**Evaluation of Results slide:**

Across the different models we implemented, Neural Network achieved the highest accuracy of 88%, compared to 83% for lasso regression and 73% for decision tree. Neural network will be a suitable model solely for the prediction of mortality among heart failure patients, whereas to understand heart failure better, we can look at the important features common across all the models, which are serum creatine, ejection fraction and age.

**Implications Slide:**

In the case of mortality prediction, it will be critical to avoid and minimize False negatives, more so than false positives, as False Negatives will incorrectly predict that a patient will survive,when in fact he will not. A false negative prediction will result in doctors performing an inaccurate diagnosis on a patient’s life expectancy and neglect the required treatment necessary for the patient. Our best performing neural network model predicted 2 false negatives, giving it a recall score of 83%. The model can be further improved to be “over-sensitive” in order to capture all true positive cases. This will result in the model compromising on precision to achieve greater recall.

**Now moving on to insights**

**Applications:**

The most prominent and obvious application of our project will be to support doctors’ evaluation of a patient’s survivability and life expectancy after diagnosis of heart failure. Clarke’s study has shown that medical professionals have a high tendency to underestimate the life expectancy of their patients, and that doctors, nurses and medical students underestimated the life expectancy in 62%, 64% and 66% respectively. These professionals display a degree of inaccuracy of 25%. This is likely due to the presence of human bias and lack of experience in some cases. In contrast, our machine learning model can deliver an accuracy of up to 88%!

**Limitations:**

Our project faced limitations in terms of the size of our dataset and the number of features for patients recorded. This dataset may not be sufficient to accurately represent the overall population of patients with Heart Failure. The traits recorded for patients were limited to largely behavioral traits and diagnosis of diseases, and there may be other factors like occupation that may possibly influence a patient’s mortality. Our predicted variable for this project is Death\_event, which indicates if the patient survives Heart Failure or not. A more meaningful output will be the remaining lifespan of patient after diagnosis.

**Future Studies:**

Besides what was demonstrated , the scope and depth of our models can be improved in a few ways to maximise the impact of our project. While we have currently managed to predict the mortality of heart failure patients, we can next seek to investigate other leading factors for this health condition. Furthermore, we aim to perform predictions on heart failure occurrence instead of mortality rates by gathering more data.

**Conclusion:**

Lastly, by increasing the size of our datasets, a more comprehensive and accurate analysis of heart failure can be achieved. With this project and future developments, we hope that it will spur greater adoption of Machine Learning and Artificial Intelligence in the healthcare field and improve our chances against critical illnesses that plague humanity.

**Thank You:**

This marks the end of our presentation, thank you for your time!