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ADVANCEMENTS IN DEEP LEARNING TECHNIQUES FOR PRECISE DIAGNOSIS ARE REVOLUTIONISING THE DETECTION OF CORONARY ARTERY DISEASE

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Abstract- This study examines the effectiveness of Neural Network (NN) and Artificial Neural Network (ANN) models in accurately predicting the occurrence of coronary artery disease (CAD) by utilising the Cleveland Heart Disease dataset. The goal is to evaluate the efficacy of these models in binary classification, assisting in the prompt identification and intervention for CAD. The methodology consists of thorough data collection, preprocessing, Exploratory Data Analysis (EDA), model training, and evaluation. Preprocessing involves addressing missing values and transforming data into a numerical format to maintain data integrity. Exploratory Data Analysis (EDA) tools, such as violin plots, count plots, histograms, and heatmaps, provide valuable insights into the distributions, patterns, and relationships present in the data. The dataset is divided into training and testing sets using stratified splitting to precisely assess the performance of the model. The results indicate that the Artificial Neural Network (ANN) model performs better than the Neural Network (NN) model, showing a smaller loss (0.33 compared to 0.35) and higher accuracy (87.60% compared to 86.36%). The exceptional performance of the ANN can be due to its sophisticated structure, which includes hidden layers that effectively capture complex data patterns. The results emphasise the potential of deep learning methods, namely artificial neural network (ANN) models, in reliably predicting the existence of coronary artery disease (CAD). This has significant implications for early identification and management in the field of cardiovascular medicine and beyond.

Keywords- *Coronary Artery Disease (CAD), Neural Network (NN), Artificial Neural Network (ANN), Predictive Modeling and Cardiovascular Medicine*

1. Introduction

Breakthroughs in Deep Learning Techniques for Accurate Diagnosis are transforming the Detection of Coronary Artery Disease. Coronary artery disease (CAD) continues to be a major cause of death globally, highlighting the pressing need for precise and effective diagnostic techniques. Conventional methods for CAD diagnosis, like as angiography and stress testing, are efficacious but frequently involve intrusive procedures, high expenses, and lengthy time requirements. On the other hand, the development of deep learning techniques provides a hopeful opportunity to enhance CAD detection[1]. This is achieved by utilising the capabilities of artificial intelligence to analyse medical imaging data with exceptional precision and effectiveness. Deep learning, a subclass of artificial intelligence, has gained considerable interest in recent years due to its exceptional capacity to acquire complex patterns and correlations within extensive datasets. This feature makes it especially suitable

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for medical image processing jobs, such as identifying and categorising cardiovascular problems like coronary artery stenosis[2]–[6]. Through the utilisation of extensive collections of labelled medical pictures, researchers can train deep neural networks to autonomously detect minor indications of CAD with exceptional sensitivity and specificity. A key benefit of deep learning-based CAD detection is its capacity to improve diagnostic precision. Traditional imaging techniques, including coronary angiography, could fail to detect initial or subtle signs of coronary artery disease (CAD), resulting in a lack of diagnosis and delayed start of treatment. Deep learning algorithms have the ability to analyse medical images at a very detailed level, down to individual pixels. This allows them to identify even the smallest irregularities that may indicate coronary artery disease (CAD). This increased sensitivity could enhance the ability of clinicians to detect and treat coronary artery disease (CAD) in its early stages, leading to earlier intervention and improved patient outcomes[7]–[11].

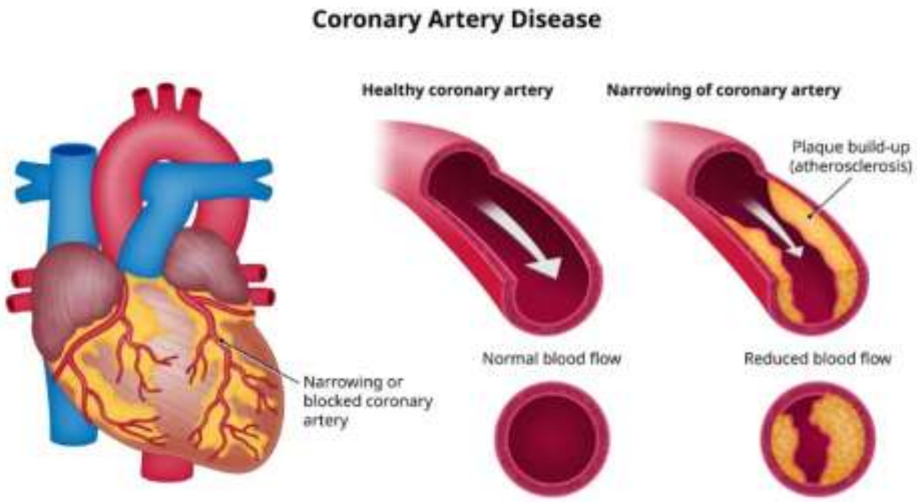

Figure 1 Coronary Artery Disease

Deep learning approaches have the potential to simplify the diagnostic process for CAD. Conventional approaches frequently necessitate the manual analysis of imaging data by skilled doctors, which can be time-consuming and susceptible to human mistakes[12]–[16]. On the other hand, deep learning algorithms have the ability to quickly analyse vast amounts of imaging data with reliable accuracy, which lessens the workload for healthcare personnel and speeds up the diagnostic process. By implementing automated CAD detection methods, these techniques have the capacity to improve clinical productivity, allowing healthcare organisations to provide prompt and cost-efficient treatment to patients with suspected CAD. The emergence of deep learning has enabled the creation of new imaging techniques that provide enhanced visualisation of coronary arteries and related diseases. Researchers have utilised convolutional neural networks (CNNs) to improve the spatial resolution and contrast of coronary computed tomography angiography (CCTA) pictures[17]–[21]. This allows for more accurate detection of coronary artery abnormalities. Furthermore, image reconstruction algorithms based on deep learning have demonstrated potential in decreasing image noise and artefacts, hence improving the diagnostic effectiveness of cardiac imaging methods. the incorporation of deep learning methods into CAD detection signifies a fundamental change in cardiovascular medicine. Through the utilisation of artificial intelligence, researchers and

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doctors can attain unparalleled levels of accuracy, efficiency, and precision in the diagnosis of CAD. As these technologies advance and develop further, they have the potential to completely transform the way CAD is managed[22]–[26].

1.1 Research Inquiry or Problem Statement

1.1.1 The clarity of expression

The amalgamation of deep learning and machine learning methodologies offers a potentially fruitful pathway for enhancing the identification of Coronary Artery Disease (CAD), a prominent contributor to both illness and death on a global scale. Deep learning, which falls under the umbrella of machine learning, utilizes neural networks to autonomously extract detailed patterns from intricate datasets, rendering it highly suitable for tasks related to computer-aided design (CAD) detection[27]–[30]. Likewise, conventional machine learning techniques, such as support vector machines and decision trees, play a role in the identification of computer-aided design (CAD) by identifying patterns within the dataset. The aforementioned methodologies demonstrate notable efficacy in diverse modalities, encompassing medical imaging and clinical data processing. Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in the automated detection of coronary artery stenosis and plaque burden through the analysis of angiographic images. Moreover, the incorporation of several modalities and the utilization of ensemble learning methods might improve the precision and resilience of predictions. In spite of notable advancements, there persist certain obstacles, including the requirement for extensive and varied datasets, as well as the imperative of guaranteeing the comprehensibility of model determinations for clinical implementation. However, the continuous advancement of these technologies has the capacity to significantly transform the diagnosis of coronary artery disease (CAD), leading to enhanced patient outcomes and reducing the strain on healthcare systems worldwide[31]–[34].

1.1.2 Relevance and Significance

The incorporation of deep learning and machine learning methodologies in the identification of Coronary Artery Disease (CAD) holds great importance and relevance, given CAD's prominent position as a primary contributor to both illness and death on a global scale. By utilizing sophisticated computational methodologies to enhance the accuracy and efficiency of CAD detection, these approaches possess the capacity to transform diagnostic methodologies, facilitating timely interventions and ultimately mitigating unfavorable consequences. The aforementioned findings have significant ramifications for public health systems, healthcare professionals, and patients, as they hold the potential to better techniques for managing coronary artery disease (CAD), increase patient outcomes, and mitigate the strain on healthcare resources[35]–[37].

2. Literature Review

Atamas 2023 et al. The study investigated the correlation between traditional risk factors and severity of coronary atherosclerosis in stable CHD patients. Significant associations were found, with hypertension, family history, and depression influencing moderate disease, while

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diabetes, family history, and inactivity were linked to severe atherosclerosis. Smoking correlated with higher Gensini scores[2].

Zong 2023 et al. The study investigates the association between NLRP1 serum levels and coronary artery stenosis severity in CAD patients. NLRP1, a protein impacting inflammation and various physiological processes, is assessed in 307 patients undergoing coronary angiography. The goal is to analyze NLRP1's impact on CAD severity[1].

Fukamachi 2022 et al. The PRAEDO AF study assessed the safety of edoxaban monotherapy in NVAF patients with stable CAD post-PCI. Results showed lower bleeding incidence (1.67% vs. 4.28%) with monotherapy, without adverse cardiac events. Edoxaban monotherapy appears safe, suggesting its potential as a treatment option in this patient population[34].

Gürler 2022 et al. The study investigates ventricular repolarization parameters in diabetic patients with CAD. Compared to those without CAD, diabetic patients with CAD exhibit significantly increased repolarization indicators. This suggests a heightened risk of abnormal heart rhythms. Further large-scale randomized trials are needed to validate these findings and inform clinical management strategies[35].

Park 2022 et al. The study examines sex-related differences in coronary artery spasm (CAS) features and outcomes. Among 5,491 individuals with nonobstructive cardiovascular disease, women had lower CAS incidence but experienced more temporary ST elevation and ischemic chest discomfort. Men exhibited higher rates of multivessel spasm. Risk factors for CAS included age, cholesterol, and myocardial bridge presence. Over 5 years, major adverse cardiac events and recurrent angina showed no significant sex-based variations, suggesting comparable long-term clinical outcomes[32].

Table.1 Literature Summary

Authors/year	Methodology used	Problem statement	Dataset used	Parameters	Ref.
Ma/2022	Peonage and CAD mortality association.	Peonage predicts mortality risk in multiverse CAD patients.	609 multiverse CAD patients dataset.	Peonage predicts mortality risk in multiverse CAD patients effectively.	[38]
Shehzadi/2022	Machine learning for heart disease diagnosis.	High-precision model to reduce ischemic heart disease mortality in Pakistan.	Machine learning on heart disease.	Machine learning parameters for precise heart disease diagnosis enhancement.	[26]
Cheng/2022	Logistic regression and	Serum interferon	CHD patient health data.	Logistic regression and	[24]

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	ANN analysis.	analysis in coronary heart disease using statistical models.		ANN model for CHD analysis parameters.	
Lu/2022	Artificial intelligence in heart disease diagnosis.	Artificial intelligence revolutionizes coronary heart disease diagnosis, addressing critical challenges.	AI advancements in coronary disease diagnosis.	AI's role in diagnosing coronary artery disease: parameters and advancements.	[23]
Aoyama/2022	Analysis of plasma fortilin levels in CAD patients.	Association of plasma fortilin levels with severity of coronary artery disease.	Plasma fortilin levels in CAD.	Fortilin levels associated with severity of coronary artery disease (CAD).	[22]

3. Research Methodology

The methodology outlined involves a thorough examination and use of the Cleveland Heart Disease dataset for binary classification, with a specific focus on predicting whether or not heart disease is present. The process commences by gathering data from the UCI repository, which provides comprehensive information about the dataset's characteristics and their relevance in the research of cardiovascular health. The process of data preprocessing is then described, which includes important tasks such as managing missing values, guaranteeing the accuracy of the data, and transforming the data into a numerical format using the Pandas module in Python. A concise pseudocode is presented, providing a systematic walkthrough of each step. After preprocessing, the focus is on Exploratory Data Analysis (EDA), which involves demonstrating several visualisation approaches such violin plots, count plots, histograms, and heatmaps. These visualisations facilitate comprehension of data distributions, patterns, and correlations, which are crucial for future analysis and modelling. Next, the procedure involves data splitting, which is a crucial phase in deep learning that ensures the evaluation and generalisation of the model. The pseudocode provides a step-by-step explanation of how to divide the dataset into training and testing sets using scikit-learn's train_test_split function. This process ensures that the proportions of different classes are maintained and that the results can be reproduced consistently. The methodology explores deep learning and modelling, specifically focusing on neural networks (NNs) and artificial

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neural networks (ANNs) as effective tools for representing and modelling complex data. The explanation encompasses the architecture of neural networks (NNs) and artificial neural networks (ANNs), their process of training, and their ability to capture complex data patterns. The methodology offers a systematic approach, starting from data collecting and ending with modelling. This allows researchers to efficiently utilise the Cleveland Heart Disease dataset for predictive analysis in the field of cardiovascular medicine.

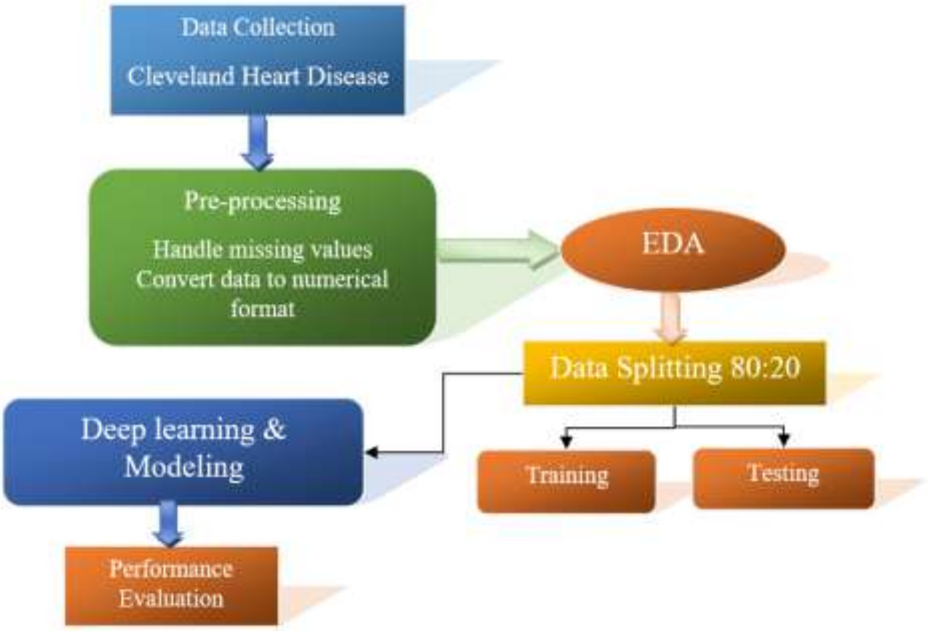

Figure 2 Proposed Flowchart

3.1 Data Collection

The Cleveland Heart Disease dataset, obtained from the UCI repository, consists of data from 303 individuals. Each individual is characterised by 14 unique features that were extracted from a larger set of 75 features. This dataset is free from any missing values, which guarantees the integrity of the data for analysis purposes. The main purpose of the dataset is to do binary classification, namely to predict the presence (1) or absence (0) of heart disease. Important variables consist of demographic information such as age and gender, as well as physiological measurements including resting blood pressure (trestbps), serum cholesterol levels (chol), and fasting blood sugar levels (fbs). Clinical markers include the nature of chest pain (cp), ECG findings at rest (restecg), maximum heart rate reached (thalach), and angina triggered by activity (exang). the dataset contains exercise-induced ST-segment depression (oldpeak), the ST segment slope at peak exercise (slope), the number of main vessels (ca), and the diagnosis of thalassemia (thal). Every characteristic provides vital insights into cardiovascular health, assisting in the development of predictive models. As an example, the abbreviation 'cp' classifies chest pain into four categories: typical angina (0), atypical angina (1), non-anginal pain (2), and asymptomatic (3). The 'restecg' feature represents three possible conditions: normal (0), ST-T wave abnormalities (1), or left ventricular hypertrophy (2). The term 'thal' refers to different types of thalassemia: normal blood flow (1), fixed defect (2), or reversible defect (3). By employing this dataset, researchers may construct deep

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learning models that effectively detect the presence of cardiac disease. By utilising extensive patient data, these models enhance diagnostic abilities, potentially resulting in enhanced patient care in the field of cardiovascular medicine.

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
280	57	1	3	110	335	0	0	143	1	3.0	1	1	3	1
281	47	1	2	130	253	0	0	179	0	0.0	0	0	1	0
282	55	0	3	128	205	0	1	130	1	2.0	1	1	3	1
283	35	1	1	122	192	0	0	174	0	0.0	0	0	1	0
284	61	1	3	148	203	0	0	161	0	0.0	0	1	3	1

Figure 3 Preview of Data

3.2 Data Pre-processing

Data pre-processing encompasses a series of essential activities that are necessary to guarantee the precision and dependability of subsequent analysis. Initially, the issue of missing data, which is frequently denoted by '?' in the dataset, needs to be resolved. This can be accomplished by eliminating rows that have missing values. To perform this procedure in Python using Pandas, can use the code snippet `data = cleveland[~cleveland.isin(['?'])]`. any remaining rows containing NaN values should be eliminated in order to preserve the integrity of the data. This may be achieved by using the code `data = data.dropna(axis=0, inplace=True)`. Following the pre-processing stage, it is crucial to evaluate the structure and data format of the DataFrame to guarantee uniformity and suitability for analytical techniques. To obtain this information, one can print the shape of the DataFrame using `data.shape` and the data types using `data.dtypes`. In order to enhance subsequent analysis, it is necessary to convert the data into a numerical representation. To do this, one can utilise the `to_numeric()` function provided by Pandas. This function can be applied to the full DataFrame by using the syntax: `data = data.apply(pd.to_numeric)`. Descriptive statistics can be generated using Pandas' `describe()` function to acquire insights into the features of the processed data. The function calculates summary statistics for each numeric variable in the DataFrame, including the mean, standard deviation, minimum, maximum, and quartile values. These statistics provide significant information about the distribution and variability of the data. By methodically carrying out these pre-processing procedures, researchers can guarantee the quality and appropriateness of the data for subsequent analyses, establishing the basis for strong and dependable conclusions in their research pursuits.

Pseudo code of Pre-processing
1. Import the necessary libraries: - Pandas for data manipulation and analysis. 2. Load the dataset: - Read the dataset file into a Pandas DataFrame. 3. Replace '?' with NaN: - Use the replace() function to replace all occurrences of '?' with NaN values.

4. Drop rows with NaN values:
  - Use the dropna() function to remove rows containing NaN values, ensuring data integrity.

5. Convert data to numeric format:
  - Apply the to_numeric() function to convert all data to numeric format, facilitating further analysis.

6. Generate summary statistics:
  - Use the describe() function to generate summary statistics for the transformed dataset, including mean, standard deviation, minimum, maximum, and quartile values.

7. Print the shape and data types of the DataFrame:
  - Print the shape of the DataFrame to display the number of rows and columns.
  - Print the data types of each column in the DataFrame.

8. Print the summary statistics:
  - Display the summary statistics generated in step 6 to provide insights into the characteristics of the dataset.

9. End.

This pseudocode provides a clear and precise explanation of the sequential procedure for preparing the dataset using the Pandas library in the Python programming language. The process begins by importing the requisite libraries and thereafter loading the dataset into a DataFrame. The code substitutes any '?' values with NaN to denote missing data. Subsequently, it eliminates rows that contain NaN values in order to maintain data integrity. The input is subsequently transformed into a numerical format with the to_numeric() method. The describe() method is used to provide summary statistics that offer insights into the properties of the dataset. Ultimately, the structure, categories of data, and summary statistics of the DataFrame are displayed to assist with subsequent analysis.

3.3 EDA (Exploratory Data Analysis)

Exploratory Data Analysis (EDA) encompasses a range of crucial visualisations that provide valuable insights into the properties of the dataset and the interactions among variables. To visualise the distribution of each numeric variable and provide a clearer understanding, a violin plot is employed, which displays quartiles. Next, a count plot is used to display the frequency of each categorical variable. The x-axis labels are rotated to enhance reading. Individual histograms offer additional understanding of the distributions and possible trends of each variable. In addition, a bar plot visually represents the occurrence of heart disease in various age groups, providing valuable information about age-related patterns, a heat map displaying the correlation matrix reveals the connections between variables, accompanied by annotations to enhance comprehension. These visualisations help you uncover trends,

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patterns, and correlations in the dataset, which are essential for further analysis and modelling.

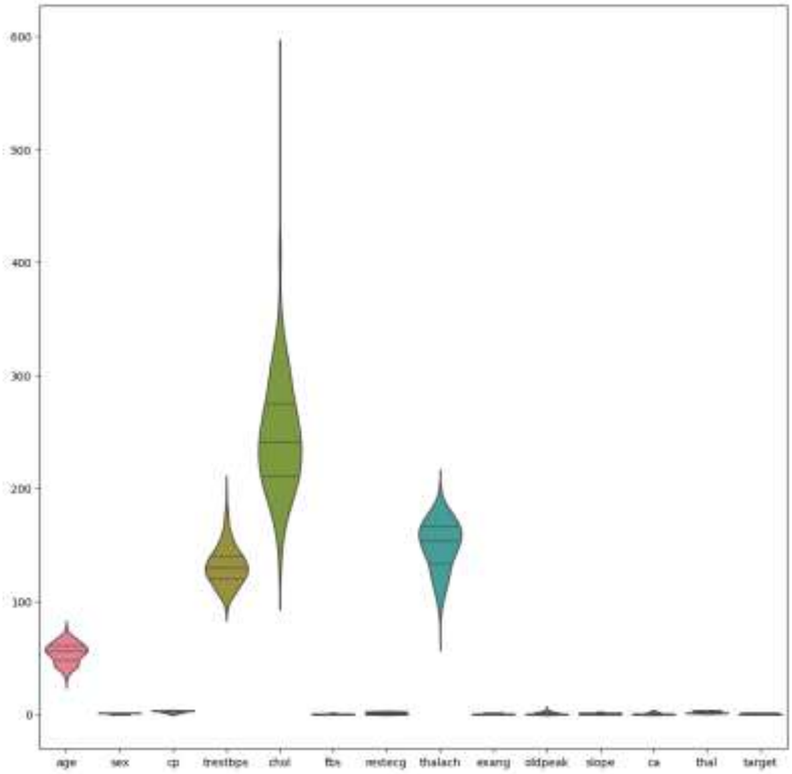

Figure 4 Violen Plot of Data Variables

The violin plot represents statistical data distributions for health-related variables such as age, sex, cholesterol levels, and others. Each 'violin' graphically represents the distribution of data points at various values, which is helpful for detecting patterns and anomalies in the dataset. It is a frequently used instrument in the field of data analysis.

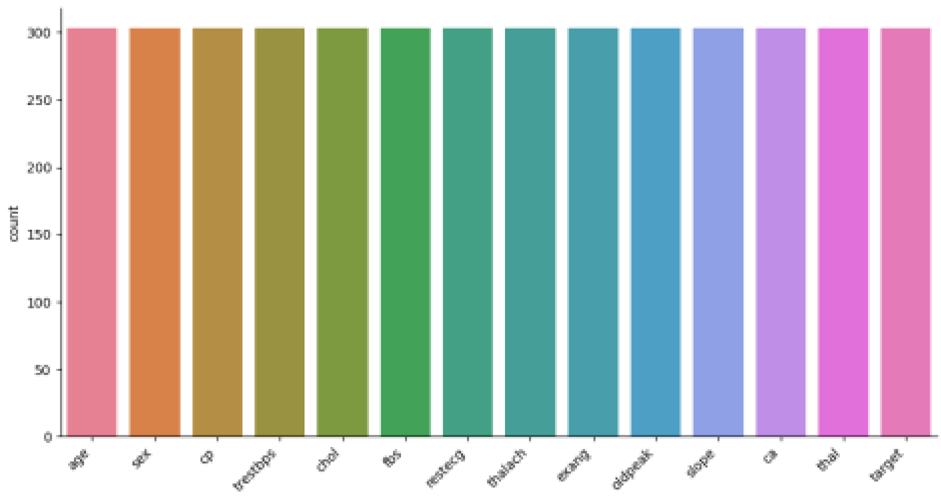

Figure 5 Cat Plot of Data Variables

Figure 5 Cat Plot of Data Variables illustrates the distribution of several categories, such as 'sex', 'cp', 'fbs', etc., in a dataset. The height of each bar represents the frequency of each category, ranging from 0 to 300. This is very helpful for analysing categorical data.

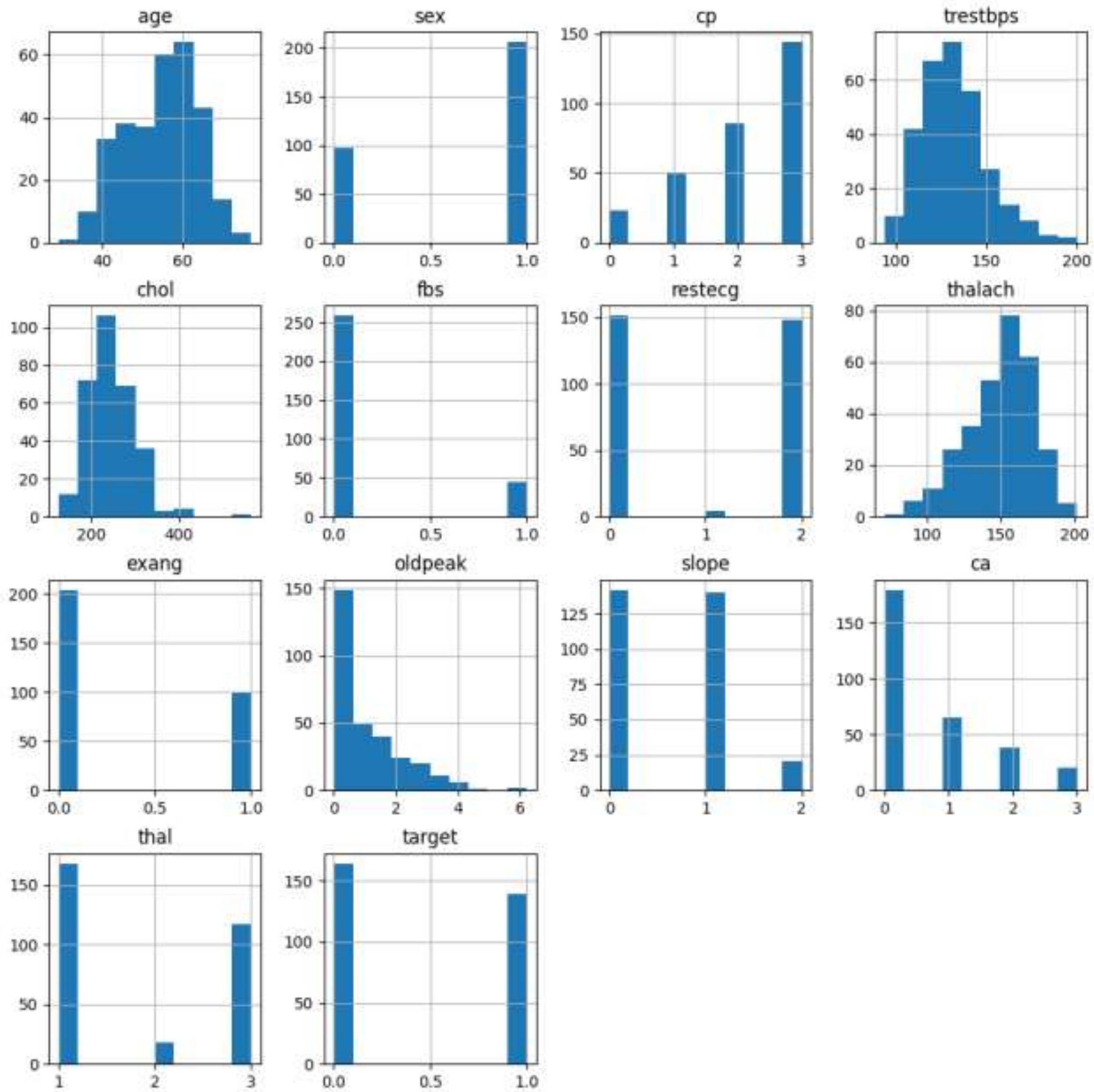

Figure 6 Histogram for each variables

The Figures display a comprehensive matrix of histograms and scatter plots, which are often utilised in statistical research to investigate the features of data. Histograms depict the distribution of a specific variable, such as age or cholesterol levels, while scatter plots analyse the connections between two variables. Utilising this visualisation technique is essential for detecting patterns, anomalies, or associations within the data, hence assisting in predictive analysis and decision-making. It is especially beneficial in the study of medical data, as comprehending the interactions between variables can result in improved forecasts of health outcomes or treatment strategies. Precise visualisations are crucial instruments in data-centric domains.

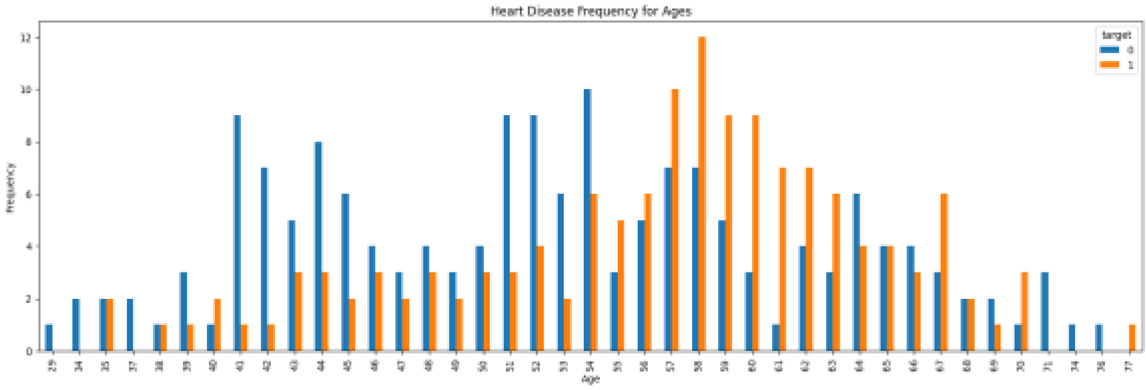

Figure 7 Heart Disease Frequency for Ages

The illustration displays a bar graph named "Heart Disease Frequency for Ages," which compares the incidence of heart disease among different age groups. The data is shown using two bar sets, one in blue and the other in orange, which indicate distinct categories. These bar sets effectively illustrate the incidence of heart disease across different age ranges. This information is valuable for conducting health-related investigations and analysis, as it provides important insights.

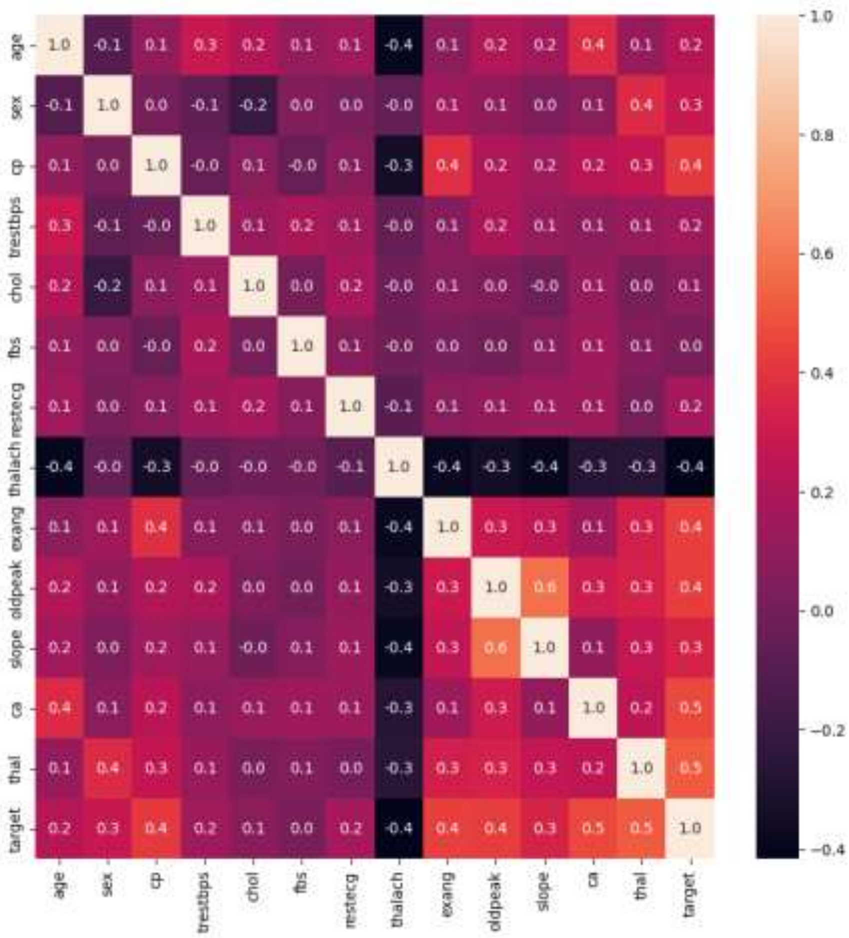

Figure 8 Heat map of all data variables

Figure 8 displays a heat map illustrating the association among several data factors. The colour of each cell represents the strength of correlation, ranging from purple (indicating negative correlation) to orange (indicating positive correlation). This allows for a visual representation of the correlations between variables.

3.4 Data Splitting

Data splitting is an essential process in deep learning that is used to assess the performance of a model and assure its capacity to generalise. The dataset is partitioned into training and testing sets using the train_test_split function from the model_selection module of scikit-learn. This procedure is crucial in order to avoid overfitting, a situation in which the model demonstrates good performance on the training data but fails to generalise to new, unseen data. The function accepts input features (X) and target variable (y), as well as other parameters like stratify for maintaining class proportions, random_state for ensuring repeatability, and test_size for determining the proportion of data assigned for testing. When test_size=0.2 is specified, 20% of the data is set aside for testing purposes, while the remaining 80% is designated for training. The resulting subsets, namely X_train, X_test, y_train, and y_test, represent the independent and dependent variables for both training and testing, respectively. Stratified splitting guarantees that the proportion of different classes in the training and testing sets accurately reflects the original dataset, which is essential for preserving the reliability of the model. This division allows the model to acquire knowledge from the training data and evaluate its effectiveness on new, unseen data during the testing phase, offering significant understanding of its resilience and ability to apply learned patterns to different situations. Data splitting is an essential process in the creation of machine learning models. It helps to ensure accurate evaluation and validation of predicted performance.

Pseudo code of Data Splitting

1. Import the necessary libraries:
  - Import the train_test_split function from the model_selection module of scikit-learn.
 	
2. Specify input features (X) and target variable (y):
  - Define X as the independent variables and y as the dependent variable.
 	
3. Split the data:
  - Use the train_test_split function to split the dataset into training and testing sets.
  - Pass X and y as arguments to the function.
  - Set stratify=y to ensure that class proportions are maintained in the splits.
  - Specify random_state for reproducibility.
  - Set test_size to determine the proportion of data allocated for testing, typically 0.2 for a 20% test set.
 	
4. Assign the resulting subsets:
  - Store the resulting subsets in variables: X_train, X_test, y_train, y_test.
 	
5. End.

This pseudocode provides an overview of the procedure for dividing a dataset into training and testing sets using the train_test_split function from the scikit-learn library. The process begins by loading the required libraries and thereafter defining the input characteristics (X) and target variable (y). The data splitting action is executed by utilising the train_test_split function, which accepts X and y as inputs, as well as other options like stratify, random_state, and test_size. Once the data is divided, the resulting subsets are allocated to variables for subsequent analysis and model training. This procedure guarantees that the model is trained on a portion of the data and assessed on new, unseen data, which enables precise evaluation of performance and validation of the model.

3.5 Deep Learning & Modeling

Deep learning, a subfield of artificial intelligence, comprises a diverse range of advanced approaches for modelling and comprehending intricate data representations. Neural Networks (NN) and Artificial Neural Networks (ANN) are notable techniques that are highly effective in addressing various tasks, including image recognition and natural language processing.

- Neural networks are composed of interconnected layers of artificial neurons (nodes) that are inspired by the structure and function of the human brain. Every individual neuron in a neural network gets input signals, which are then multiplied by specific

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weights assigned to them. The resulting values are then processed by an activation function, which ultimately generates an output. Neural networks (NNs) may acquire complex patterns and correlations in data by arranging numerous layers of neurons, which allows them to generate accurate predictions and classifications.

- Artificial Neural Networks, a distinct variant of neural networks, typically denote models that feature numerous concealed layers positioned between the input and output layers. The presence of hidden layers in artificial neural networks (ANNs) enables them to acquire hierarchical representations of data, thereby capturing intricate aspects and correlations that may not be apparent in less sophisticated models. Artificial neural networks (ANNs) perform exceptionally well in tasks that involve input data with a high number of dimensions or when the interactions between variables are nonlinear and intricate.

Both neural networks (NNs) and artificial neural networks (ANNs) are trained using optimisation methods to minimise a preset loss function. This is achieved by iteratively modifying the weights and biases of the neurons. During this process, the models acquire the ability to draw general conclusions from the data they are trained on, enabling them to make precise predictions on data that they have not encountered before. neural networks (NNs) and artificial neural networks (ANNs) are fundamental elements of deep learning, providing robust capabilities for representing intricate data and addressing a wide range of practical issues.

Pseudo code of Model implementation

1. Import necessary libraries:
  - Import Sequential, Dense, Dropout, Adam, and regularizers from the Keras library.
 	
2. Define a function to build the Keras model:
  2.1 Create a Sequential model instance.
  2.2 Add the input layer and the first hidden layer:
    - Use the add() method of the model to add a Dense layer with 16 neurons, input dimension of 13,
     'normal' kernel initializer, 'relu' activation function, and L2 regularization with a penalty
     parameter of 0.001.
  2.3 Add dropout regularization to the first hidden layer:
    - Use the add() method of the model to add a Dropout layer with a dropout rate of 0.25.
  2.4 Add the second hidden layer:
    - Use the add() method of the model to add another Dense layer with 8 neurons, 'normal' kernel initializer,
     'relu' activation function, and L2 regularization with a penalty parameter of 0.001.
  2.5 Add dropout regularization to the second hidden layer:
    - Use the add() method of the model to add a Dropout layer with a dropout rate of 0.25.

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2.6 Add the output layer:
- Use the add() method of the model to add a Dense layer with 2 neurons and 'softmax' activation function.

2.7 Compile the model:
- Define an Adam optimizer with a learning rate of 0.001.
- Compile the model using categorical crossentropy loss and accuracy as the evaluation metric.

2.8 Return the built model.

3. Create the model:
- Call the create_model() function to instantiate the model.

4. Print the summary of the model:
- Use the summary() method of the model to print a summary of the model architecture.

5. End.

This pseudocode offers a systematic and detailed instruction set for constructing the Keras deep learning model as outlined in the above code sample. The text describes the construction of the model's architecture, which includes the input, hidden, and output layers. It also explains how the model is compiled, specifying the loss function, optimizer, and evaluation metric. Lastly, it showcases the process of creating an instance of the model and displaying a concise overview of its structure.

Table.2 Hyper parameter Details

Models	Neural network, Artificial Neural Network
Hidden Layer 1 Neurons	16
Hidden Layer 2 Neurons	8
Input Dimension	13
Activation Function	'relu'
L2 Regularization	0.001
Output Activation	'softmax'
Optimizer	Adam
Evaluation Metric	Accuracy

1) Adam Optimization

Adam is an algorithm that combines elements of momentum and RMSprop optimisation techniques to enhance its overall performance. The calculation shown below determines the update rule for the parameters θ in the Adam optimisation method:

$$\theta_{t+1} = \theta_t \frac{\alpha \cdot m_t}{\sqrt{v_t}+\epsilon} \quad (1)$$

Theta represents the parameters of the model, alpha denotes the learning rate, m t signifies the exponentially decaying average of prior gradients, v t represents the exponentially

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decaying average of previous squared gradients, and epsilon is the small constant that prevents division by zero in the Adam optimisation update method.

2) ReLU

The Rectified Linear Unit, commonly referred to as ReLU, is a widely used activation function in neural networks. If the input is positive, it directly outputs the current value; otherwise, it outputs zero. ReLU promotes sparsity in activations and mitigates the issue of vanishing gradients that arise during training. It is a popular choice in deep learning architectures since it is both simple and effective.

$$f(x) = \max(0, x) \tag{2}$$

Here, x represents the input to the function, and the outcome is f(x) = f(x). The ReLU function returns positive inputs (x) directly, while returning zero for non-positive inputs. Neural networks primarily depend on this straightforward piecewise-linear function for training, as it encourages sparsity and mitigates the vanishing gradient problem.

3) Softmax

Softmax is a crucial component of neural networks that is utilised to standardise the scores based on the input. The calculation goes as follows: for each input value, compute the exponential and then divide it by the sum of all the exponentials. To ensure the appropriate representation of probabilities, this normalising procedure guarantees that the output values fall within the range of zero to one. By utilising softmax, decision-making tasks such as classification become more manageable, as the network's output can now be interpreted as the probability of each class. Machine learning tasks heavily depend on the predictions made by neural networks. Softmax is a crucial tool used to convert these predictions into meaningful probabilities.

$$Softmax(x_i) = \frac{e^{xi}}{\sum j^{e^{xj}}} \tag{3}$$

4. Result & Discussion

4.1 Performance Evaluation

The assessment of model performance utilised accuracy and loss metrics to evaluate the efficacy of the suggested models. Accuracy was used as a metric to assess the model's capability to accurately identify emotions. It represented the ratio of properly predicted cases to the total number of instances. Meanwhile, the loss metric measured the difference between anticipated and actual values, giving an understanding of how well the model was improving throughout training and its potential to reduce errors. A complete study was done to assess the models' skill in accurately recognising emotions while optimising predicting outcomes, taking into account both accuracy and loss.

4.1.1 Accuracy

The assessment of classification models in deep learning frequently depends on the fundamental metric of accuracy. The metric measures the proportion of correctly predicted instances out of the total number of instances in a given dataset. The mathematical expression of accuracy entails calculating the ratio of correct predictions to the total number of predictions provided by the model. While accuracy provides a straightforward assessment of a model's overall correctness, it may not be suitable for imbalanced datasets where one class dominates. The accuracy metric is widely used in various applications due to its clear

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interpretation and simple calculation, offering crucial insights into the effectiveness of classification algorithms.

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \tag{4}$$

4.1.2 Loss

The loss metric, also known as the cost or objective function, is crucial in deep learning as it measures the difference between predicted and actual values. It serves as a metric for evaluating the model's performance during the training phase. The main goal of training a deep learning model is to minimise the loss function, hence improving the projected accuracy of the model. There are multiple loss functions specifically tailored for different types of tasks, such as regression, classification, and reinforcement learning.

$$Loss = -\frac{1}{m}\sum_{i=1}^{m} \mathcal{Y}i.\log(\mathcal{Y}i) \tag{5}$$

Table 3 Performance Evaluation of Proposed Models

Model	Loss	Accuracy
Neural Network	0.35	86.36
Artificial Neural Network	0.33	87.60

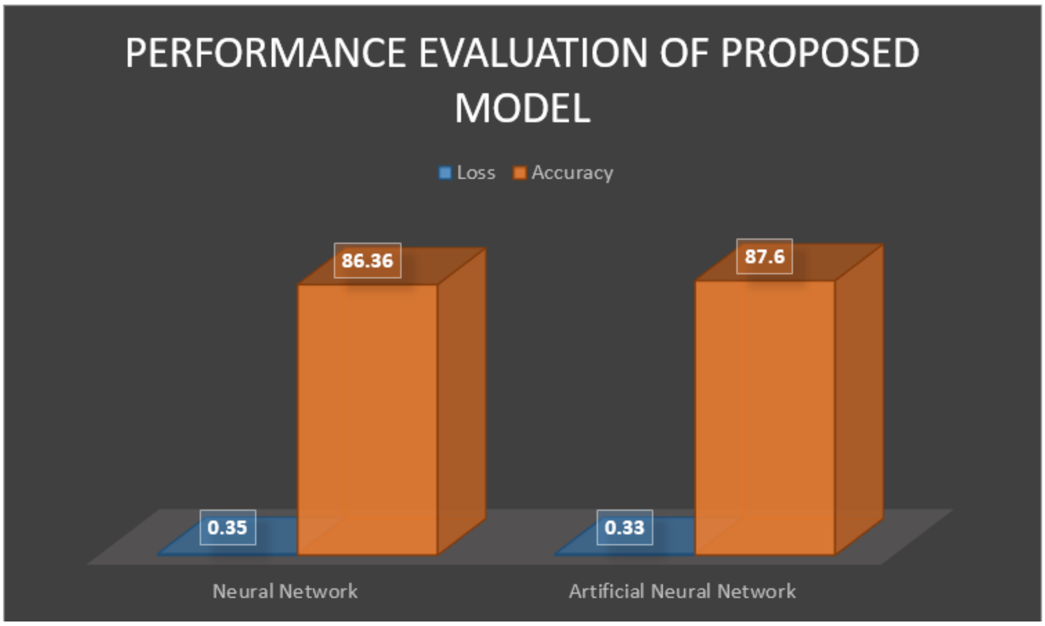

Figure 9 Performance Graph of Proposed Models

Table 3 displays the performance assessment of two suggested models: a Neural Network (NN) and an Artificial Neural Network (ANN). The performance of each model is evaluated using two primary metrics: loss and accuracy. Loss quantifies the discrepancy between the model's predictions and the true values, whereas accuracy gauges the proportion of correctly classified occurrences. The Neural Network (NN) model obtains a loss value of 0.35 and an accuracy rate of 86.36%. Conversely, the Artificial Neural Network (ANN) model demonstrates somewhat better performance, with a reduced loss of 0.33 and an increased accuracy of 87.60%. The results indicate that the Artificial Neural Network (ANN) model performs better than the Neural Network (NN) model in terms of reducing prediction errors and accurately identifying cases. The disparity in performance between the two models can be ascribed to the artificial neural network's intricate structure, which encompasses numerous concealed layers. The presence of extra hidden layers in the artificial neural network (ANN) allows it to acquire a deeper understanding of complex patterns and correlations present in the data, resulting in enhanced performance when compared to the simpler neural network (NN) model. The performance evaluation demonstrates the efficacy of deep learning approaches, specifically Artificial Neural Networks, in effectively modelling and categorising intricate datasets. These models exhibit encouraging potential for many applications, such as image recognition, natural language processing, and predictive analytics.

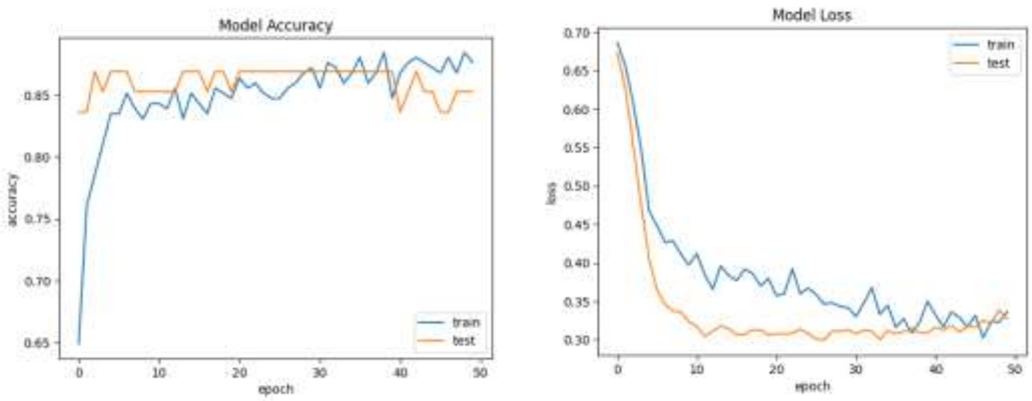

Figure 10 Accuracy and Loss graph of ANN model

Table.4 Comparative analysis of the previous model and the proposed model

Models	**Accuracy**	**References**
DL-PPG	83.8	[39]
Decision Trees	83	[40]
Proposed ANN	**87.6**	**--**

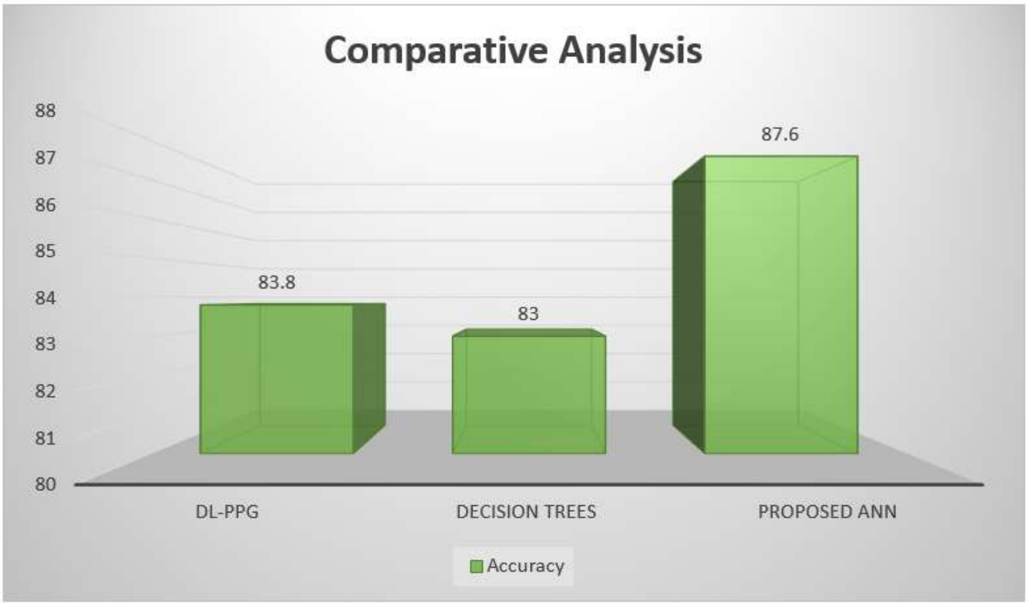

Figure 11 Comparative Analysis Graph

Table 4 displays a comparative analysis of various models, evaluating their accuracy scores in predicting the existence of a specific condition, most likely coronary artery disease (CAD) or a linked cardiovascular health indicator. The table assesses the effectiveness of three models: DL-PPG, Decision Trees, and the Proposed Artificial Neural Network (ANN). The DL-PPG model demonstrates a commendable accuracy rate of 83.8%, signifying its proficiency in accurately categorising instances. Decision Trees, a conventional machine learning technique, attain a marginally lower accuracy rate of 83%. On the other hand, the Proposed ANN model has the best level of accuracy compared to the other two models, with a rate of 87.6%.

The superior accuracy of the Proposed Artificial Neural Network (ANN) model indicates its superior performance in properly predicting the presence of the condition compared to both Deep Learning Photoplethysmography (DL-PPG) and Decision Trees. The improvement in performance can be ascribed to the artificial neural network's capacity to capture complicated patterns and correlations within the information, especially when the data includes non-linear relationships or complex variables pertaining to cardiovascular health.

findings suggest that the Proposed Artificial Neural Network (ANN) model performs better than both DL-PPG and Decision Trees in terms of accuracy. This makes it a highly promising option for predictive modelling in the field of cardiovascular medicine.

5. Conclusion

In conclusion, this study explored the field of cardiovascular medicine by testing the accuracy of prediction models for Coronary Artery Disease (CAD), namely Neural Network (NN) and Artificial Neural Network (ANN) models. Detailed findings were attained by following an approach that included data pretreatment, Exploratory Data Analysis (EDA), training the model, and evaluation. The results demonstrated that the ANN model outperformed the NN model when it came to correctly predicting the existence of CAD. The ANN's capacity to capture complicated data patterns efficiently was proved by its reduced loss (0.33 vs. 0.35) and higher accuracy (87.60% vs. 86.36%), which can be attributed to its complex structure that incorporates hidden layers. The study also stressed the need for intelligent EDA techniques and strong data preparation to guarantee accurate predictions. These methods helped with the precise assessment of model performance and deepened our comprehension of the dataset's properties. In sum, the research sheds light on the promise of state-of-the-art ML methods, and ANN models in particular, for the field of cardiovascular medicine. Positive findings point to new ways to diagnose and treat coronary artery disease (CAD), which will improve patient care and clinical decision-making for cardiovascular disease management.

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