# Analysis and Prediction of Cardio Vascular Disease using Machine Learning Classifiers

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## I. INTRODUCTION:

The field of machine learning has experienced remarkable advancements, becoming increasingly popular and accessible. Its applications span a wide range of domains, including face detection, system security, disease diagnosis, drug discovery, and numerous other transformative areas that have significantly impacted the lives of individuals. Unlike conventional programming methods, the fundamental principle behind building machine learning applications lies in enabling models to learn from patterns in training data without explicit instructions. These models then use inference to generate meaningful predictions.

Machine learning techniques such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM) are widely recognized as effective predictive models. However, one of their main challenges is their "black box" nature, where the reasoning behind their predictions is often not transparent. Most predictive models are trained using historical data to forecast future scenarios. In critical domains like healthcare, understanding the rationale behind a model's prediction is essential. This can help stakeholders make informed decisions, whether it's selecting appropriate medical treatments or assessing the risks of investment strategies.

In healthcare, machine learning models play a vital role, especially in life-critical scenarios such as recommending surgical procedures. Such decisions demand a high degree of accuracy and reliability to prevent life-threatening consequences. Therefore, it is imperative to thoroughly understand the reasoning behind a model's recommendations before acting on them.

**Methodology:** All the machine learning models used in this research utilize supervised learning methods. These methods leverage instances from the heart disease dataset to learn patterns and generate general hypotheses for predictions. Decision Trees (DT) are among the supervised machine learning models frequently employed for solving classification problems. A significant advantage of DT models is their ability to map non-linear relationships while providing clear and interpretable results. For this reason, DT models receive greater focus in this section.

Further analysis was conducted using the J48 Decision Tree classifier. Attribute selection was performed using the J48 classifier as a wrapper substitute evaluator method (see Table VI). The DT model was built in 1.1 seconds on the same machine specifications used for other models, including Multilayer Perceptron (MLP), Naive Bayes (NB), Support Vector Machine (SVM), and Random Forest (RF). The J48 model achieved an accuracy of 76.38%, which, while relatively low compared to some previous models, was better than the RF model. Despite the superior accuracy of some other models, they were less interpretable, often acting as "black boxes."

A comparison of Table V and Table VI reveals that the selected attributes for the RF and DT models were nearly identical, with one key difference. Both models agreed on selecting attributes such as *sex*, *ca*, and *thal*, but disagreed on *slope* and *oldpeak*. From Table VI, it can be concluded that the most frequently selected attributes for the J48 DT model were *thal*, *ca*, *oldpeak*, *sex*, and possibly *cp* as well.

Sample classification trees generated during the evaluation of the DT models are shown in Figures 9 to 12. In these classification trees, the root node represents the attribute with the highest purity, as it is most effective at distinguishing between patients with and without heart disease. This attribute is followed by others that contribute to the prediction as the tree progresses downward.

**Conclusion:** This paper demonstrated a comprehensive analysis and understanding of the Cleveland heart dataset. Various machine learning classifiers were designed and evaluated to develop the most effective diagnostic model. However, as highlighted in the interpretation section, certain issues must be considered to better understand the machine learning models. If the evaluation of the four models—MLP, NB, SVM, and RF—was based solely on initial metrics such as accuracy, precision, recall, and F1-score, there was a risk of selecting an inaccurate model.

For instance, the MLP model achieved an accuracy of 84.25% using an SVM-based attribute selection method and an 8-feature set. However, its feature ranking score, based on the 50% threshold used in this research, was 15—three times that of the RF model. This result indicated that choosing the MLP model as the primary diagnostic tool for heart disease would have been inappropriate due to its lower feature-set efficiency.

The investigative analysis conducted in this study provided a solid foundation for understanding the Cleveland heart dataset. These efforts were further enhanced by interpretation analysis, which introduced the new Feature Ranking Consistency (FRC) index. This index served as an informative metric, enabling a clearer distinction between models based on the importance of their feature sets. Ultimately, the RF model was selected as the final diagnostic model based on post-hoc interpretation analysis. Despite its slightly lower accuracy (79.92%) compared to the MLP model, the RF model struck a necessary balance between transparency and accuracy. This choice ensured the model's authenticity and interpretability, making it a better candidate for heart disease diagnosis.

The findings of this research are anticipated to benefit the machine learning community by providing a foundation for post-hoc prediction model interpretation analysis on clinical datasets.

### Future Work

Several potential directions for future research could be considered:

1. **Combining the Cleveland and Hungarian Datasets**: Merging these datasets and performing additional analyses may enhance accuracy and provide deeper insights into model transparency. While challenges like missing data could arise, the 100% increase in data instances might offset this issue.

2. **Association Rule Analysis**: Conducting association rule analysis could improve model interpretability and provide a better understanding of Decision Tree models. However, rule post-processing may be necessary to eliminate redundancy.
3. **Further Post-Hoc Interpretation Analysis**: Conducting more detailed post-hoc prediction model interpretation analyses could help validate and deepen our understanding of the designed models.