Springboard – DCS

Capstone Project 2

Predicting Fetal Cardiac Health Outcomes Using Cardiotocogram Data

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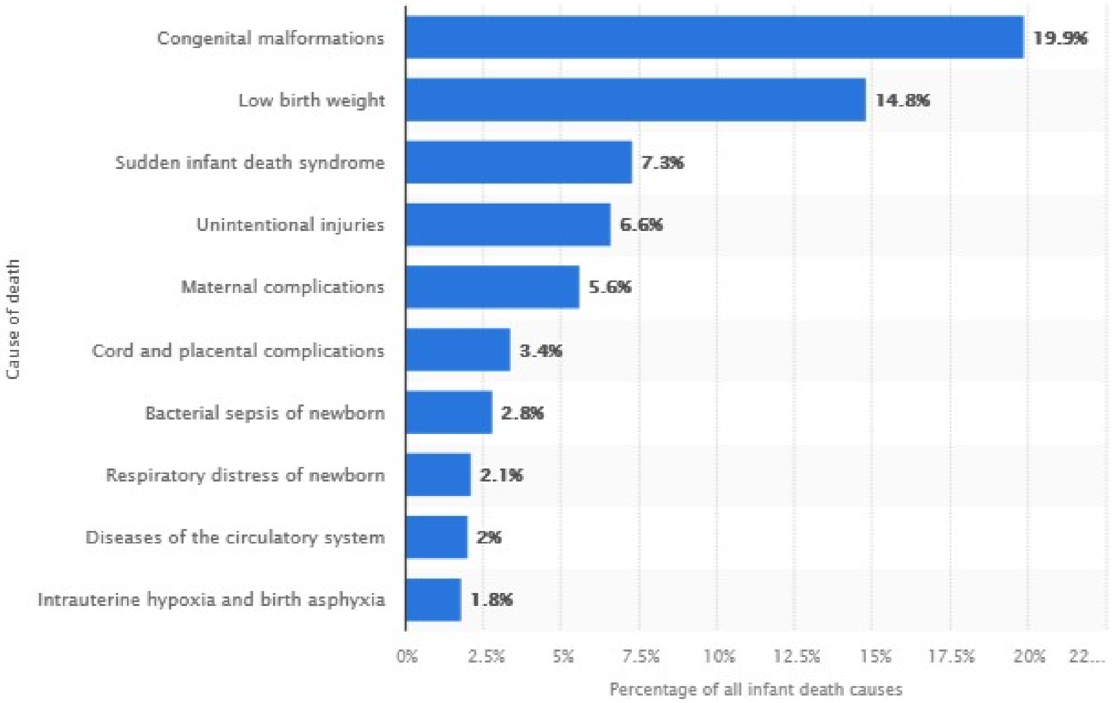
Introduction



- Congenital malformations like heart defects (CHD), are responsible for nearly 20% of infant deaths.

- CHDs affect nearly 1% of children born alive, totaling nearly 40,000 cases per year.

- Of those 1% of children born with CHDs, about 25% are critical.

https://www.statista.com/statistics/946675/leading-causes-of-infant-death-in-the-us/

Introduction

Cardiotogography (CTG) is a non-invasive, in-utero fetal heart-health test that obstetricians use to detect the presence of CHD.

Interpreting the results usually requires a highly trained physician, who carefully considers the multiple measurements of the CTG in order to classify fetuses as either normal, suspect, or pathological.

Accurate diagnosis is a critical step for our stakeholders:
Affected children, parents, obstetricians, surgeons, and hospitals.

Goal:

Develop a machine learning model that uses CTG data to quickly and accurately predict the cardiac status of a fetus.

Approach: Data Acquisition and Wrangling

Data is from University of California Irvine Machine Learning Repository

Ayres de Campos et al. (2000) SisPorto 2.0 A Program for Automated Analysis of Cardiotocograms. J Matern Fetal Med 5:311-318

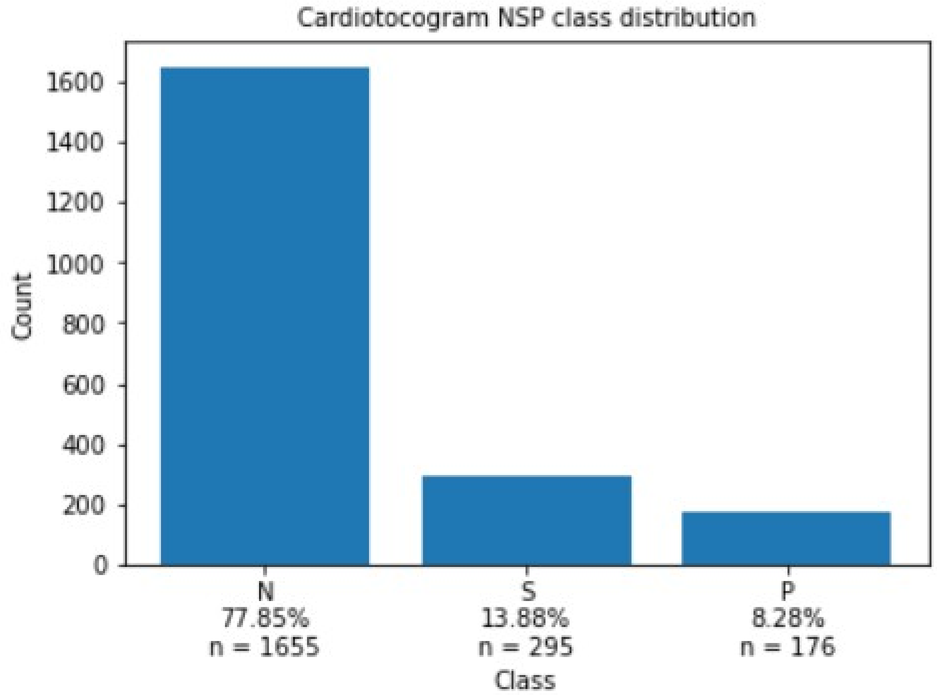
Our project only used the columns corresponding to features suggested in the data file, totaling 21 independent variables for 2126 CTG instances

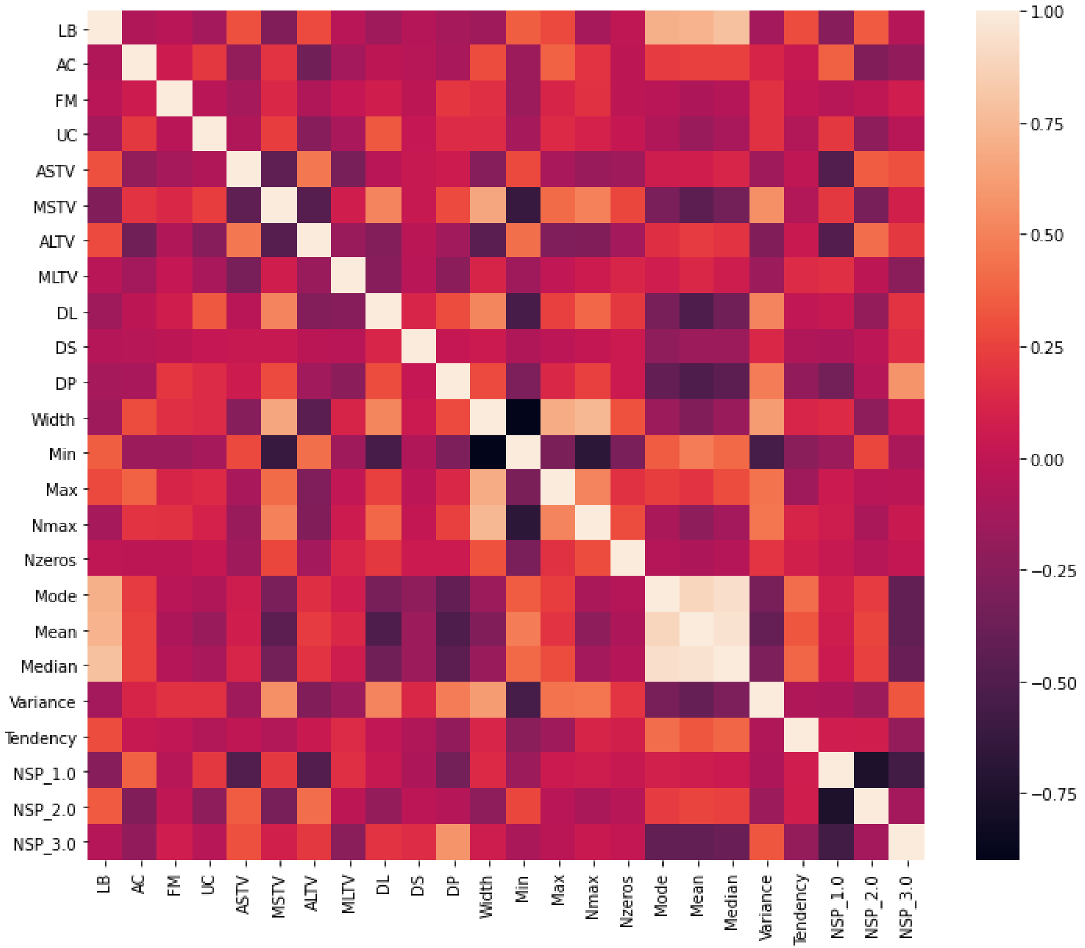
Our data:

- Each CTG instance classified as Normal, Suspect, or Pathological by a medical professional

- Includes “Suspect” as a class designation, which we eliminated from modeling

- Highly imbalanced





Feature correlations:

- Highly correlated features with features:
  >Mean, Median, Mode
  >Min, Width

- Highly correlated features with target:
  >ASTV and ALTV with Normal class
  >Mean/Median/Mode with Pathological class

Baseline Modeling

Goal of modeling: High sensitivity (good detection abilities)

Performance metric of choice: Recall (True Positives / All Positives)

Reason: Medical classification problems tend to value reducing false negatives

Good is Bad

- Initial algorithm chosen for model-building was Logistic Regression

- Model performance without any tuning achieved improbable results

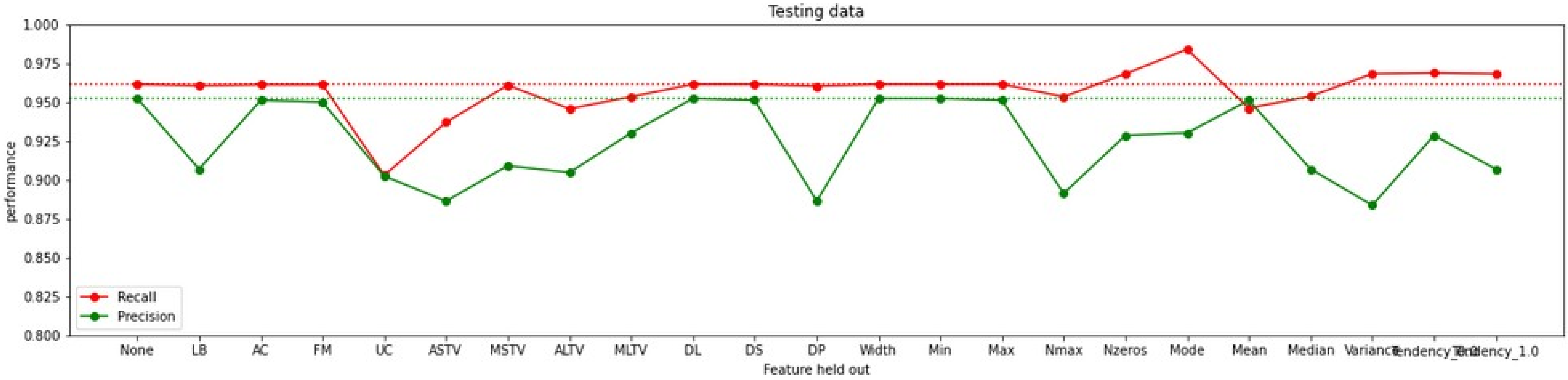
- >90% on all standard performance metrics

- Recall score = 0.91

- Data leakage is a likely culprit

Classification Report for Test Data

	precision	recall	f1-score	support
N	0.99	1.00	0.99	414
P	0.95	0.91	0.93	44
accuracy			0.99	458
macro avg	0.97	0.95	0.96	458
weighted avg	0.99	0.99	0.99	458



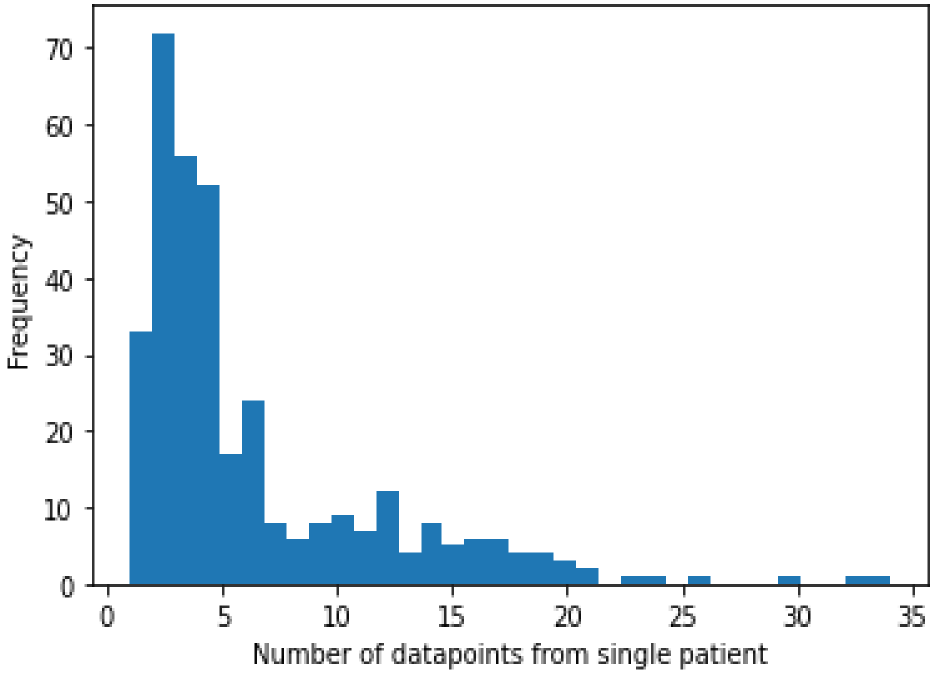
<u>Investigating single features for leakage</u>

- Using a feature hold-out function, the model was repeatedly run.

- Precision and Recall scores for each iteration were charted.

- No obvious signs that one feature is the source of the data leakage issue.

Leakage Located



- Further review of the data showed that most subjects had multiple CTG data entries

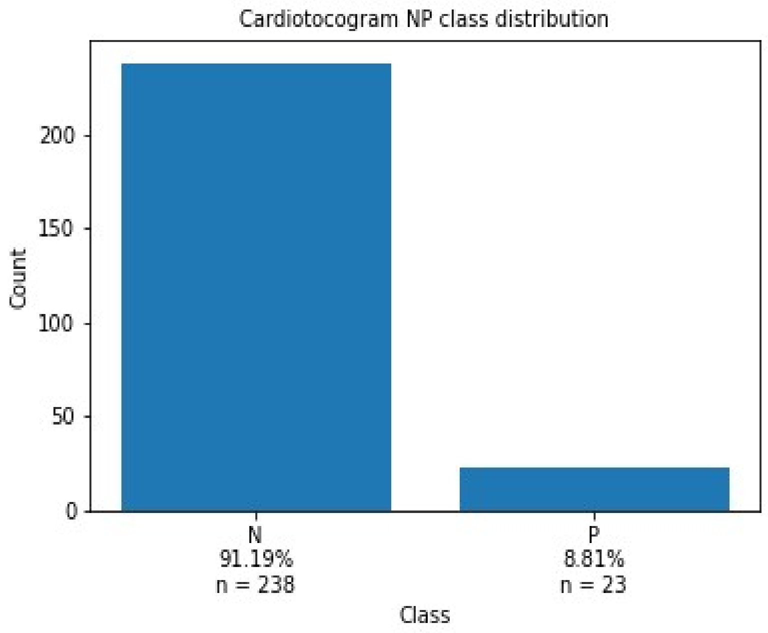
- Data from subjects was ending up in both the training set and the testing set for modeling

- The model was over-fit to the particular patients involved

Redo EDA

- Using grouping and aggregation, we condensed the data from 2126 to 352 data-points

- Class imbalance remained ~10:1



Redo Baseline Modeling

- Repeating our steps from before, we used Logistic Regression

- Again, the results are astoundingly good. Too good.

- Recall = 1.00

- The leakage issue is not solved

```
Classification Report for Test Data
              precision    recall  f1-score   support

           N       1.00      0.99      0.99        72
           P       0.88      1.00      0.93         7

    accuracy                           0.99        79
   macro avg       0.94      0.99      0.96        79
weighted avg       0.99      0.99      0.99        79
```

The problem of leakage is consistent:

Comparing cross-validation performance when using over-sampling techniques on the data show similarly excellent results.

	Recall Score
None LogisticRegression(C=100, max_iter=5000, solver='saga')	0.935462
None RandomForestClassifier()	0.783333
RandomOverSampler() LogisticRegression(C=100, max_iter=5000, solver='saga')	0.987933
RandomOverSampler() RandomForestClassifier()	1.000000
BorderlineSMOTE() LogisticRegression(C=100, max_iter=5000, solver='saga')	0.987987
BorderlineSMOTE() RandomForestClassifier()	0.991017
SMOTENC(categorical_features=[20, 21]) LogisticRegression(C=100, max_iter=5000, solver='saga')	0.985011
SMOTENC(categorical_features=[20, 21]) RandomForestClassifier()	0.993939
ADASYN() LogisticRegression(C=100, max_iter=5000, solver='saga')	0.981872
ADASYN() RandomForestClassifier()	0.993939
KMeansSMOTE() LogisticRegression(C=100, max_iter=5000, solver='saga')	0.987933
KMeansSMOTE() RandomForestClassifier()	0.987987
SVMSMOTE() LogisticRegression(C=100, max_iter=5000, solver='saga')	0.985011
SVMSMOTE() RandomForestClassifier()	0.997024

Findings

Unfortunately, upon further inspection of the raw data, we discovered:

1. The CTG entries corresponding to each patient overlapped in time. Some of the data-points encompassed entirely the rest of that patient's data.

2. Some unseen data leakage is continuing to occur, even after the fixes we established.

Findings

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Conclusions

Based on our findings, we strongly recommend making the following concrete data collection improvements:

1. Supply the data team with CTG data from more subjects. Increasing the testing is a more reliable approach than artificially oversampling limited data.

2. Include in future data collection only a single data entry per patient. This was a cause of major information leakage, led to over-fitting during modeling, and is a bad practice for the type of problem that we are trying to solve.

3. Ensure a standard amount of time that each CTG may collect data for.

Thank you to AJ, my mentor,
for helping to steer me in the proper direction throughout this project.