

# Heart Disease Prediction Using Machine Learning

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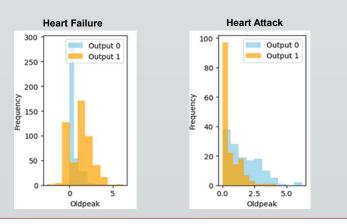
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### Abstract

Heart attacks and heart failure rank among the most common heart diseases in the general population. This study aims to employ machine learning to predict the likelihood of an individual developing these diseases. The results, presented as binary, can empower individuals to make informed decisions about their health. To achieve this goal, this study will combine the 'Heart Failure At first, our goal was to combine the 'Heart Failure Prediction Dataset' with the 'Heart Attack Analysis & Prediction Dataset. However, due to substantial differences in distinct features, we opted to focus exclusively on the heart failure dataset. The expectation is that our model's predictions will provide patients and users with valuable insights into their heart health, enabling them to take proactive measures. Given the high mortality rate associated with heart disease and heart failure in the absence of protective measures, this research endeavor seeks to transform unpredictable events into manageable ones.

#### Background

- Heart attack occurs when blood flow to a part of the heart muscle is blocked, usually by a blood clot. This blockage can deprive the heart muscle of oxygen and cause damage or death to that part of the heart.
- Heart failure is a chronic condition where the heart muscle does not pump blood as well as it should



#### Methods

- Basic Support Vector Classification model
- Basic Linear Regression model
- Basic Random Forest Classifier
- Random Forest using Grid Search for hyper parameter optimization and using trial and error to find the best model
- Basic Multi-Layer Perceptron
- Multi-Layer Perceptron using 3 layers and Logistic activation
- Multi-Layer Perceptron with Keras Sequential models: 20% Dropout rate, tuning of hyperparameter for optimization
- Multi-Layer Perceptron with Keras Functional models: 20% Dropout rate, Different architecture test and tuning of hyper parameter
- Feature Modification for Complexity Analysis: Removed specific features such as Sex, FastingBS, RestingECG, RestingBP from the original dataset. This simplification aims to evaluate the models' performance with reduced feature dimension.

Random Forest Non Base Confusion Matrix 80 True Neg False Pos 16 0 38.04% 8.70% 60 Actual 40 True Pos False Neg 4 94 2.17% 51.09% - 20 0 1 Predicted

| Results  |            |                         |          |            |                      |
|----------|------------|-------------------------|----------|------------|----------------------|
| accuracy | recall_pos | model                   | accuracy | recall_pos | model                |
| 0.8750   | 0.9388     | SVM                     | 0.8641   | 0.9184     | SVM                  |
| 0.8859   | 0.9388     | LR                      | 0.8859   | 0.9388     | LR                   |
| 0.8587   | 0.9286     | RF base                 | 0.8696   | 0.9286     | RF not Base          |
| 0.8913   | 0.9592     | RF not Base             | 0.8696   | 0.9286     | RF not Base          |
| 0.8478   | 0.8571     | MLP base                | 0.8696   | 0.9592     | RF2 not Base         |
| 0.8315   | 0.8980     | MLP with 3 layers       | 0.8587   | 0.9184     | MLP base             |
| 0.8478   | 0.9184     | Seq 2 Layers Relu BC    | 0.8587   | 0.9082     | MLP with 3 layers    |
| 0.8370   | 0.9082     | Fn 2 Layers Relu BC     | 0.8478   | 0.9286     | Seq 2 Layers Relu BC |
| 0.8533   | 0.9286     | Fn 3 Layers Relu MSE    | 0.8587   | 0.9388     | Fn 2 Layers Relu BC  |
| 0.8750   | 0.9388     | Fn 2 Layers Sigmoid MSE | 0.8533   | 0.8980     | Fn 3 Layers Relu MSE |
|          |            |                         | 0.8587   | 0.9184     | Fn 4 Layers Relu MSE |
|          |            |                         | 0.8750   | 0.9184     | Fn 2 Layers Sig MSE  |

## Conclusion

- Random Forest had the best accuracy and a high recall of 96% for true positive
- MLP being a more flexible models and good at finding pattern in complex dataset was not able to match to Random Forest

#### **Future Direction**

- Expanding the dataset is essential for enhancing accuracy. Main issue encountered during the training of models such as MLP and Random Forest was the rapid overfitting.
- The mean squared error yielded a significantly lower loss compared to binary cross-entropy, suggesting that greater emphasis should be placed on the former.

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