**Model Testing**

Using the seven models provided from the workshop, I trained each model and evaluated them using Balanced Accuracy, F1 Macro and Prediction Time as the main metrics. Additionally, confusion matrices were analysed to identify False Positives, False Alarms, and Gray Areas. I also did some very light edits to some of the models to help them perform better without using up too much of my time.

From the above criteria, Neural Network (MLP) and k-Nearest Neighbours were the first 2 models I excluded. Their False Positive rates were too high to be considered. SVM still had comparatively high False Positive rates while Random Forest models were much slower (0.06s) compared to the other models (<0.01s). I decided to keep Decision Tree (for having the lowest False Positive rate) and Gradient Boosting (for its extremely low False Alarm rates) to do more detailed testing.

After additional testing, we chose Gradient Boosting as the final model for this datathon.

This model is then constructed in a custom ThresholdClassifier to adjust how the %confidence for a sample to be placed at a certain class. This classifier also included a reject margin that reassigns uncertain samples to class 2 instead of risking a wrong class 1 or class 3 classification. By adding the reject margin, the model actually did slightly worse producing more false alarms (pred = 2, true = 1) but I felt this was important to keep false positives low.

The final Gradient Boosting model together with the ThresholdClassifier pipeline provided the best trade-off between having very low false positive rate yet low enough false alarms to ensure trust in clinicians. This model is therefore suitable in helping obstetric practitioners in identifying fetal cases at risk without generating excessive false alarms.