# MORTALITY RISK PREDICTION OF HEART FAILURE PATIENTS

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**Project Overview:** The primary goal of this project is to predict the likelihood of mortality in patients with heart failure leveraging their clinical records using machine learning algorithms of four classification models that were trained using test data. This includes understanding demographics, biomarkers, and comorbidities in the data used, the hyperparameters used that influenced the accuracy score and F-1 weighted average score of the models. The analysis aims to identify correlations, and insights that can inform stakeholders in the healthcare industry, contributing to the development of early detection and identification of high-risk patients' interventions, personalized care management strategies, preventive measures to improve patient outcomes and reduce healthcare costs as well.

**Data Source**: Kaggle https://www.kaggle.com/datasets/aadarshvelu/heart-failure-prediction-clinical-records/data?select=heart_failure_clinical_records.csv

**Question:**

Estimates from the 2024 American Heart Association (AHA) report says that one-third of US adults have at least one risk factor. This project seeks to answer:

"How does comorbid health conditions and lifestyle factors influence the risk of dying from heart failure?"

**Tools used**: Data Visualization – Tableau; to highlight patterns and trends in the data set for decision making after cleaning data in python library.

Predictive Modelling – Python; extracted data set and imported into python using Pandas and NumPy libraries, trained a test set and applied it to four classification models: Random Forest, Logistic Regression, Decision Tree and K-Nearest Neighbors.

**RESULTS:**

**Model 1 – Random Forest Classifier (Grid Search)**

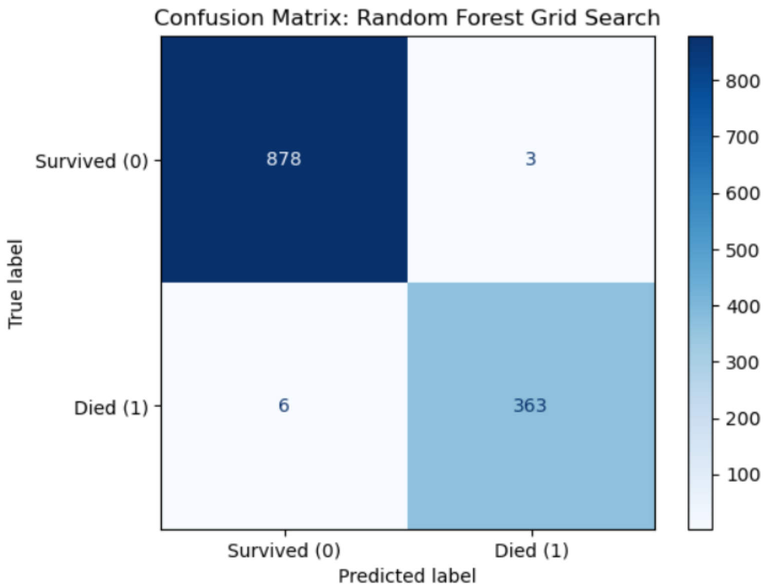
Model predicted weighted average F1 score and accuracy rate of 99%.

```
{'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 50}
0.9928
[[878   3]
 [  6 363]]
              precision    recall  f1-score   support

           0       0.99      1.00      0.99       881
           1       0.99      0.98      0.99       369

    accuracy                           0.99      1250
   macro avg       0.99      0.99      0.99      1250
weighted avg       0.99      0.99      0.99      1250
```

**Grid Search Confusion Matrix for Random Forest**




The matrix [[878 3] [6 363]] shows the count of true negatives (878), false positives (3), false negatives (6) and true positives (363).

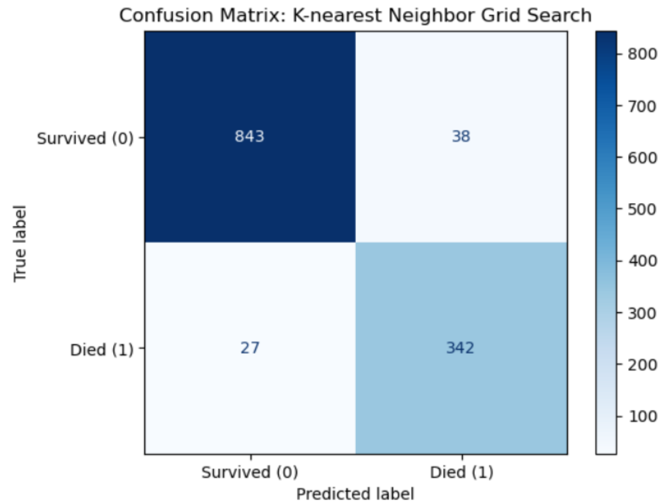
### Model 2 –K-Nearest Neighbor Classifier (Grid Search)

```
{'algorithm': 'auto', 'n_neighbors': 5, 'weights': 'distance'}
0.948
[[843  38]
 [ 27 342]]
              precision    recall  f1-score   support

           0       0.97      0.96      0.96       881
           1       0.90      0.93      0.91       369

    accuracy                           0.95      1250
   macro avg       0.93      0.94      0.94      1250
weighted avg       0.95      0.95      0.95      1250
```

### Confusion Matrix




Model predicted weighted average F1 score of 95% and accuracy rate of 95% as well

The matrix [[843 38] [27 342]] shows the count of true negatives (843), false positives (38), false negatives (27) and true positives (342).

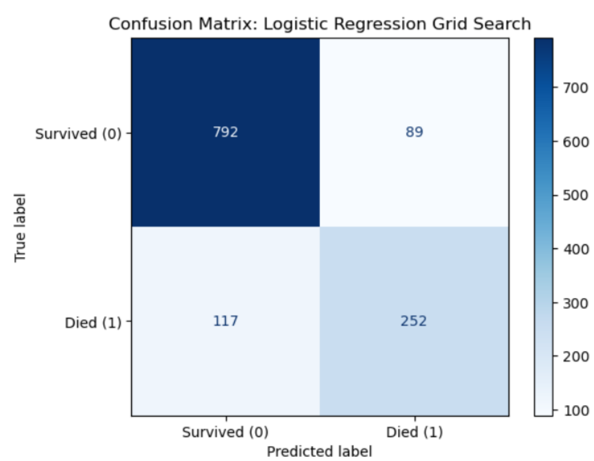
### Model 3 –Logistic Regression (Grid Search)

```
{'C': 0.1, 'max_iter': 100, 'solver': 'liblinear'}
0.8352
[[792  89]
 [117 252]]
              precision    recall  f1-score   support

           0       0.87      0.90      0.88       881
           1       0.74      0.68      0.71       369

    accuracy                           0.84      1250
   macro avg       0.81      0.79      0.80      1250
weighted avg       0.83      0.84      0.83      1250
```

### Confusion Matrix




Model predicted weighted average F1 Score of 83% and accuracy rate of 84%

The matrix [[792 89] [117 252]] shows the count of true negatives (792), false positives (89), false negatives (117) and true positives (252).

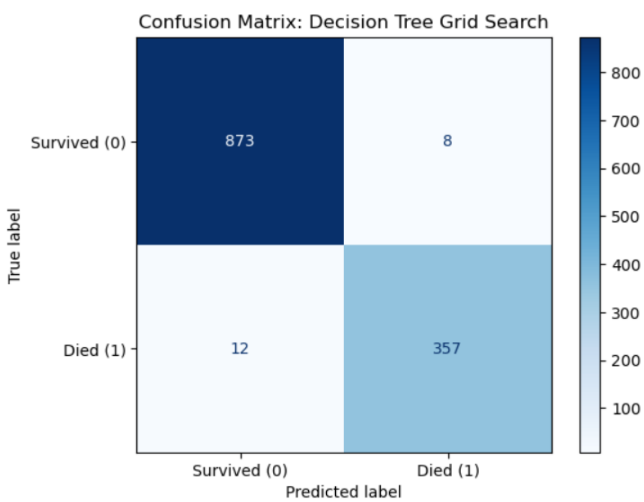
### Model 4 – Decision Tree (Grid Search)

```
{'criterion': 'gini', 'max_depth': 10, 'min_samples_leaf': 1, 'min_samples_split': 2, 'splitter': 'best'
0.984
[[873   8]
 [ 12 357]]
              precision    recall  f1-score   support

           0       0.99      0.99      0.99       881
           1       0.98      0.97      0.97       369

    accuracy                           0.98      1250
   macro avg       0.98      0.98      0.98      1250
weighted avg       0.98      0.98      0.98      1250
```

### Confusion Matrix




Model predicted weighted average and accuracy rate of 98%

The matrix [[873 22] [33 584]] shows the count of true negatives (873), false positives (8), false negatives (12) and true positives (357).

### INSIGHTS:

Comparing the four models above, it can be realized that Models 2, 3, and 4 had a lower weighted average of F-1 score than Model 1 which makes Model 1 a robust model as it has the highest weighted average. Model 1 also predicted 99% of the Class 1.

Model 3 predicted the least of Class 1 with 74% precision. Model 2, 3, 4 accurately predicted less percentage of class 1 than class 0 in terms of recall and precision but Model 4 has slightly better precision than Model 2 for Class 1 but Model 1 has the highest precision almost closer to the best score which is 1.0.

All models except model 3 are good at predicting high values of true negatives and true positives and hence accuracy is high. However, Model 2 also has a slightly higher false positive and false negative rate compared to Model 1, which may lead to more misdiagnoses.

**Clinical Suitability**: Model 1 is highly clinically suitable as it provides robust predictions, ensuring minimal misclassification of critical events like deaths. Model 4 is also clinically suitable, offering a balance between interpretability and prediction accuracy. Model 3 is less clinically suitable due to lower accuracy and recall for critical cases of death, potentially missing life-threatening situations. Model 2 is moderately clinically suitable. While it performs well, the higher false negatives may pose risks in missing critical cases of death.

**Recommendations**

- **Comorbidity Management:** Develop programs that address the most impactful comorbid conditions in this case it is Anaemia followed by Diabetes which contribute significantly to mortality risk.
- **Healthcare Prioritization:** Identify high-risk patients early and prioritize them; those with low Ejection Fraction as we saw that those who had EF of 20-25 and died were the majority, enabling targeted interventions and resource allocation.
- **Use Model 1 (Random Forest Classifier)** for its superior performance in both clinical accuracy and reliability. It is the most robust model for critical healthcare predictions with minimal errors and use **Model 4 (Decision Tree Classifier)** as back up model as it offers a balance between interpretability and accuracy, making it an excellent alternative in contexts requiring simpler, transparent models for clinician decision support.