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Heart Failure Detection Using Scaled Conjugate Gradient Method and Naïve Bayes

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ABSTRACT

Heart failure known as high mortality rates is a serious pathophysiological condition characterized and substantial long-term healthcare costs. Early detection is crucial, as the disease tends to progress without timely and appropriate intervention. This study aims to predict the risk of heart failure using structured clinical data and to leverage deep learning techniques to enhance the accuracy of risk assessment. The core objective is to demonstrate that early identification of heart failure indicators can significantly improve patient outcomes, potentially distinguishing between life and death. Recognizing these early warning signs provides a better opportunity for preventive care and timely treatment. To achieve this, two algorithms were employed: the Scaled Conjugate Gradient method within an Artificial Neural Network (ANN) framework, and the Naïve Bayes classifier. A Feed-Forward Neural Network (FFNN) was utilized as the primary classifier to detect the presence of heart failure. The neural network architecture used in this study consisted of 12 input neurons, 20 hidden layers, and a single output layer. The performance results revealed that the ANN achieved an accuracy of 86.7%, while the Naïve Bayes classifier reached an accuracy of 76.9%. Overall, the ANN demonstrated best performance in detecting heart failure, especially with a large number of hidden neurons, highlighting its potential as an effective diagnostic tool.

1. INTRODUCTION

The World Health Organization (WHO) has classified heart disease as one of the leading causes of death worldwide. From the data heart disease observations, approximately 17.9 million lives annually, accounting for roughly 31% of all global deaths (Luo et al., 2024). One critical manifestation of heart disease is heart failure (HF) which is a condition when the heart cannot pump the blood smoothly to reach the body's requirement for oxygen and nutrients. The heart failure happens when the heart becomes weak to sustain their workload, leading to symptoms such as dyspnea (shortness of breath), reduced exercise tolerance, and

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fluid retention. This fluid buildup often results in pulmonary and peripheral edema (Malik et al., 2025). While "heart failure" and "congestive heart failure" are terms often used interchangeably, the latter refers to a specific, more severe form of HF that typically requires urgent medical attention. HF is a chronic and progressive condition that significantly impairs quality of life and increases the risk of mortality. It reflects a weakened heart muscle that struggles to pump sufficient blood throughout the body. As a result, individuals with HF often experience a diminished quality of life and increased healthcare needs. Due to its high prevalence, significant mortality rate, and substantial healthcare costs, heart failure remains a major global health concern. Early and accurate diagnosis is essential to managing the disease effectively (Porumb et al., 2020). Despite medical advances, HF continues to be one of the most costly and deadly health conditions worldwide (Reddy et al., 2021).

HF is influenced by several interconnected factors, including anemia, age, blood pressure, creatine phosphokinase (CPK), and diabetes. Anemia worsens HF by reducing oxygen delivery, thereby increasing cardiac workload and leading to poorer outcomes. It is commonly associated with chronic kidney disease (CKD) and diabetes, creating a complex interplay that heightens cardiovascular risk. Older adults are at a higher risk of developing heart failure due to common risk factors such as hypertension and coronary artery disease. As these conditions become more prevalent with age, the incidence of heart failure is expected to continue rising in the coming decades (Vigen et al., 2012). Hypertension acts both as a cause and consequence of HF; uncontrolled blood pressure can lead to arterial stiffness and elevated pulse pressure, which are linked to anemia. In hypertensive patients, anemia may result from reduced red blood cell deformability and the impact of anti-hypertensive medications on erythropoiesis. Additionally, elevated CPK levels, which indicate muscle damage including myocardial injury, are important markers of ongoing cardiac stress or infarction.

Diagnosing and analyzing heart failure (HF) involves numerous interconnected factors, often making it challenging for physicians to reach timely and accurate decisions. To assist in this complex process, Artificial Neural Networks (ANN) have become valuable tools in medical applications, particularly in HF detection. Inspired by the structure of the human brain, ANN are a type of deep neural network capable of modeling non-linear and complex relationships. These systems are composed of layers of interconnected artificial neurons: input, hidden, and output layers where signals are transmitted, processed, and propagated. A key strength of ANN lies in their ability to handle large and complex datasets. By learning from training data, they continuously improve their accuracy, making them highly effective for classification and clustering tasks (IBM Cloud Education, 2020). While traditional machine learning methods have also been applied to HF prediction, ANN offer superior adaptability and learning capabilities. However, a notable drawback is that the size and structure of ANN architectures are typically determined by trial and error or prior experience, and their performance heavily depends on selecting the right configuration. Adding new features to the system can also affect its accuracy (Maad, 2021).

In industrial contexts, ANN provides cost-effective solutions by reducing material usage (Filippis et al., 2018). In healthcare, their predictive power can support early intervention, potentially lowering the need for expensive surgeries and treatments. To harness these benefits, healthcare systems require advanced data storage, analysis, and data mining techniques to extract meaningful insights from vast datasets (Santos-Pereira et al., 2022). While data mining has already proven successful in fields like marketing and retail, its application in healthcare is still evolving. As big data continues to grow, neural networks are revolutionizing both industry and daily life by advancing artificial intelligence. Given the rising mortality rates from heart failure, ANN are especially suited for big data-driven medical applications, helping physicians predict disease outcomes and manage large volumes of patient data, thereby reducing the burden on clinical experts.

This research focuses on accurately predicting the presence of HF using two distinct algorithms: Scaled Conjugate Gradient (SCG) and Naïve Bayes (NB). The proposed models utilize only 13 attributes (as shown in Table 1). These observed features form the core basis for testing, which generally yields reliable results. SCG is an optimization method employed for training neural networks, offering benefits such as faster

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convergence compared to traditional backpropagation and greater efficiency when handling large datasets. On the other hand, Naïve Bayes is a simple, yet effective probabilistic classifier based on Bayes' Theorem, operating under the “naïve” assumption that features are conditionally independent given the class label. Despite this often unrealistic assumption, Naïve Bayes has demonstrated strong performance in medical applications (Girdonia et al., 2019).

Neural Networks are one of the most powerful and widely used machine learning models today. Neural Network models are inspired by the structure of the human brain, capable of capturing complex non-linear relationships in data. The ANN with an appropriate network structure can handle the correlation or dependence between input variables and is known for its ability to learn complex patterns and relationships in data. Furthermore, the Scaled Conjugate Gradient (SCG) method is a neural network training algorithm. Basim et al. (2025) in their research have proved the effectiveness of these methods is illustrated in the context of training artificial neural networks. Experimental results show that the improvement SCG methods achieves competitive performance in terms of convergence rate and accuracy.

Naive Bayes are probabilistic model used in machine learning and data analysis. Naive Bayes assumes that all features are independent of each other, given the class label. This simplifying assumption makes Naive Bayes computationally efficient and easy to implement. Naive Bayes is often used in text classification and spam filtering tasks due to its simplicity and good performance in practice. Naive Bayes algorithms accurately categorize news headlines into different classes. This algorithm is well-established and widely used machine learning algorithm known for its simplicity and effectiveness in text classification tasks (Merve et al., 2024).

Thus, the objective of this research is to identify highly accurate methods for detecting heart failure. The sub objectives are to use structured data to predict the risk of heart failure and to use deep learning to determine the specific risk of heart failure specifically on Neural Network and Naïve Bayes.

The study’s findings highlight the critical importance of early detection in heart failure, which can mean the difference between life and death. Recognizing the early signs of heart failure significantly improves our ability to detect threats in time. Medical history remains one of the most reliable indicators for predicting the likelihood of developing heart disease. This study is particularly significant because it helps identify appropriate treatment targets, advancing our goal of improving both the quality and longevity of life for patients with heart failure. Timely detection is essential, as the condition progressively worsens without proper intervention. Therefore, early diagnosis is crucial to ensure effective treatment. Additionally, many existing treatments for heart failure remain under-researched. Health authorities must prioritize heart failure management to reduce its growing economic burden and improve patient outcomes.

The rest of this paper is organized as follows. The second section explains on the data and methodology, consisting of essential steps of Neural Network and Naïve Bayes. In the third section present the results, findings and discussion of the analysis. Finally, the fourth section presents the conclusions and future works.

2. METHODOLOGY

This study employed a quantitative research methodology to develop and evaluate predictive models for heart failure (HF) detection. The approach involved using two distinct classification algorithms: an Artificial Neural Network (ANN) and a Naïve Bayes classifier, to predict a patient's 'death event' during a follow-up period. The following sections detail the experimental setup, from data acquisition and preprocessing to model training and performance evaluation.

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2.1 Dataset information

The research utilized secondary data from the Heart Failure Clinical Records Dataset, sourced from the UCI Machine Learning Repository (UCI Machine Learning Repository, 2025). The dataset comprises 13 attributes from the medical records of 299 patients. It contains 12 input features and one target variable. The input features, which include a mix of demographic data, physiological measurements, and clinical observations, are detailed in Table 1 below. This rich feature set allows the models to learn complex relationships between patient characteristics and heart failure outcomes. The target variable, Death event, is a crucial Boolean attribute indicating whether a patient passed away during the follow-up period.

Table 1. Overview of Attributes

Attributes	Description
Age	Age of the patient (years)
Anemia	Decrease of red blood cells or hemoglobin (Boolean)
High blood pressure	If the patient has hypertension (Boolean)
Creatinine phosphokinase (CPK)	Level of the CPK enzyme in the blood (mcg/L)
Diabetes	If the patient has diabetes (Boolean)
Ejection fraction	Percentage of blood leaving the heart at each contraction (percentage)
Platelets	Platelets in the blood (kilo platelets/mL)
Sex	Woman or man (binary)
Serum creatinine	Level of serum creatinine in the blood (mg/dL)
Serum sodium	Level of serum sodium in the blood (mEq/L)
Smoking	If the patient smokes or not (Boolean)
Time	Follow-up period (days)
Death event (target)	If the patient deceased during the follow-up period (Boolean)

Source: UCI Machine Learning Repository (2025)

2.2 Artificial Neural Network (ANN) Implementation

The Artificial Neural Network (ANN), specifically a Multi-Layer Perceptron (MLP), was designed as a two-layer Feed-Forward Neural Network (FFNN). The implementation of the ANN followed a systematic process:

- Step 1: Data Preprocessing and Partitioning - Categorical attributes were converted to numerical values using dummy variables. The 299 samples were then randomly divided into three distinct categories: 70% for training (209 samples), 15% for validation (45 samples), and 15% for testing (45 samples).
- Step 2: Model Architecture - The ANN architecture was defined with 12 input neurons, 20 hidden neurons, and a single output neuron. The network used sigmoid hidden neurons and softmax output neurons.
- Step 3: Model Training - The training process employed the Scaled Conjugate Gradient (SCG) backpropagation algorithm. Training was automatically terminated when the generalization performance ceased to improve, indicated by an increase in the cross-entropy error of the validation samples.
- Step 4: Prediction Generation - The trained model was used to predict outcomes on the unseen testing dataset.
- Step 5: Performance Evaluation - The overall testing results were evaluated using several key metrics, including the confusion matrix, error histogram, and receiver operating characteristic (ROC) curves, to assess the model's accuracy, precision, and recall.

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Fig. 1 presents the flowchart of ANN process.

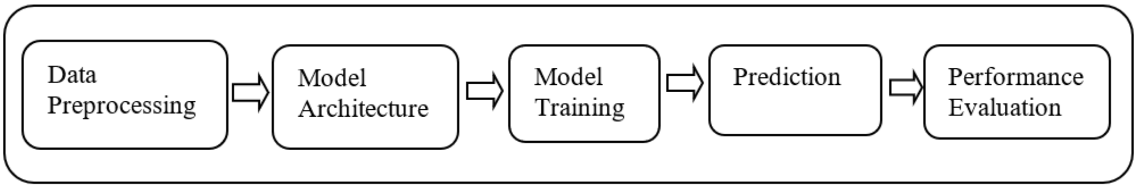

Fig. 1. Flowchart of ANN process

2.3 Naïve Bayes (NB) algorithm implementation

The Naïve Bayes (NB) classifier was chosen as a second model for its probabilistic foundation and computational simplicity. The algorithm is grounded in Bayes' probability theorem and operates under the "naïve" assumption that its features are conditionally independent given the class label. Despite this often-unrealistic assumption, Naïve Bayes has demonstrated strong performance in medical applications. The implementation of the Naïve Bayes algorithm in this study followed a systematic process:

- Step 1: Data Acquisition and Preparation - The dataset was imported into the analytical software. No missing or erroneous values were found.
- Step 2: Data Partitioning - The dataset was divided into distinct training and testing sets, incorporating a 5-fold cross-validation to ensure a robust model evaluation.
- Step 3: Model Selection and Training - The Naïve Bayes classifier was selected and applied to the training dataset, where the algorithm learns the probabilistic relationships within the data.
- Step 4: Prediction Generation - The trained model was then used to predict outcomes on the unseen testing dataset.
- Step 5: Performance Evaluation - Finally, the model's accuracy was assessed by comparing the predicted outcomes with the actual values in both the training and testing sets.

Fig. 2 presents the flowchart of Naïve Bayes process.

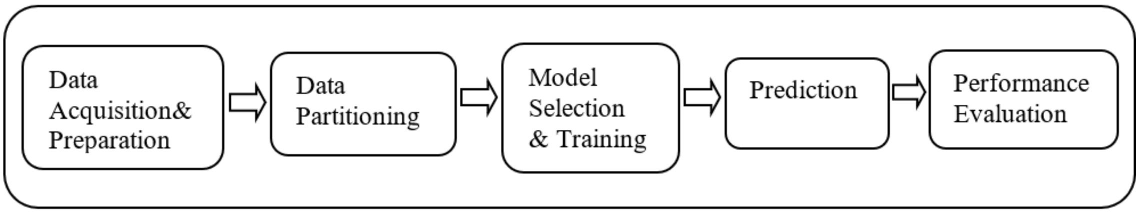

Fig. 2. Flowchart of Naïve Bayes process

2.4 Baseline Method

The Naïve Bayes classifier served as the baseline method for this study. As a probabilistic model with a strong assumption of feature independence, its performance provides a benchmark against which the more complex ANN can be compared. By establishing this baseline, the research can determine if the increased architectural complexity and computational cost of the ANN lead to a statistically significant improvement in predictive accuracy.

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2.5 Reproducibility of the proposed work

To ensure the reproducibility of the research, the experimental setup was meticulously documented. The models were implemented using the MATLAB software environment, leveraging its built-in tools such as the Neural Network Pattern Recognition Tool (nprtool) for data assignment and the SCG training function for the ANN model. All random seeds were fixed to a constant value, which guarantees that data splits and model initializations remain identical across multiple runs. This practice eliminates a source of variability, ensuring that the results are consistent and can be replicated by other researchers.

2.6 Performance metrics

The performance of both models was evaluated using several key metrics derived from a confusion matrix. This approach is particularly important in medical applications, where the costs associated with different types of errors vary significantly. A confusion matrix is a table, as shown in Table 2, that summarizes the results of a predictive model by counting the number of correct and incorrect predictions. It quantifies outcomes into four categories:

- True Positive (TP): Positive instances correctly identified.
- True Negative (TN): Negative instances correctly predicted as negative.
- False Positive (FP): Negative instances incorrectly classified as positive.
- False Negative (FN): Positive instances incorrectly classified as negative.

Table 2. Confusion matrix of the predictive model

		Actual Values (Target)	
		0	**1**
Predicted Values (Output)	**0**	TN	FN
	1	FP	TP

Source: Adapted from Swaminathan and Tantri (2024).

The four main metrics used to evaluate the model's performance are:

- Accuracy: The overall proportion of correct predictions. While a useful starting point, it can be misleading in cases of class imbalance.
- Precision: The ratio of true positives to all positive predictions. High precision is crucial when a false positive (incorrectly predicting a death event) could lead to unnecessary emotional distress or costly interventions.
- Recall (Sensitivity): The ratio of true positives to all actual positive cases.
  Recall is arguably the most critical metric in this study, as a false negative (failing to predict a death event) has severe, potentially life-threatening consequences.
- F1-Measure: The harmonic mean of precision and recall. It provides a single metric that balances the trade-off between the two.

The formulas for these metrics are:

$$Recall = \frac{TP}{TP + FN} \tag{1}$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

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$$F1 - measure = \frac{2 \times Presicion \times Recall}{Precision + Recall} \tag{4}$$

These metrics provide a nuanced understanding of the model's predictive capabilities

3. RESULTS AND DISCUSSION

A total of 209 patient data samples were used in the training of the Artificial Neural Network (ANN), with 45 samples used for validation. The input model has been trained for testing using Scaled Conjugate Gradient (Trainscg) algorithm.

The ANN training tool is shown in Fig. 3 below. Once the tool has ended, the model can open the plot. The ANN architecture shows that the model has a two-layer Feed-Forward Neural Network with sigmoid hidden and *softmax* output neurons. Besides, the training of the Trainscg algorithm shows the model training function updates the weight and bias value according to the Scaled Conjugate Gradient optimization. The ANN training will evaluate the best validation performance in the ANN and choose the cross-entropy to plot the performance.

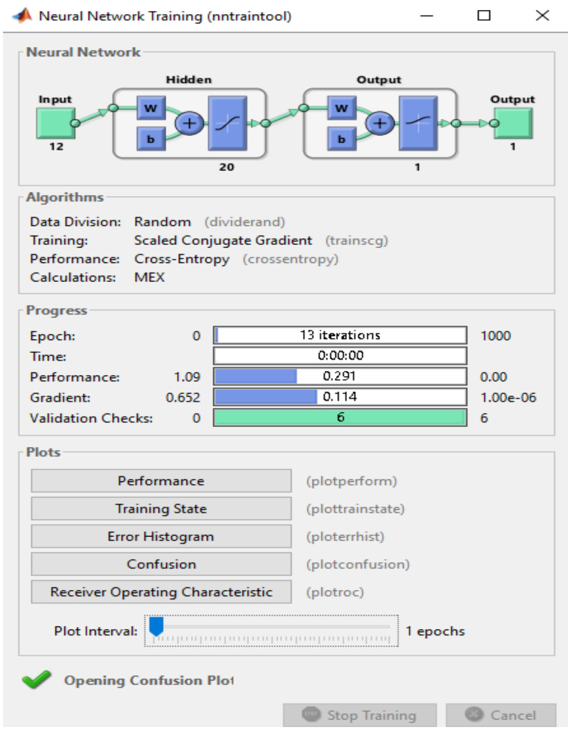

Fig. 3. NN training tool

Fig. 4 shows the trend of the train, validation, and test performance in detail. From this plot, the x-axis represents the epochs, while the y-axis represents Cross Entropy which is the minimization value of our error function. The training curve was seen decreasing with the increase of epoch number till it reached 13 epochs. It shows that the trend has appeared near the best-dotted line and to be specific, it means that the training has been done successfully and converged. The best validation performance is 0.38873 at epoch 7. The training finishes after six consecutive epochs and then increases in validation error in the default configuration. The best performance comes from the epoch with the lowest validation error.

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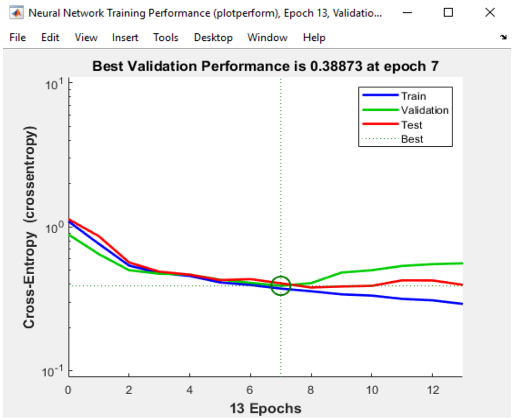

Fig. 4. NN training performance

The ANN training state, shown in Fig. 5, displays two different types of graphs. The epochs are represented on the x-axis, while the gradient value and failed validation check are represented on the y-axis. The network weights are balanced throughout the training phase to reduce the gradient, which depicts the evolution of the 0.11382 minimum gradient. Meanwhile, the second graph shows that the network stops training after six consecutive failures, where the validation check is used to stop artificial neural networks from learning.

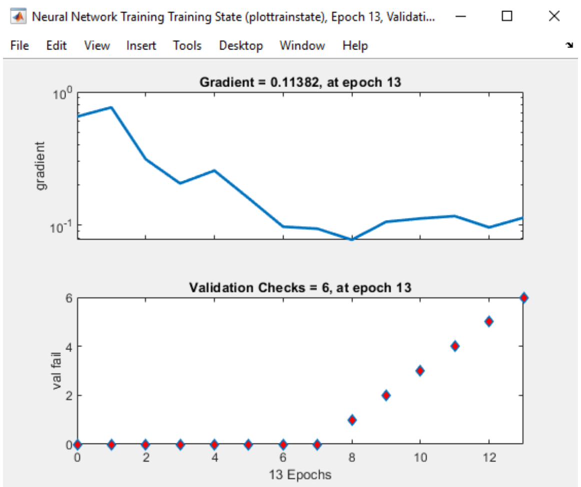

Fig. 5. NN training state

The error in histogram occurred between target and predicted values after training a Feed-Forward Neural Network (FFNN). Based on Fig. 6, the plot shows the error histogram with 20 bins. The bin corresponding to the error is (-0.02027). The height of the bin for training datasets lies below but near 70. The validation and test datasets lie between 70 and 90, and this means the error lies between that range.

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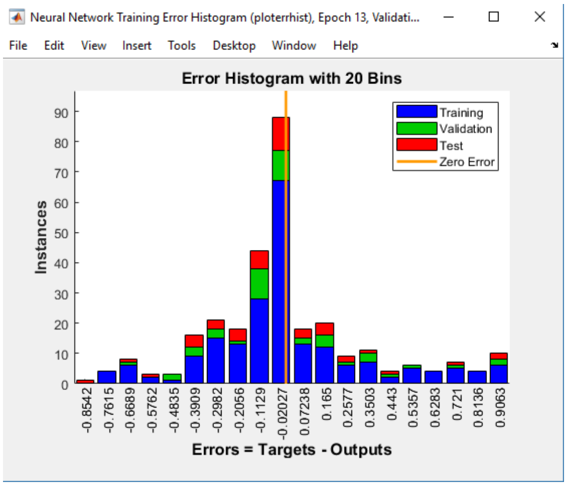

Fig. 6. NN training error histogram

Next is the Receiver Operating Characteristic (ROC) on the ANN and Naïve Bayes. The ROC curve depicts the true-positive (TP) rate versus the false-positive (FP) rate for the learned classifier currently in use. The best feasible prediction approach would result in a point in the upper left corner of the ROC space, with 100% sensitivity and 100% specificity. For example, Fig. 7 shows that the ANN generates the best ROC because it appeared near the coordinate (0,1).

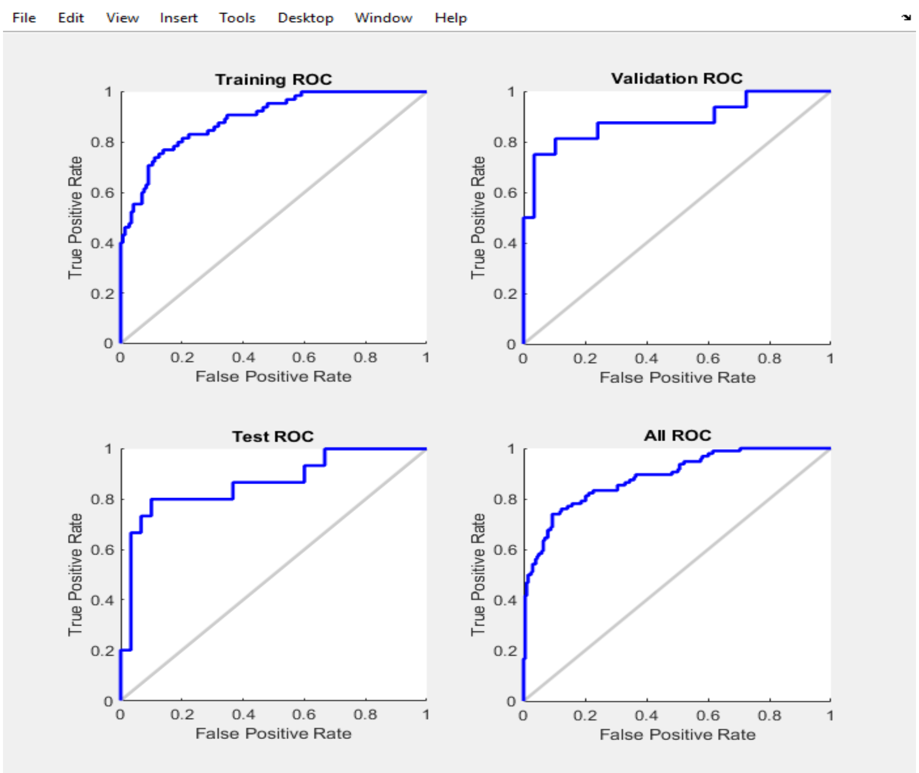

Fig. 7. ROC of ANN

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The red marker indicates the performance of the currently selected classifier on the plot. For example, Fig. 8 shows the ROC curve for patients who do not suffer from heart disease, which an FP rate of 0.54 means that the present classifier wrongly allocates 54% of the data to the positive class. On the other hand, with a TP rate of 0.92, the current classifier correctly allocates 92% of the observations to the positive class. It also shows a large Area Under Curve (AUC) of 0.87, indicating better classifier performance.

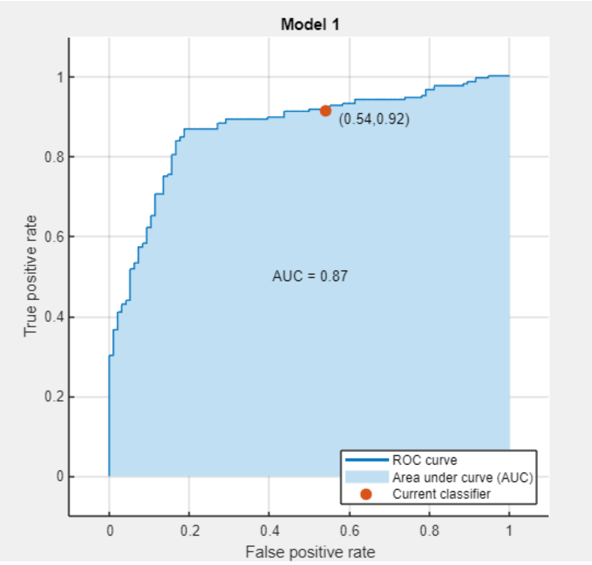

Fig. 8. ROC of Naïve Bayes

Next, the performance criteria will be calculated by employing the Equation (1) - (4) as follows.

ANN:

$$Recall = \frac{27}{27+3} \times 100\% \qquad = 90\%$$

$$Accuracy = \frac{27+12}{27+3+3+12} \times 100\% \qquad = 86.7\%$$

$$Precision = \frac{27}{27+3} \times 100\% \qquad = 90\%$$

$$F1 - measure = \frac{2 \times 0.9 \times 0.9}{0.9+0.9} \times 100\% \qquad = 90\%$$

Naïve Bayes:

$$Recall = \frac{186}{186+17} \times 100\% \qquad = 91.6\%$$

$$Accuracy = \frac{186+44}{186+44+17+52} \times 100\% \qquad = 76.9\%$$

$$Precision = \frac{186}{186+52} \times 100\% \qquad = 78.2\%$$

$$F1 - measure = \frac{2 \times 0.916 \times 0.782}{0.916+0.782} \times 100\% \qquad = 84.4\%$$

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Based on Table 3 below, ANN shows higher accuracy than Naïve Bayes, 86.7% and 76.9%, respectively. ANN showed high accuracy because it can handle a large amount of dataset provided, yet it can indirectly discover complex non-linear interactions between dependent and independent variables. Even though Naïve Bayes has lower accuracy than ANN, but the result still shows that Naïve Bayes also has a good accuracy range. Naïve Bayes is a simple yet powerful algorithm to be chosen. This can be proven by a previous study by Dangare and Apte (2012) which revealed the comparison results between ANN and Naïve Bayes in predicting heart disease, which is 99.25% and 94.44%, respectively. Similarly, Sajja and Kalluri (2020) have proved the results of the comparison between ANN and Naïve Bayes in their study, which are ANN and Naïve Bayes showed 86.97% and 77.04%, respectively. Overall, this indicates that ANN has better performance for this dataset.

Table 3. Comparison of performance measure of ANN and Naïve Bayes

Algorithm	Sensitivity	Precision	F1 Score	Accuracy
ANN	90.0%	90.0%	90.0%	86.7%
Naïve Bayes	91.6%	78.2%	84.4%	76.9%

4. CONCLUSION

The present study was designed to show that the classification of heart disease is important in our daily lives. This is because it can assist doctors and experts in screening the process of detecting heart failure in the patient. In order to identify highly accurate methods for detecting heart failure, there are two methods used in this study, the Artificial Neural Network (ANN) and the Naïve Bayes. This study found that using ANN with 20 hidden layers gave us good accuracy. The advantage of a ANN is that it can detect complicated non-linear correlations between dependent and independent variables without requiring extensive statistical training. The acquired result demonstrates that the training data created allows the ANN to predict the output for the testing dataset. This study indicates that ANN produced 86.7% testing accuracy while Naïve Bayes showed 76.9% testing accuracy. Overall, ANN showed significant results in the diagnosis of heart disease. This shows us that the results of this study support the idea that deep learning can be used to determine the specific risk of heart failure by using structured datasets.

Implementing a future study exploring the potential of ANN is an inspiring prospect. The research could be broadened to encompass longitudinal studies of patients, thereby enhancing the accuracy of heart disease prediction. This study proposes the application of a Multi-Layer Perceptron Neural Network (MLPNN), which has shown promising results. Its implementation could assist domain experts and individuals in the field in planning for improved diagnosis and providing patients with early diagnosis results. The MLPNN performs admirably, even without retraining, and has the potential to reduce the number of hidden layers while enhancing the number of patient-related attributes. Future studies involving NN should be applied in real-world applications, offering the potential to alleviate the burden on experts and benefit the health community while reducing costs.

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6. CONFLICT OF INTEREST STATEMENT

The authors agree that this research was conducted in the absence of any self-benefits, commercial or financial conflicts and declare the absence of conflicting interests with the funders.

7. AUTHORS' CONTRIBUTIONS

Norpah Mahat: Conceptualisation, supervision and writing original draft and investigation; **Norazwana Saidin @ Zubir**: Conceptualisation, methodology and formal analysis; **Jasmani Bidin**: Writing Introduction; **Izleen Ibrahim**: Methodology; **Sharifah Fhahriyah**: Results and discussion; **Mohamad Najib Mohamad Fadzil**: Conclusion and future work; **Siti Sarah Raseli**: Writing- review and editing, and validation.

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