# **Exploring Neural network with Machine Learning**

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**Predicting Survival Of Patients With Heart Failure From Serum Creatinine And Ejection Fraction Alone**

**Exploratory Data Analysis:**

**A graph with a number of blue squares

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Interpretation of the image, which is a bar plot showing the distribution of the DEATH\_EVENT variable.

**Understanding the Plot**

* Title: "Distribution of Death Event" clearly indicates what the plot represents – how many patients fall into each category of the DEATH\_EVENT variable.
* X-axis: Labelled "DEATH\_EVENT," it shows the two categories:
  + 0: Represents patients who *did not* die during the follow-up period.
  + 1: Represents patients who *died* during the follow-up period.
* Y-axis: Labelled "count," it shows the number of patients in each category.
* Bars: The height of each bar corresponds to the number of patients in that category.

**Interpretation:**

Based on the visual, below are the visualisations:

* **Class Imbalance:** There's a clear difference in the height of the bars. The "0" (no death event) category has significantly more patients than the "1" (death event) category. This indicates a class imbalance in the dataset.
* **Majority Class:** The majority of patients in the dataset did not experience a death event during the follow-up period.
* **Minority Class:** A smaller proportion of patients experienced a death event.

The class imbalance is a crucial consideration for machine learning models. If left unaddressed, the model might be biased towards predicting the majority class ("0"), leading to poor performance in identifying patients at risk of death (class "1"). This is because the model has more examples of the majority class to learn from and might struggle to recognize the patterns associated with the minority class.

1. **Classification:**   
   The heart failure prediction problem usually described as a classification problem.  Specifically, it's a binary classification problem because there are only two possible outcomes:  
   Class 0: Patient did not die during the follow-up period.  
   Class 1: Patient died during the follow-up period.

In a classification problem, the model is usually trained to distinguish between

data points, in this case, patients' records with clinical features, into one of a predefined classes or categories. The model takes the patient features as input and outputs a prediction of which class it thinks the patient is, that is, 0 or 1.

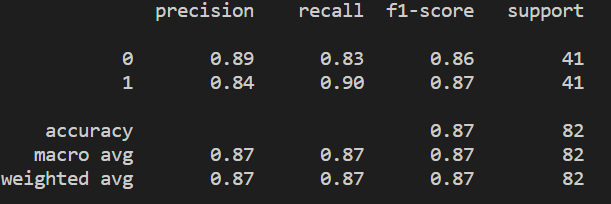
1. **Class Distribution**

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Description automatically generated

This is the original distribution of the target variable in original dataset before oversampled it with SMOTE. This gives 203 instances of the patient not dying in the follow-up period-class 0-and 96 instances where the patient did die-class 1, further confirming class imbalance went ahead to balance with SMOTE.

**3. Classification Report:**



This is the core of the model evaluation.

Interpretation of the metrics:  
**Precision:**  Out of all the patients the model predicted to be in a class (0 or 1), what proportion actually belonged to that class?  
**Class 0 (no death event):** Precision is 0.89. When the model predicts "no death event," it's correct 89% of the time.  
**Class 1 is the event of death**: Precision is 0.84. It means that 84% of the time, when the model predicts "death event," it is correct.  
**Recall:** Of all the patients who actually belong to a class (0 or 1), how many does the model correctly identify?  
Class 0 is no death event, and recall is 0.83. It means that the model correctly identified 83% of the patients who did not die.  
Class 1 is the death event, and recall is 0.90, meaning the model correctly predicted 90% of the patients actually died.  
**F1-score:** The F1-score is the harmonic mean of precision and recall. This balanced measure takes both false positives and false negatives into consideration. The higher, the better. For F1-score, both classes are around 0.86-0.87, which is quite good in terms of balance between precision and recall.  
**Support:** The number of samples in each class in the test set. This is 41 for each class after using SMOTE to balance the classes in the training set. It is balanced to allow for the proper evaluation here, but on a real world application, the would want to test on original unbalanced data as well.  
**Accuracy:** In general, this is the overall general accuracy of the model on the test set. Here, it is 0.87, meaning that the model rightly classified 87% of patients in the test set.  
Macro avg: The unweighted average of precision, recall, and F1-score across both classes.  
**Weighted avg:** Weighted average of precision, recall, and F1-score. The weights are the number of samples in each class. Because the test set is balanced, the weighted average equals the macro average, and both are the same as the overall accuracy.  
**Interpretation:**  
The model seems to perform fairly well. The model's overall accuracy is 87% with well-balanced precision and recall for both classes. F1-scores ranging from 0.86 to 0.87 are reflective of a very good balance between the correctly identified number of patients who will die and reduction in the number of false alarms. Remember, though, this set is balanced by SMOTE. The probably will want to test it on original unbalanced data to get a proper idea of how it would perform in the real world.  
**Further Analysis:**  
Confusion Matrix: The confusion matrix also included in the output gives a breakdown of the model's predictions-true positives, true negatives, false positives, and false negatives. Have a look at the confusion matrix for an idea about where the model is making mistakes.  
**ROC Curve and AUC:** Plot the Receiver Operating Characteristic curve, which will give further detail on the performance of the model, especially in terms of its ability to discriminate between the two classes.    
  
**Real-world Test:** As mentioned, the model needs to be tested on the original imbalanced data to understand how it will perform in a real-world scenario.  
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Reference:

<https://archive.ics.uci.edu/dataset/519/heart+failure+clinical+records>

[www.abrinternationaljournal.org](https://www.abrinternationaljournal.org)  
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