# Comparative Analysis of MLP and RBF Neural Networks for Heart Disease Diagnosis: The Impact of Feature Selection on Model Performance

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**Abstract:**

In this study, we investigate the impact of feature selection and the number of features on the performance of learning models for heart disease diagnosis, focusing on two neural network architectures: the Multilayer Perceptron (MLP) and Radial Basis Function (RBF). The research aims to assess the performance of these models using feature sets of 5, 10, and 13 features, selected based on their correlation with the target variable. Our results show that the MLP model consistently outperforms the RBF model, achieving the highest accuracy of 98.3% when utilizing 13 features. However, we found that simply increasing the number of features does not always guarantee improved performance, as irrelevant features can introduce noise and hinder model optimization. This was particularly evident in the RBF network, where the model trained on 10 features outperformed the one using all 13.

The use of advanced feature selection techniques, such as correlation-based selection, contributed to enhancing the model's accuracy and reducing overfitting. This study highlights the importance of balancing feature quantity with feature relevance and optimizing model architecture for improved heart disease diagnosis. The findings suggest that while MLP demonstrates better performance across different feature sets, careful feature selection and complexity management are key to achieving optimal results in medical data analysis.

**Keywords:** Heart Disease Diagnosis, Multilayer Perceptron Neural Network (MLP), Radial Basis Function Neural Network (RBF).

## 1 Introduction

Heart disease is one of the leading causes of death worldwide, making accurate and early diagnosis a critical priority in healthcare [1]. Electrocardiogram (ECG) data, which records the electrical activity of the heart, has been widely used to diagnose heart disease [2]. However, manually analyzing ECG data can be challenging due to the complexity and variability of heart signals. This has led to an increasing interest in leveraging machine learning techniques, particularly neural networks, to automate and enhance the diagnosis process.

In recent years, neural networks have demonstrated great potential in medical diagnostics [3], offering the ability to model complex and nonlinear relationships in data. Among the various types of neural networks, Multilayer Perceptron (MLP) and Radial Basis Function (RBF) networks have gained significant attention for their efficacy in classification tasks [4]. Both models belong to the family of feedforward neural networks [5], where data flows from the input layer to the output layer without loops, ensuring efficient learning and prediction processes.

The MLP, a fully connected network with multiple hidden layers, is known for its capability to learn intricate patterns in large datasets. It uses activation functions such as ReLU and sigmoid to capture nonlinear relationships, making it highly suitable for complex tasks like heart disease diagnosis [6]. On the other hand, the RBF network uses radial basis functions as its activation functions and typically has only one hidden layer. The RBF network focuses on the distance between input data points and predefined centers, which allows it to process data quickly, though it may be less effective in handling highly complex patterns compared to MLP [7].

While both MLP and RBF networks have proven to be effective for classification tasks, one of the key factors that influences their performance is the selection and number of features used in the training process [8]. Feature selection is critical in medical diagnostics, as using irrelevant or redundant features can reduce the model's accuracy and increase the risk of overfitting [9]. Therefore, this study aims to investigate the impact of different feature sets (5, 10, and 13 features) on the

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performance of MLP and RBF neural networks for heart disease diagnosis.

The main objectives of this research are as follows:

- To compare the performance of MLP and RBF neural networks in heart disease diagnosis using various feature sets.
- To analyze how the number and selection of features affect model accuracy and efficiency.
- To explore the advantages and limitations of MLP and RBF networks in handling medical data.

By addressing these objectives, this study seeks to provide a comprehensive understanding of how feature selection and neural network architecture influence the accuracy and effectiveness of heart disease diagnosis systems. In Figure 1, the overall the overall process and performance of the heart disease diagnosis system based on feature selection and neural network architecture is illustrated.

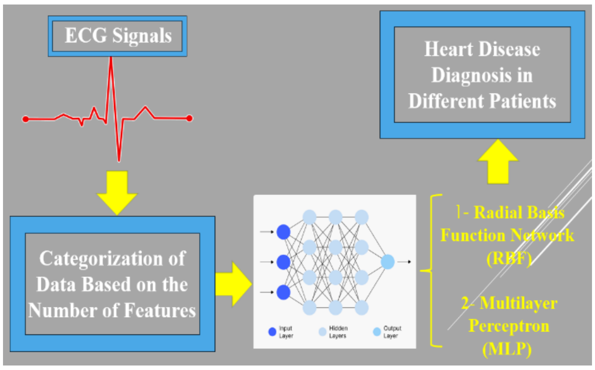


Figure 1: The general algorithm of the research methodology

### A. Related work

In recent years, the use of machine learning and deep learning algorithms for heart disease diagnosis has gained significant attention from researchers. Algorithms such as the Multilayer Perceptron (MLP) and Radial Basis Function (RBF) Networks have been widely adopted due to their ability to detect complex patterns in medical data. However, studies have shown that MLP performs less effectively on certain datasets compared to other models like Random Forest, underscoring the importance of hybrid algorithms for handling complex data. One limitation of this study is the lack of comprehensive hyperparameter tuning, an issue that has been addressed in other research through more thorough optimization [10]. Another study compared the performance of MLP and improved MLP in heart disease diagnosis, showing that the improved MLP performed better in terms of accuracy and execution time. However, this research was limited to comparisons with other algorithms [11].

In another study, the proposed system achieved an accuracy of 92.9% for MLP and 93.7% for RBF. Although the difference in accuracy and sensitivity between the two models was small, the study did not fully optimize the hyperparameters [12]. Multilayer Feedforward Neural Networks (MLPNNs) demonstrated higher accuracy compared to statistical methods such as Logistic Regression (LR) and Quadratic Discriminant Analysis (QDA), but performed worse than Recurrent Neural Networks (RNNs) in modeling time-series data [13].

Another study examined feature selection for optimizing machine learning algorithms. Results showed that filter methods improved accuracy in some models like j48, while reducing performance in models like MLP and Random Forest (RF) [14]. In the study by Mehrabi et al., precise feature selection significantly improved the performance of MLP and RBF in distinguishing between COPD and CHF. MLP achieved a sensitivity of 83.9% and specificity of 86%, while RBF showed a sensitivity of 81.8% and specificity of 88.4% [15].

Another study introduced a modified version of MLP with additional inputs similar to RBFN networks. This research found that CBP and ECBP networks outperformed MLP and RBFN, and the modifications made to MLP significantly improved classification and approximation tasks [16]. In another study, a system was designed for real-time heart disease prediction using MLP, trained with two datasets: UCI heart disease and cardiovascular heart disease data. It achieved an accuracy of 85.71% and 87.30%, respectively, showing a 12-13% improvement over previous studies [17].

Moreover, a comparison between MLP and RBF algorithms revealed that MLPs perform better with larger datasets, while RBFs are more effective with smaller datasets. These results highlight the importance of dataset size in optimizing neural network algorithms [18]. Another study showed that the MLP model, with an accuracy of 82%, could serve as a non-invasive alternative for CAD diagnosis, improving patient outcomes and reducing unnecessary interventions [19].

## 2 Materials & Methods

### A. Dataset

In this study, we utilized heart disease data from GitHub [20], which consists of 303 samples. Each sample contains 13 distinct features, listed in Table 1, which outlines these attributes along with their descriptions and value ranges. The features cover a range of demographic, clinical, and medical test results that are typically associated with cardiovascular conditions. These features are crucial for analyzing the likelihood of heart disease development in individuals.

| Attribute | Description | Value Description |
|---|---|---|
| **age** | Patient's age | Numeric values: Patient's age in years |
| **sex** | Gender of the patient | 0: Female, 1: Male |
| **cp** | Chest pain type | 0: No chest pain, 1: Typical angina, 2: Atypical angina, 3: Asymptomatic |
| **trestbps** | Resting blood pressure | Numeric values: Patient's blood pressure in mm Hg |
| **chol** | Serum cholesterol level | Numeric values: Patient's cholesterol level in mg/dL |
| **fbs** | Fasting blood sugar | 0: Normal blood sugar (less than 120 mg/dL), 1: High blood sugar (above 120 mg/dL) |
| **restecg** | Resting electrocardiographic results | 0: Normal, 1: ST-T wave abnormality, 2: Left ventricular hypertrophy |
| **thalachh** | Maximum heart rate achieved | Numeric values: Maximum heart rate of the patient in beats per minute |
| **exng** | Exercise induced angina | 0: No pain, 1: Pain |
| **oldpeak** | ST depression induced by exercise relative to rest | Numeric values: Amount of ST depression in millivolts |
| **slp** | Slope of the peak exercise ST segment | 0: Downsloping, 1: Flat, 2: Upsloping |
| **caa** | Number of major vessels colored by fluoroscopy | 0 to 4: Indicates the number of major vessels affected. 0: No vessels are affected, 1 to 4: Higher numbers indicate more severe disease. |
| **thal** | Type of thalassemia | 1: Normal, 2: Fixed defect, 3: Reversible defect |
| **output** | Target label | 0: No heart disease, 1: Heart disease |

Table 1: Data Attributes

## B. Data Classification by Feature Count

In this study, cardiac signal data from various individuals was used as input, with each data point consisting of 13 different features related to heart activity. The primary aim of this research was to examine how the number of features affects the accuracy of heart disease diagnosis using two distinct neural networks, MLP and RBF. These networks were evaluated separately under three different conditions, and their results were compared.

To assess the impact of the number of features on diagnostic accuracy, the data was divided into three categories. In the first category, 5 key features were used; in the second, 10 features; and in the third category, all 13 features were employed. Each dataset was then fed into a neural network, and the diagnostic accuracy was measured for each category. This method allowed us to precisely evaluate and compare the influence of each feature set on the model’s diagnostic accuracy.

Feature selection for the models was performed using a correlation matrix, as shown in Figure 2.

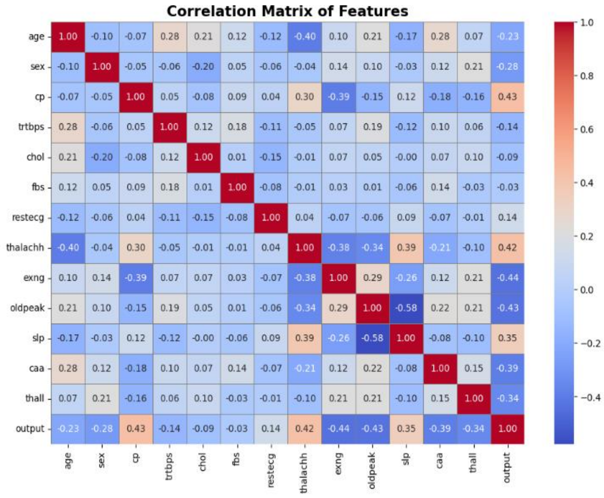


Figure 2: Correlation Matrix of Various Features with the Target Variable (Heart Disease Diagnosis)

This matrix demonstrates the correlation between different features and the target variable (heart disease diagnosis). Features with the highest positive or negative correlation with the target variable were chosen as the primary features.

The correlation matrix is a statistical tool that shows the correlation between two or more variables using Pearson's correlation coefficient ($\rho$). The formula for Pearson's correlation coefficient is:

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} = \frac{\sum (X_i - \mu_X)(Y_i - \mu_Y)}{\sqrt{\sum (X_i - \mu_X)^2} . \sqrt{\sum (Y_i - \mu_Y)^2}}$$

- X and Y are two different features.
- $cov(X,Y)$ is the covariance between the two features.
- $\sigma_X$ and $\sigma_Y$ are the standard deviations of features X and Y.
- $\mu_X$ and $\mu_Y$ are the means of features X and Y.

This formula shows that the correlation coefficient is a dimensionless measure that quantifies the strength and direction of the linear relationship between two variables. Using this metric in the correlation matrix helps identify and select the features with the most significant impact on the target variable (heart disease diagnosis).

- 13-Feature Category:

In this category, all available features from the dataset were used. The goal was to analyze all factors affecting heart disease and use the full scope of information for a more accurate prediction.

- 10-Feature Category:

In this category, features that had a strong correlation with the target were selected, but the total number was limited to 10. These features include cp, thalachh, exng, oldpeak, slope, thal, ca, age, sex, and restecg. This reduction was made to simplify the model and prevent overfitting.

- 5-Feature Category:

In this category, the five features with the highest correlation with the output were selected: cp, thalachh, exng, oldpeak, and slope. These features were chosen to simplify the model and speed up the training process while still maintaining high diagnostic accuracy.

By selecting these three feature sets, deep learning models of varying complexity were evaluated to determine the optimal combination of features for more accurate and efficient heart disease prediction.

## C. Neural Networks

In this study, two neural networks, MLP (Multilayer Perceptron) and RBF (Radial Basis Function), were used. These networks were chosen because both belong to the family of feedforward neural networks and share many architectural similarities. Both consist of input, hidden, and output layers, and the flow of information in each is feedforward, meaning data moves from the input layer to the output layer without any backward loops.

Feedforward neural networks are among the oldest and most well-known architectures in artificial neural networks. These networks feature one or more hidden layers responsible for processing inputs and producing the final output. In this architecture, the neurons in each layer are fully connected to the neurons in the next layer, meaning that each neuron in one layer is connected to all neurons in the subsequent layer.
The general calculation formula in a feedforward neural network is as follows [21]:

$$h_1 = \phi(W_1^T x)$$

$$h_{p+1} = \phi\left(W_{p+1}^T h_p\right)$$

$$\text{o} = \phi(W_k^T h_k)$$

Where:

- W is the weight matrix.
- x is the input.
- h represents the hidden layers.
- $\phi$ is the activation function.

- **Radial Basis Function Network (RBF)**

RBF networks are a specific type of feedforward neural network, with the main difference from MLP being the type of hidden layer and activation function. In RBF networks, there is only one hidden layer, and the neurons in this layer use radial basis functions to process the inputs. The radial basis function is usually defined as:

$$\phi(r) = e^{(-\beta \|x-c\|^2)}$$

Where:

- $\|$ x-c $\|$ is the Euclidean distance between the input x and the center c.
- $\beta$ is a parameter that determines the spread of the radial function.

RBF networks are typically used for classification problems and, due to their simpler structure and fewer hidden layers, have a faster learning process. The hidden layer neurons in these networks activate based on the distance of inputs from pre-determined centers, making the tuning and training faster.

- **Multilayer Perceptron (MLP)**

MLP consists of multiple hidden layers, where each neuron in one layer is connected to all neurons in the next layer. This network can model complex relationships between inputs and outputs using non-linear activation functions such as ReLU or sigmoid.

In the MLP network used in this study, the ReLU activation function is used in the hidden layers, which is defined as follows:

$$f(x) = \max(0, x)$$

However, in the output layer of this network, the sigmoid function is used, defined as:

$$\sigma_x = \frac{1}{1 + e^{-x}}$$

This combination allows the hidden layers to learn complex and non-linear patterns, while the output layer using the sigmoid function produces output as probabilities between 0 and 1 for binary classification.

The MLP network can learn more complex patterns as the number of hidden layers increases. Unlike RBF, which has only one hidden layer, MLP can have multiple hidden layers, making it more suitable for solving more complex problems with diverse data.

The main difference between the two networks, MLP and RBF, lies in the type of hidden layer and the activation function:

- In RBF, the hidden layer neurons use radial basis functions that activate based on the distance between inputs and pre-determined centers.
- In MLP, the hidden layer neurons use non-linear activation functions such as ReLU, and the output layer uses the sigmoid function for binary classification.

Additionally, RBF networks typically have only one hidden layer and a faster learning process, while MLP networks, with multiple hidden layers, take longer to train but can solve more complex problems and simulate non-linear systems.

## 3 Results and Discussion

In this section, we analyze and compare the performance of MLP (Multilayer Perceptron) and RBF (Radial Basis Function) networks using three different feature sets (5, 10, and 13 features). The results are evaluated based on various performance metrics, including accuracy, precision, recall, and F1-score, for both classes "Heart Disease Present" (Class 1) and "Heart Disease Absent" (Class 0). The comparison is depicted in Figures 3 and 4, along with the table 2, summarizing the numerical performance values for both networks.

As seen in Figure 3, both MLP and RBF networks perform better as more features are included. The MLP model generally outperforms the RBF model, achieving the highest accuracy of 98.36% with 13 features, while the RBF network achieves 83.61% accuracy with the same feature set. The MLP model shows consistent performance even with 10 and 5 features, recording 95.08% and 91.80% accuracy, respectively. In contrast, the RBF network experiences a sharp drop in performance with fewer features, reaching 78.69% accuracy when only 5 features are used.

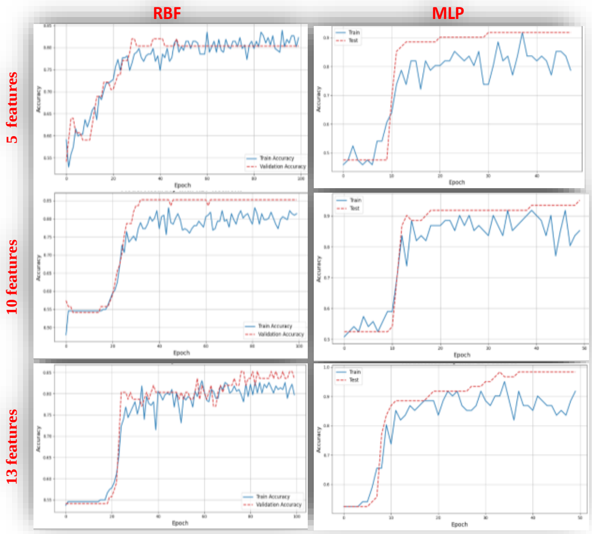


Figure 3. Accuracy Diagram of the Model

Figure 4, illustrates the loss reduction trends during the training process. The MLP network shows the lowest loss throughout the training process, particularly with 13 features, indicating better adaptation to the data. The RBF network also reduces its loss as the number of features increases, but it generally performs less optimally than the MLP. When using 5 features, both networks show slower loss reduction, particularly the RBF model, where the final loss remains significantly higher.

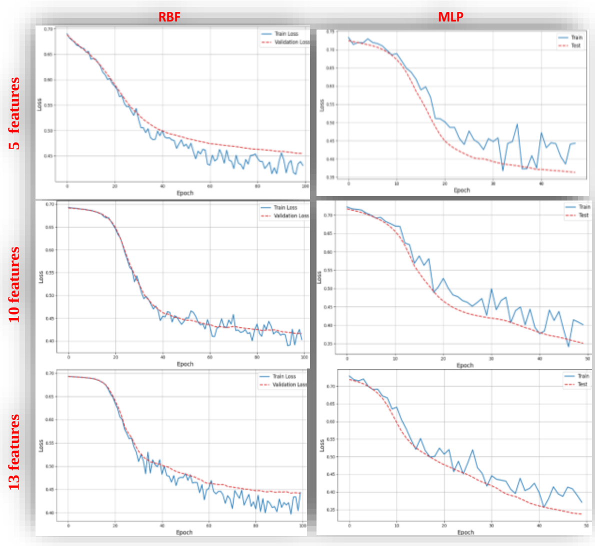


Figure 4. Loss Diagram of the Model

Table 2, provides a detailed comparison of precision, recall, and F1-score for both networks. These metrics are calculated as follows:

- **Precision:**

Measures the ratio of correctly predicted positive samples to the total number of predicted positives [22]:

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

Where TP is the number of true positives and FP is the number of false positives. The MLP model with 13 features achieved a precision of 100% for Class 1, indicating no false positives. The RBF model, on the other hand, shows a lower precision, especially when fewer features are used.

- **Recall:**

Measures the ratio of correctly predicted positive samples to the total number of actual positives [23]:

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

Where FN is the number of false negatives. The MLP model shows a perfect recall of 100% for both classes when 13 features are used, while the RBF network shows lower recall values, particularly with 5 features (81%).

- **F1-Score:**

Provides a balance between precision and recall [23]:

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

The MLP model achieved the highest F1-scores for both classes using 13 features, highlighting its ability to balance precision and recall effectively. The RBF model exhibited lower F1-scores, particularly with fewer features, indicating less efficient performance.

| Metric | MLP | | | RBF | | |
|---|---|---|---|---|---|---|
| | 13 Features | 10 Features | 5 Features | 13 Features | 10 Features | 5 Features |
| Accuracy | 98.36% | 95.08% | 91.80% | 83.61% | 85.25% | 78.69% |
| Precision (Class 0) | 96.67% | 96.43% | 92.86% | 85% | 91% | 78% |
| Precision (Class 1) | 100% | 93.94% | 90.91% | 83% | 82% | 79% |
| Recall (Class 0) | 100% | 93.10% | 89.66% | 79% | 75% | 75% |
| Recall (Class 1) | 96.88% | 96.88% | 93.75% | 88% | 94% | 81% |
| F1-Score (Class 0) | 98.31% | 94.74% | 91.23% | 81% | 82% | 76% |
| F1-Score (Class 1) | 98.41% | 95.39% | 92.31% | 85% | 87% | 81% |

Table 2. Comparison of Selected Neural Network Models Performance

The results indicate that the MLP model consistently outperforms the RBF model across all metrics and feature sets. The MLP model shows higher accuracy, precision, recall, and F1-scores, particularly with 13 features. The RBF network, although faster to train, struggles to match the MLP's performance, especially when fewer features are used.

Despite the MLP model requiring more computational resources due to its complex structure, it offers superior performance in predicting heart disease. Conversely, the RBF model, though simpler and faster, may still be useful in situations where speed and simplicity are more critical than accuracy, particularly when limited features are available.

## 4 Conclusions

In this study, the performance of two neural network models, MLP and RBF, was investigated using different.

feature sets (5, 10, and 13 features) for heart disease detection. The results demonstrated that while an increase in the number of features generally improved model accuracy, the relevance and impact of the features played a crucial role in overall model performance.

One key finding from the results was that simply increasing the number of features does not always guarantee better performance, especially when irrelevant or less impactful features are included. This was particularly evident in the case of the RBF model. While the RBF network performed better with 10 features compared to 13, suggesting that not all features contributed positively to the model's learning process. The addition of less relevant features likely introduced noise, reducing the model's efficiency and making it harder to optimize.

On the other hand, the MLP model consistently outperformed the RBF model across all feature sets. The MLP model, with its multi-layer architecture and ability to model complex relationships between features, demonstrated superior learning capabilities. With 13 features, it achieved the highest accuracy of 98.36%, confirming that MLP can better leverage a larger set of features when relevant data is provided. This highlights the importance of selecting an appropriate model architecture for complex, nonlinear tasks like heart disease diagnosis.

The innovation in this research lies in the detailed comparison between the MLP and RBF models across different feature sets, providing insights into how feature selection impacts model performance. Additionally, this study emphasizes that focusing solely on the number of features is not enough; careful attention must be given to the relevance and impact of these features. By using a combination of correlation-based feature selection and neural network models, this research contributes to a deeper understanding of how feature importance influences machine learning outcomes in medical diagnosis.

In summary, while increasing the number of features can improve model accuracy, the key to success lies in selecting the most impactful and relevant features. The MLP model showed robust performance across all datasets, making it a better choice for heart disease prediction compared to RBF, which was more sensitive to the quality and number of features. This research provides a valuable framework for future studies aiming to optimize feature selection and model architecture for better predictive outcomes in medical data analysis.

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