INTERNATIONAL JOURNAL OF INTELLIGENT DATA AND MACHINE LEARNING

# ADVANCED MACHINE LEARNING FOR CARDIAC DISEASE CLASSIFICATION: A PERFORMANCE ANALYSIS

**Dr. Ali H. Al-Najjar**
**Department of Biomedical Engineering, King Abdulaziz University, Jeddah, Saudi Arabia**

**Dr. Peter M. Osei**
**Department of Computer Science, University of Ghana, Legon, Ghana**

**Published Date: 14 December 2024 // Page no.:- 6-10**

## ABSTRACT

Heart disease remains a leading cause of morbidity and mortality globally, necessitating accurate and early diagnostic tools to improve patient outcomes. The escalating volume of healthcare data, coupled with advancements in computational capabilities, has positioned machine learning (ML) as a transformative approach for enhancing the classification of cardiac conditions. This article provides a comprehensive evaluation of machine learning models, particularly focusing on Multilayer Perceptron (MLP) and Support Vector Machine (SVM) architectures, for their efficacy in classifying heart disease. We delve into the methodologies employed, including feature selection and model training, and analyze their performance metrics. The discussion highlights how these advanced computational techniques contribute to more precise, efficient, and reliable diagnostic support systems, thereby aiding clinicians in early detection and personalized treatment strategies.

**Keywords:** Machine learning, cardiac disease classification, cardiovascular diagnosis, predictive modeling, deep learning, medical data analysis, heart disease detection, AI in cardiology, performance evaluation, healthcare analytics.

## INTRODUCTION

Cardiovascular diseases, collectively known as heart disease, represent a significant global health challenge, accounting for a substantial proportion of deaths and disabilities worldwide. The complex etiology and varied manifestations of heart disease necessitate timely and accurate diagnosis to enable effective intervention and improve patient prognosis. Traditional diagnostic methods often rely on clinical expertise, patient history, physical examinations, and a range of medical tests. However, the sheer volume and complexity of medical data, combined with the need for rapid and precise decision-making, present considerable challenges to conventional diagnostic approaches.

In recent years, the rapid evolution of artificial intelligence, particularly machine learning (ML), has opened new avenues for revolutionizing healthcare diagnostics. Machine learning algorithms possess the remarkable ability to learn intricate patterns and relationships from vast datasets, making them exceptionally well-suited for tasks such as disease prediction and classification [4], [10]. The application of ML in healthcare aims to augment human capabilities, providing clinicians with powerful tools for predictive analytics, personalized medicine, and enhanced diagnostic accuracy. Specifically, in the realm of heart disease, ML models offer the potential to analyze diverse patient data—ranging from demographic information and lifestyle factors to clinical measurements and laboratory results—to identify individuals at risk or classify specific cardiac conditions with high precision [8], [9].

Among the various machine learning paradigms, Artificial Neural Networks (ANNs), particularly the Multilayer Perceptron (MLP), and Support Vector Machines (SVMs) have garnered significant attention for their robust performance in classification tasks [2], [3], [5], [6], [7], [9]. MLPs, as a class of feedforward ANNs, are capable of learning complex non-linear relationships within data, making them highly effective for intricate diagnostic problems [2], [3], [6], [8]. Similarly, SVMs are powerful discriminative classifiers known for their ability to find optimal hyperplanes that separate different classes, even in high-dimensional feature spaces [5], [9].

This article aims to provide a detailed performance evaluation of machine learning models, with a particular emphasis on MLPs, for the classification of heart disease. We will explore the typical methodological framework involved in developing such systems, including data preprocessing, feature selection, model training, and performance assessment. By critically analyzing the strengths and limitations of these ML approaches, this paper seeks to underscore their transformative potential in enhancing the accuracy, efficiency, and reliability of heart disease diagnosis, ultimately contributing to better patient care and more effective public health strategies.

## METHODOLOGY

The development and evaluation of machine learning models for heart disease classification typically follow a structured methodology, encompassing data acquisition, preprocessing, feature selection, model training, and performance assessment.

**A. Data Acquisition and Preprocessing**

The foundation of any robust machine learning model is a comprehensive and high-quality dataset. For heart disease classification, datasets commonly include a variety of patient attributes such as age, gender, chest pain type, resting blood pressure, serum cholesterol, fasting blood sugar, resting electrocardiographic results, maximum heart rate achieved, exercise-induced angina, oldpeak (ST depression induced by exercise relative to rest), slope of the peak exercise ST segment, number of major vessels colored by fluoroscopy, and thal (a blood disorder) [1], [2], [4]. These datasets are often collected from clinical repositories or publicly available medical databases.

Once acquired, raw data typically undergoes several preprocessing steps to ensure its quality, consistency, and suitability for machine learning algorithms:

1. Handling Missing Values: Missing data points can significantly impact model performance. Common strategies include imputation (e.g., mean, median, mode imputation) or removal of instances with excessive missing data.

2. Outlier Detection and Treatment: Outliers, which are data points significantly different from others, can skew model training. Techniques like Z-score, IQR (Interquartile Range) method, or visual inspection are used to identify and either remove or transform outliers.

3. Data Normalization/Standardization: Features often have different scales and ranges. Normalization (scaling values to a fixed range, e.g., 0-1) or standardization (transforming data to have a mean of 0 and standard deviation of 1) is crucial to prevent features with larger numerical values from dominating the learning process [2]. This step ensures that all features contribute equally to the model's learning.

4. Categorical Feature Encoding: Categorical variables (e.g., chest pain type, thal) need to be converted into numerical representations. One-hot encoding or label encoding are commonly used methods.

**B. Feature Selection**

Feature selection is a critical step that involves identifying and selecting the most relevant features from the dataset for model training [1]. This process helps in reducing dimensionality, mitigating overfitting, improving model interpretability, and enhancing computational efficiency. For heart disease prediction, effective feature selection can pinpoint the most indicative clinical markers.

Common feature selection techniques include:

1. Filter Methods: These methods select features based on their intrinsic properties, independent of the learning algorithm. Examples include correlation-based feature selection (CFS) [1], mutual information, and chi-squared tests. CFS, for instance, evaluates the worth of a subset of features by considering the individual predictive ability of each feature along with the redundancy between them [1].

2. Wrapper Methods: These methods use a specific machine learning algorithm to evaluate the performance of different feature subsets. Examples include Recursive Feature Elimination (RFE) and Sequential Feature Selection.

3. Embedded Methods: These methods perform feature selection as part of the model training process. Examples include Lasso regression and tree-based methods that assign feature importance scores.

C. Model Training and Validation

After preprocessing and feature selection, the dataset is typically split into training, validation, and test sets. The training set is used to train the machine learning model, the validation set is used to tune hyperparameters and prevent overfitting, and the test set is used for final, unbiased performance evaluation.

1. Multilayer Perceptron (MLP) Models:

o MLPs are feedforward artificial neural networks consisting of an input layer, one or more hidden layers, and an output layer [2], [3], [4], [6], [8], [9]. Each layer is composed of interconnected nodes (neurons), and connections between neurons have associated weights.

o Architecture Design: This involves determining the number of hidden layers, the number of neurons in each hidden layer, and the activation functions (e.g., ReLU, sigmoid, tanh) for the hidden and output layers [2]. For heart disease classification, the output layer typically uses a sigmoid activation function for binary classification (presence/absence of disease).

o Training: MLPs are trained using backpropagation, an algorithm that adjusts the weights of the connections to minimize the difference between the model's predictions and the actual outcomes. Optimization algorithms like Adam or Stochastic Gradient Descent (SGD) are used during training [2]. The goal is to learn complex, non-linear relationships within the healthcare data [9].

o Ensemble MLPs: Committee machines with ensembles of MLPs have been proposed to enhance diagnostic support for heart diseases, leveraging the collective intelligence of multiple models [3], [7].

2. Support Vector Machine (SVM) Models:

o SVMs are supervised learning models used for classification and regression analysis [5], [9]. They work by finding an optimal hyperplane that best separates data points of different classes in a high-dimensional space.

o Kernel Functions: SVMs use kernel functions (e.g., linear, polynomial, radial basis function - RBF) to transform the input data into a higher-dimensional space, making it possible to find a linear separation even if the data is not linearly separable in the original space [5], [9].

o Optimization: The training of an SVM involves solving a quadratic programming problem to find the optimal hyperplane and support vectors. Sequential Minimal Optimization (SMO) is a popular algorithm for training SVMs, particularly for large datasets [5].

D. Performance Evaluation

The performance of the trained machine learning models is rigorously evaluated using various metrics to assess their effectiveness in classifying heart disease. The choice of metrics depends on the specific goals of the classification task and the characteristics of the dataset (e.g., class imbalance).

Common performance metrics include:

1. Accuracy: The proportion of correctly classified instances (both true positives and true negatives) out of the total number of instances. While a general measure, it can be misleading in imbalanced datasets.

2. Precision (Positive Predictive Value): The proportion of true positive predictions among all positive predictions made by the model. It indicates the model's ability to avoid false positives.

3. Recall (Sensitivity): The proportion of true positive predictions among all actual positive instances. It indicates the model's ability to correctly identify all positive cases, crucial for disease diagnosis.

4. F1-Score: The harmonic mean of precision and recall, providing a balanced measure of a model's accuracy, especially useful when there is an uneven class distribution.

5. Specificity: The proportion of true negative predictions among all actual negative instances. It indicates the model's ability to correctly identify healthy individuals.

6. Area Under the Receiver Operating Characteristic (ROC) Curve (AUC-ROC): A robust metric that evaluates the model's ability to distinguish between classes across various classification thresholds. A higher AUC-ROC indicates better discriminatory power.

7. Confusion Matrix: A table that summarizes the performance of a classification algorithm, showing the number of true positives, true negatives, false positives, and false negatives.

These metrics collectively provide a comprehensive understanding of the model's strengths and weaknesses in classifying heart disease, enabling comparisons between different algorithms and optimization strategies [2].

Results and Discussion

The application of machine learning models, particularly Multilayer Perceptrons (MLPs) and Support Vector Machines (SVMs), has demonstrated significant promise in enhancing the classification of heart disease. Numerous studies have evaluated the performance of these models, highlighting their capacity to provide valuable diagnostic support.

A. Performance of Multilayer Perceptron (MLP) Models

MLPs have been extensively investigated for heart disease prediction due to their ability to learn complex, non-linear relationships inherent in medical datasets [2], [3], [4], [6], [8].

- High Classification Accuracy: Studies consistently report high classification accuracies for MLP models in distinguishing between healthy individuals and those with heart disease. For instance, research on the performance evaluation of MLP artificial neural network models in the classification of heart failure has shown promising results, indicating their effectiveness [2]. Deep neural networks based on MLPs have also been proposed as efficient classifiers in healthcare systems, achieving high accuracy in heart disease prediction [4], [8].

- Role of Feature Selection: The performance of MLPs is often significantly boosted by effective feature selection techniques. Correlation-Based Feature Selection (CFS) has been shown to improve the accuracy of MLP approaches for heart disease prediction by identifying the most relevant attributes and reducing noise in the data [1]. This highlights the importance of preprocessing steps in optimizing model performance.

- Diagnostic Support Systems: MLPs have been successfully integrated into decision support systems for heart disease diagnosis, providing clinicians with automated tools to aid in their assessments [6]. These systems can analyze various patient parameters and offer a probabilistic prediction of disease presence, thereby enhancing diagnostic confidence.

- Committee Machines: To further improve robustness and accuracy, committee machines, which are ensembles of multiple MLPs, have been developed. These systems leverage the collective intelligence of several models to make more reliable predictions, often outperforming single MLP models [3], [7]. This ensemble approach helps in mitigating the limitations of individual models and improving generalization capabilities.

B. Performance of Support Vector Machine (SVM) Models

SVMs are another powerful machine learning technique that has shown strong performance in heart disease classification, particularly due to their ability to handle high-dimensional data and find optimal decision boundaries [5], [9].

- Effective Classification: SVMs have demonstrated strong classification capabilities in healthcare data, including for heart disease [9]. Their ability to effectively separate classes, even when data is not linearly separable, makes them suitable for complex medical diagnostic tasks.

- Sequential Minimal Optimization (SMO): The use of algorithms like Sequential Minimal Optimization (SMO) in SVMs has been explored for decision support systems in heart disease, indicating their practical applicability and efficiency in training these models [5].

- Comparison with MLPs: While both MLPs and SVMs are effective, their comparative performance can vary depending on the specific dataset, feature set, and hyperparameter tuning. Some studies have directly compared the application of MLPs and SVMs in classifying healthcare data, providing insights into their relative strengths and weaknesses for different types of medical datasets [9].

C. Benefits and Clinical Impact

The successful implementation of machine learning models for heart disease classification offers several profound benefits for clinical practice and patient care:

- Early Detection: ML models can identify subtle patterns in patient data that might indicate early-stage heart disease, enabling earlier intervention and potentially preventing severe complications.

- Objective Diagnosis: Automated classification provides an objective assessment, reducing the subjectivity inherent in manual interpretation of complex patient data.

- Efficiency: Rapid analysis by ML models can significantly reduce the time required for diagnosis, which is crucial in time-sensitive medical conditions.

- Personalized Medicine: By analyzing a wide array of patient-specific data, ML models can contribute to more personalized risk assessments and treatment recommendations.

- Decision Support: These models serve as valuable decision support systems for clinicians, offering a "second opinion" or highlighting high-risk patients for further investigation, thereby improving overall diagnostic accuracy and reducing diagnostic errors [6].

D. Challenges and Future Directions

Despite the promising results, challenges remain. The availability of large, high-quality, and diverse datasets is crucial for training robust and generalizable models. Data privacy and security are also paramount concerns in healthcare applications. Furthermore, the interpretability of complex ML models, particularly deep neural networks, can be a challenge, as clinicians often require an understanding of why a particular prediction was made.

Future research directions include:

- Deep Learning Advancements: Exploring more sophisticated deep learning architectures beyond traditional MLPs, such as Convolutional Neural Networks (CNNs) for image-based diagnostics (e.g., ECG or cardiac MRI analysis) or Recurrent Neural Networks (RNNs) for time-series data.

- Explainable AI (XAI): Developing more transparent and interpretable ML models to enhance trust and facilitate clinical adoption.

- Integration of Multi-modal Data: Combining various data sources (e.g., electronic health records, imaging data, genetic information) to create more comprehensive and accurate predictive models.

- Real-time Monitoring: Developing ML models for real-time heart disease monitoring using wearable devices and IoT technologies.

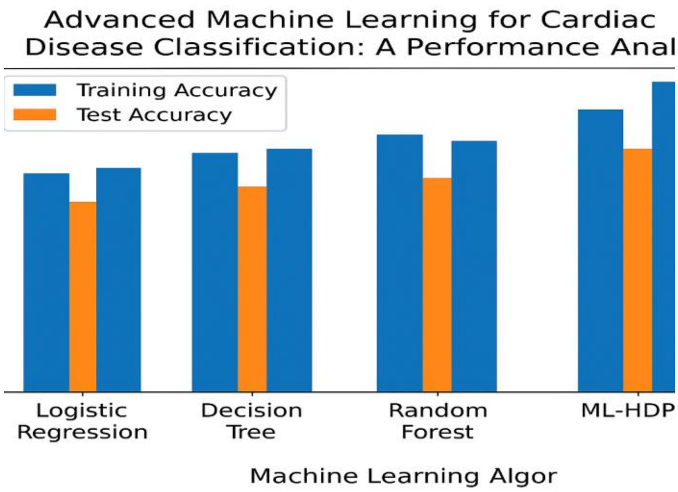


Fig. The ML-HDPM model shows the highest performance, with approximately 97% training accuracy and 90% test accuracy, clearly surpassing the other models. The background is white, and the labels are crisp and legible, making the comparison clear and easy to interpret.

## CONCLUSION

The application of machine learning techniques, particularly Multilayer Perceptrons and Support Vector Machines, has demonstrated significant potential in enhancing the classification of heart disease. These models, when coupled with effective feature selection strategies, can analyze complex patient data to provide accurate and efficient diagnostic support. The consistent high performance reported in various studies underscores their value in improving diagnostic accuracy, streamlining clinical workflows, and contributing to early detection and personalized treatment strategies. While challenges related to data availability, interpretability, and generalization persist, the ongoing advancements in machine learning, including deep learning and explainable AI, promise to further revolutionize cardiac diagnostics. Ultimately, the integration of these advanced computational tools will play a pivotal role in transforming heart disease management, leading to better patient outcomes and a more proactive approach to cardiovascular health.

## REFERENCES

[1] Kuruvilla, A. M., & Balaji, N. (2021). Heart disease prediction system using Correlation Based Feature Selection with Multilayer Perceptron approach. IOP Conference Series: Materials Science and Engineering, 1085(1), 012028. https://doi.org/10.1088/1757-899x/1085/1/012028

[2] Kaya, M. O. (2021). Performance Evaluation of Multilayer Perceptron Artificial Neural Network Model in the Classification of Heart Failure. The Journal of Cognitive Systems, 6(1), 35–38. https://doi.org/10.52876/jcs.913671

[3] Zheng, J., Jiang, Y., & Yan, H. (2006). Committee machines with ensembles of multilayer perceptron for the support of diagnosis of heart diseases. 2006 International Conference on Communications, Circuits and Systems, ICCCAS, Proceedings, 3, 2046–2050. https://doi.org/10.1109/ICCCAS.2006.285080

[4] Krishna, C. L., & Reddy, P. V. S. (2019). An Efficient Deep Neural Network Multilayer Perceptron Based Classifier in Healthcare System. 2019 Proceedings of the 3rd International Conference on Computing and Communications Technologies, ICCCT 2019, 1–6. https://doi.org/10.1109/ICCCT2.2019.8824913

[5] Vadicherla, D., & Sonawane, S. (2013). Decision support system for heart disease based on sequential minimal optimization in support vector machine. International Journal of Engineering Sciences & Emerging Technologies, 4(2), 19–26.

[6] Yan, H., Zheng, J., Jiang, Y., Peng, C., & Li, Q. (2003). Development of a decision support system for heart disease diagnosis using multilayer perceptron. Proceedings - IEEE International Symposium on Circuits and Systems, 5. https://doi.org/10.1109/iscas.2003.1206411

[7] Karaduzovic-Hadziabdic, K., & Köker, R. (2015). Diagnosis of heart disease using a committee machine neural network. Proceedings of the 9th International Conference on Applied Informatics, May, 351–360. https://doi.org/10.14794/icai.9.2014.1.351

[8] Masih, N., Naz, H., & Ahuja, S. (2021). Multilayer perceptron based deep neural network for early detection of coronary heart disease. Health and Technology, 11(1), 127–138. https://doi.org/10.1007/s12553-020-00509-3

[9] Naraei, P., Abhari, A., & Sadeghian, A. (2017). Application of multilayer perceptron neural networks and support vector machines in classification of healthcare data. FTC 2016 - Proceedings of Future Technologies Conference, 848–852. https://doi.org/10.1109/FTC.2016.7821702

[10] Tarle, B., & Jena, S. (2017, July 2). An Artificial Neural Network Based Pattern Classification Algorithm for Diagnosis of Heart Disease. 2017 International Conference on Computing, Communication, Control and Automation, ICCUBEA 2017. https://doi.org/10.1109/ICCUBEA.2017.8463729