detailed Explanation of the Pie Chart on Heart Disease and Blood Sugar.**

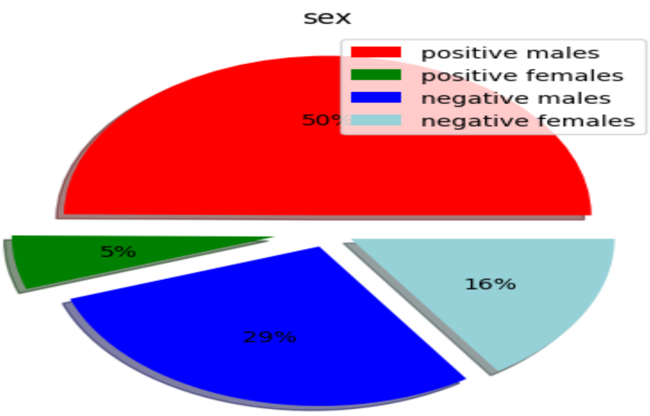

Fig 25. distribution of test results based on sex

In Fig20,represents the distribution of test results based on sex, divided into four categories:

1. **Positive Males (Red - 50%):**This group makes up half of the total population, meaning that 50% of all individuals in the study are males who tested positive.
2. **Positive Females (Green - 5%):**This category is much smaller, showing that only 5% of the total individuals are females who tested positive.
3. **Negative Males (Blue - 29%):**This segment represents 29% of the total population, indicating males who tested negative.
4. **Negative Females (Light Blue - 16%):**This section accounts for 16% of the total population, representing females who tested negative

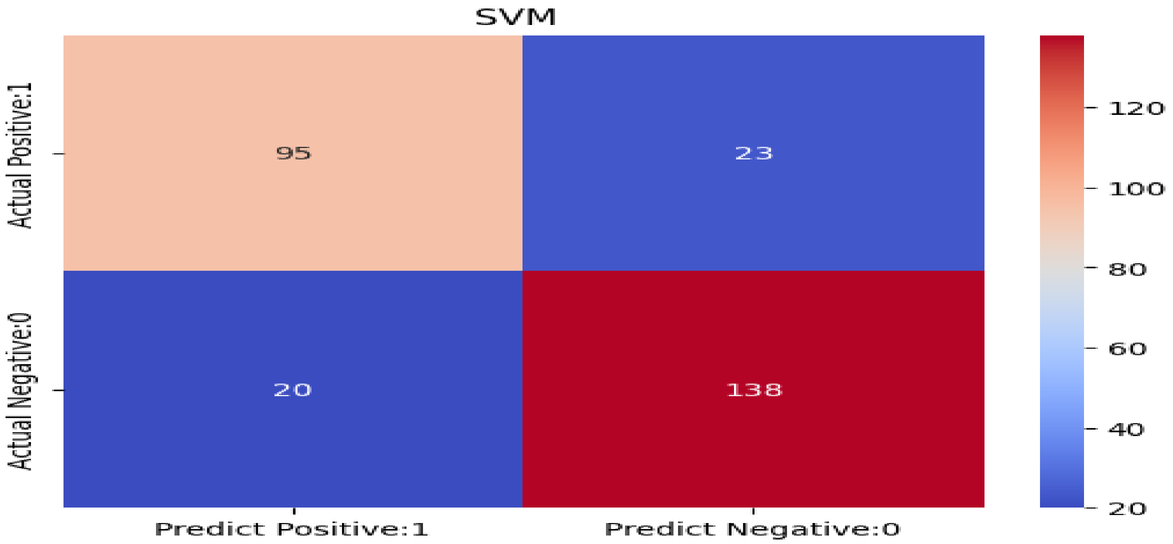

Fig 26. Confusion matrix for an SVM

From this, you can calculate key performance metrics:

- **Accuracy** = (TP + TN) / (TP + TN + FP + FN)
  = (95 + 138) / (95 + 138 + 20 + 23)
  = 233 / 276 ≈ **84.42%**
- **Precision (Positive Predictive Value)** = TP / (TP + FP)
  = 95 / (95 + 20)
  = 95 / 115 ≈ **82.61%**
- **Recall (Sensitivity, True Positive Rate)** = TP / (TP + FN)
  = 95 / (95 + 23)
  = 95 / 118 ≈ **80.51%**
- **Specificity (True Negative Rate)** = TN / (TN + FP)
  = 138 / (138 + 20)
  = 138 / 158 ≈ **87.34%**

- **F1 Score** = 2 × (Precision × Recall) / (Precision + Recall) ≈ 2 × (0.8261 × 0.8051) / (0.8261 + 0.8051) ≈ **81.75%**

This shows that the SVM model performs well, with a good balance between precision and recall. If you want improvements, you might fine-tune hyperparameters or try different kernel functions.

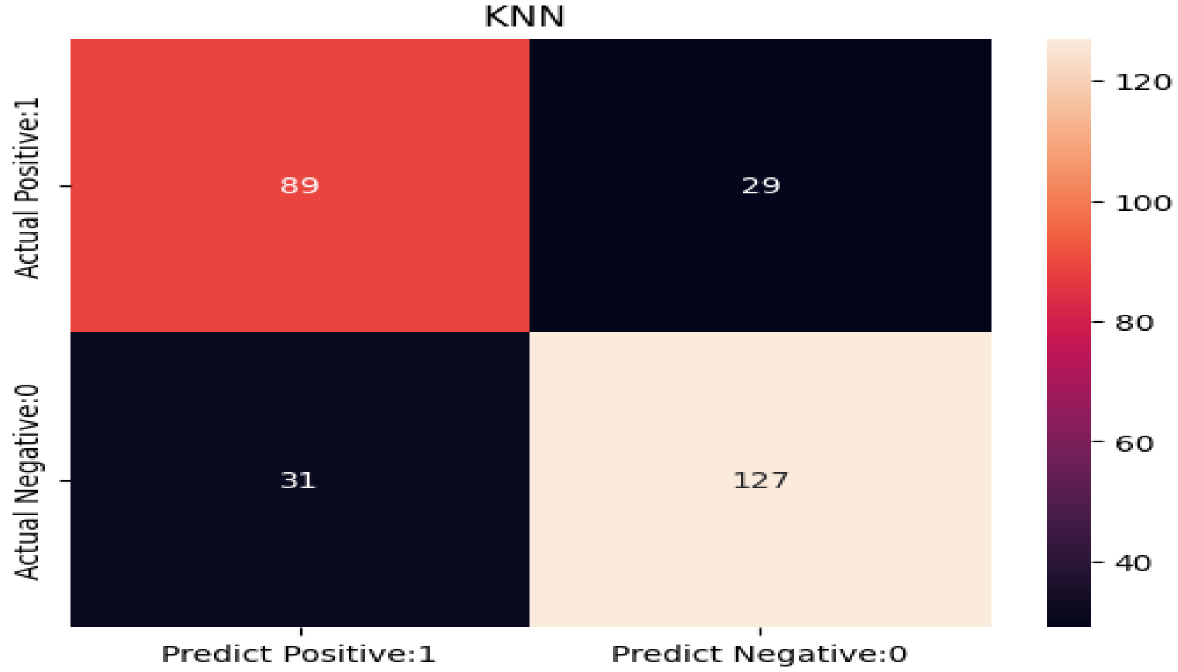

Fig 27. confusion matrix for a K-Nearest Neighbours (KNN)

This is a confusion matrix for a K-Nearest Neighbours (KNN) classification model. Here's the breakdown of the values:

- **True Positives (TP)**: 89 (correctly predicted positive cases)
- **False Negatives (FN)**: 29 (actual positives incorrectly classified as negatives)
- **False Positives (FP)**: 31 (actual negatives incorrectly classified as positives)
- **True Negatives (TN)**: 127 (correctly predicted negative cases)

From this, you can calculate key performance metrics:

1. **Accuracy** = $\frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} = \frac{89+127}{89+127+31+29} = \frac{216}{276} = 0.783 = 78.3\%$
2. **Precision** = $\frac{\text{TP}}{\text{TP+FP}} = \frac{89}{89+31} = \frac{89}{120} = 0.742 = 74.2\%$
3. **Recall (Sensitivity)** = $\frac{\text{TP}}{\text{TP+FN}} = \frac{89}{89+29} = \frac{89}{118} = 0.754 = 75.4\%$
4. **F1-Score** = $2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} = 0.748 = 74.8\%$

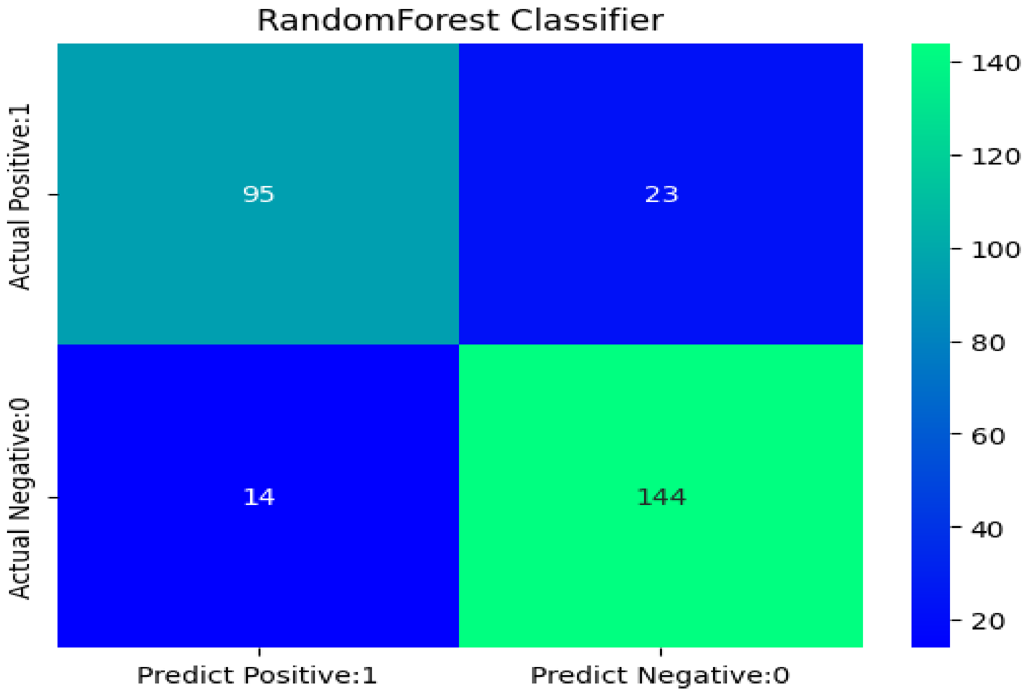

Fig28. (Random Forest Classifier)

In Fig28, represents:

- **True Positives (TP):** 95 (Actual Positive, Predicted Positive)
- **False Positives (FP):** 14 (Actual Negative, Predicted Positive)
- **False Negatives (FN):** 23 (Actual Positive, Predicted Negative)
- **True Negatives (TN):** 144 (Actual Negative, Predicted Negative)

This confusion matrix represents the performance of a **Random Forest Classifier** in a binary classification problem. It compares the actual labels with the predicted labels to assess how well the model distinguishes between the two classes.

	Predicted Positive (1)	**Predicted Negative (0)**
Actual Positive (1)	**95** (True Positive)	**23** (False Negative)
Actual Negative (0)	**14** (False Positive)	**144** (True Negative)

- **True Positives (TP) = 95**
- The model correctly identified 95 positive cases.
- **False Negatives (FN) = 23**
- The model incorrectly predicted 23 actual positive cases as negative.

- **False Positives (FP) = 14**
- The model incorrectly predicted 14 actual negative cases as positive.
- **True Negatives (TN) = 144**
- The model correctly identified 144 negative cases.

Using these values, we can calculate the following key metrics:

- **Accuracy:** 86.6% (Overall correctness)
- **Precision:** 87.2% (Reliability of positive predictions)
- **Recall:** 80.5% (Ability to detect actual positives)
- **F1-Score:** 83.7% (Harmonic mean of precision & recall)

The model performs **well overall,** with a **high precision (87.2%),** meaning it makes few false positive errors. The recall (80.5%) is slightly lower, meaning some actual positives (23 cases) are misclassified as negatives. The F1-score (83.7%) suggests a **good balance between precision and recall. I**f recall is more critical (e.g., medical diagnosis where missing a positive case is dangerous), we might need to **adjust the threshold or retrain the model.**

```
Report of SVM
          precision    recall  f1-score   support
        0       0.83      0.81      0.82       118
        1       0.86      0.87      0.87       158
   accuracy                         0.84       276
  macro avg       0.84      0.84      0.84       276
weighted avg       0.84      0.84      0.84       276
#####################################################
Report of KNN
          precision    recall  f1-score   support


        0       0.74      0.75      0.75       118
        1       0.81      0.80      0.81       158
   accuracy                         0.78       276
  macro avg       0.78      0.78      0.78       276
weighted avg       0.78      0.78      0.78       276
#####################################################
Report of SVM
          precision    recall  f1-score   support
        0       0.87      0.81      0.84       118
        1       0.86      0.91      0.89       158
   accuracy                         0.87       276
  macro avg       0.87      0.86      0.86       276
weighted avg       0.87      0.87      0.87       276
```

```
######################################################
Report of SVM
              precision    recall  f1-score   support
           0       0.80      0.81      0.80       118
           1       0.85      0.85      0.85       158
    accuracy                           0.83       276
   macro avg       0.83      0.83      0.83       276
weighted avg       0.83      0.83      0.83       276
              precision    recall  f1-score   support
           0       0.83      0.81      0.82       118
           1       0.86      0.87      0.87       158
    accuracy                           0.84       276
   macro avg       0.84      0.84      0.84       276
weighted avg       0.84      0.84      0.84       276
######################################################
Report of KNN
              precision    recall  f1-score   support
           0       0.74      0.75      0.75       118
           1       0.81      0.80      0.81       158
    accuracy                           0.78       276
   macro avg       0.78      0.78      0.78       276
weighted avg       0.78      0.78      0.78       276
######################################################
Report of SVM
              precision    recall  f1-score   support

           0       0.87      0.81      0.84       118
           1       0.86      0.91      0.89       158
    accuracy                           0.87       276
   macro avg       0.87      0.86      0.86       276
weighted avg       0.87      0.87      0.87       276
######################################################
Report of SVM
              precision    recall  f1-score   support
           0       0.80      0.81      0.80       118
           1       0.85      0.85      0.85       158
    accuracy                           0.83       276
   macro avg       0.83      0.83      0.83       276
weighted avg       0.83      0.83      0.83       276
```

Machine Learning & Predictive Analytics Prepare Data for Modelling

Model 1: Logistic Regression

```
precision    recall  f1-score   support
0       0.77      0.67      0.71        30
1       0.71      0.81      0.76        31
accuracy                          0.74        61
macro avg       0.74      0.74      0.74        61
weighted avg       0.74      0.74      0.74      61
```

Model 2: K-NN (K-Nearest Neighbors)

```
precision    recall  f1-score   support
0       0.78      0.70      0.74        30
1       0.74      0.81      0.77        31
accuracy                          0.75        61
macro avg       0.76      0.75      0.75        61
weighted avg       0.76      0.75      0.75        61
```

Model 3: SVM (Support Vector Machine)

```
           0       0.80      0.67      0.73  30
          1       0.72      0.84      0.73      31
accuracy                          0.75        61
macro avg       0.76      0.75      0.75        61
weighted avg       0.76      0.75      0.75        61
```

Model 4: Naives Bayes Classifier

```
precision    recall  f1-score   support
0       0.79      0.73      0.76        30
1       0.76      0.81      0.78        31
accuracy                          0.77        61
macro avg       0.77      0.77      0.77        61
weighted avg       0.77      0.77      0.77        61
```

Model 5: Decision Trees

```
precision    recall  f1-score   support
0       0.68      0.70      0.69        30
1       0.70      0.68      0.69        31
accuracy                          0.69        61
macro avg       0.69      0.69      0.69        61
weighted avg       0.69      0.69      0.69        61
```

Model 6: Random Forest

```
precision    recall  f1-score   support
```

```
0      0.88     0.70     0.78       30
1      0.76     0.90     0.82       31

accuracy                        0.80       61
macro avg       0.82     0.80     0.80       61
weighted avg       0.81     0.80     0.80       61
```

```
Model 7: XGBoost
precision    recall  f1-score   support
0      0.75     0.70     0.72       30
1      0.73     0.77     0.75       31
accuracy                        0.74       61
macro avg       0.74     0.74     0.74       61
weighted avg       0.74     0.74     0.74       61
```

```
Feature: 0, Score: 0.07814
Feature: 1, Score: 0.04206
Feature: 2, Score: 0.16580
Feature: 3, Score: 0.07477
Feature: 4, Score: 0.07587
Feature: 5, Score: 0.00828
Feature: 6, Score: 0.02014
Feature: 7, Score: 0.12772
Feature: 8, Score: 0.06950
Feature: 9, Score: 0.09957
Feature: 10, Score: 0.04677
Feature: 11, Score: 0.11667
Feature: 12, Score: 0.07473
```

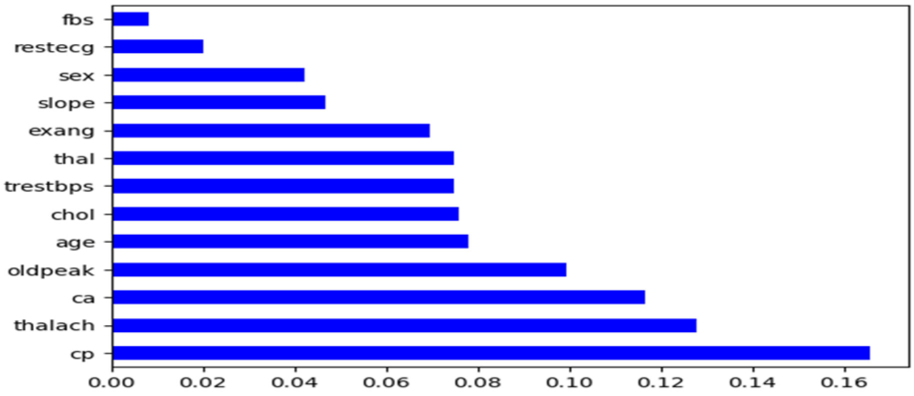

Fig 29. Feature importance values for a machine learning model

In Fig 29, appears to be a horizontal bar chart displaying feature importance values for a machine learning model. Here's a breakdown of what it represents:

1. Feature Importance: The chart ranks various features based on their contribution to the model's predictions. The longer the bar, the more significant the feature.

2. Top Features: The most important features include:

- cp (Chest Pain Type)
- thalach (Maximum Heart Rate Achieved)
- ca (Number of Major Vessels)
- oldpeak (ST Depression Induced by Exercise)

3. Less Important Features: The shortest bars represent features that have minimal influence, such as fbs (Fasting Blood Sugar) and restecg (Resting Electrocardiographic Results).

4. Possible Context: This could be related to a heart disease prediction model, where the listed features come from a dataset like the UCI Heart Disease dataset.

5. Conclusion

This research demonstrates an effective feature selection method for heart disease prediction. Our findings show that reducing features indiscriminately degrades classifier performance, while selecting the most relevant ones enhances accuracy. The incremental feature selection method achieves over 90% of the best performance, highlighting the importance of key features. The selection methods by consistently improving classifier accuracy across datasets.. These results confirm the value of optimizing feature selection for heart disease prediction. Additionally, eliminating irrelevant or redundant features not only improves model performance but also enhances computational efficiency, reducing training time and overfitting risks. These findings emphasize the importance of feature selection in medical diagnostics and suggest that can be a valuable tool for improving predictive modelling in healthcare applications.

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