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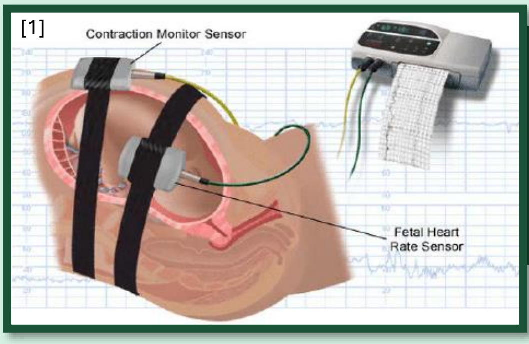
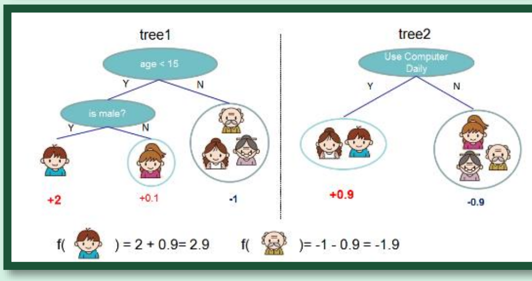
DEVELOPING MACHINE LEARNING METHODS TO IDENTIFY HIGH RISK PREGNANCIES

[1]





[7]

To help achieve the SDG goal 3.2 [3], cardiotography (CTG) data [4] monitoring foetal health was used to train a classification algorithm. The dataset consisted of 21 features and one target variable, classifying each instance as **normal**, **suspect**, or **pathological**. This multiclass classification problem required rebalancing of the dataset to allow classifiers to detect suspect and pathological instances, which are rarer but more crucial to detect [5]. Repeated stratified k-fold cross validation reduced the likelihood of overfitting [6].

TARGET 3·2

5 YRS

END ALL PREVENTABLE DEATHS UNDER 5 YEARS OF AGE [2]

XGBoost (extreme gradient boosting) [7] is an ensemble of multiple Decision Trees. It calculates the sum of predictions from each tree and uses a quantile sketch function to handle weighted data and efficiently calculate the split of each tree based on the distribution of features. A regularisation parameter, shrinkage, and subsampling prevent overfitting.

Feature Selection (FS)

Classifier performance can be enhanced and overfitting avoided by removing irrelevant features [8], [9].

To compare performance, XGBoost was either trained with all **21** features or **7** relevant features, chosen based on their correlations [10] and mutual information [11].

Resampling

SMOTE: Synthetic Minority Over-Sampling Technique. Increases the number of instances in minority classes by generating samples between each instance and its k-nearest neighbour [12].

RUS: (Repeated) Random Under-Sampling. Reduces the number of instances in majority classes by (repeatedly) selecting random instances.

Assessment: Performance Metrics

Recall: How many relevant instances of a class are detected [13].

Precision: How well a model correctly predicts a given instance of a class [13].

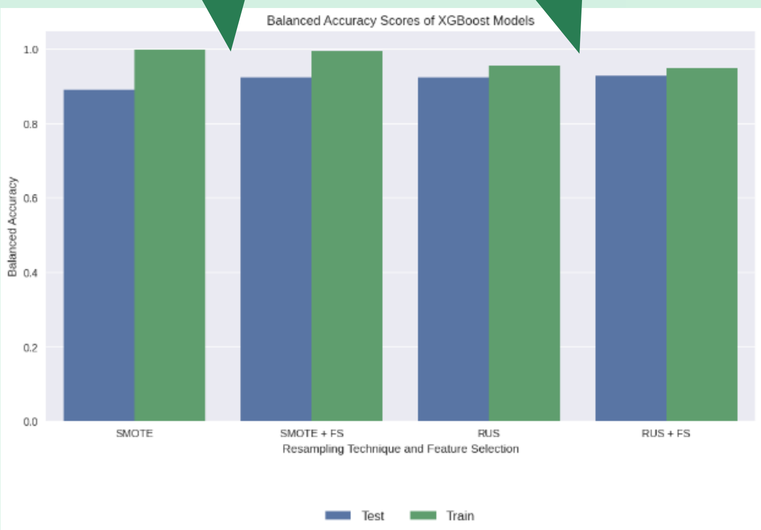
F_β: Summary statistic of a class, β = 2 values Recall twice as much as Precision [14]. Important in medicine to create a less-discriminant classifier [13].

Balanced Accuracy: Accuracy of a classifier that accounts for class imbalance [15].

SMOTE: higher Train Accuracy; the models might have overfit on replicated samples

RUS: smaller difference between Train and Test accuracy; models are more generalisable.

Model	Precision			Recall			F_β		
	N	S	P	N	**S**	**P**	N	S	**P**
SMOTE	0.96	0.87	0.91	0.98	0.78	***0.91***	0.98	0.79	0.91
SMOTE+FS	0.98	0.78	0.97	0.96	0.86	***0.94***	**0.97**	**0.84**	**0.95**
RUS	1.00	**0.61**	0.80	0.88	***0.95***	***0.94***	0.90	0.85	0.91
RUS+FS	1.00	**0.62**	0.77	0.87	***0.97***	***0.94***	**0.89**	**0.87**	**0.90**



FS increased Test Accuracy and lowered the difference between Test and Train Accuracy by reducing the likelihood of overfitting; models with FS perform better.

In Summary: Prioritising ***high Recall of S and P*** is important in a medical context to lower the False Negative rate and save lives [13]. However, **low Precision** should still be avoided where possible to reduce the False Positive rate and prevent unnecessary medical interventions. $F_{\beta=2}$ strikes a balance between these two metrics. SMOTE + FS had a **higher F_β for P and N**, whilst RUS + FS a higher **F_β for S**. However, given the similar values between the SMOTE + FS and RUS + FS models overall, the latter should be favoured due to the lower likelihood of overfitting to the train data.

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