Fetal Health Study

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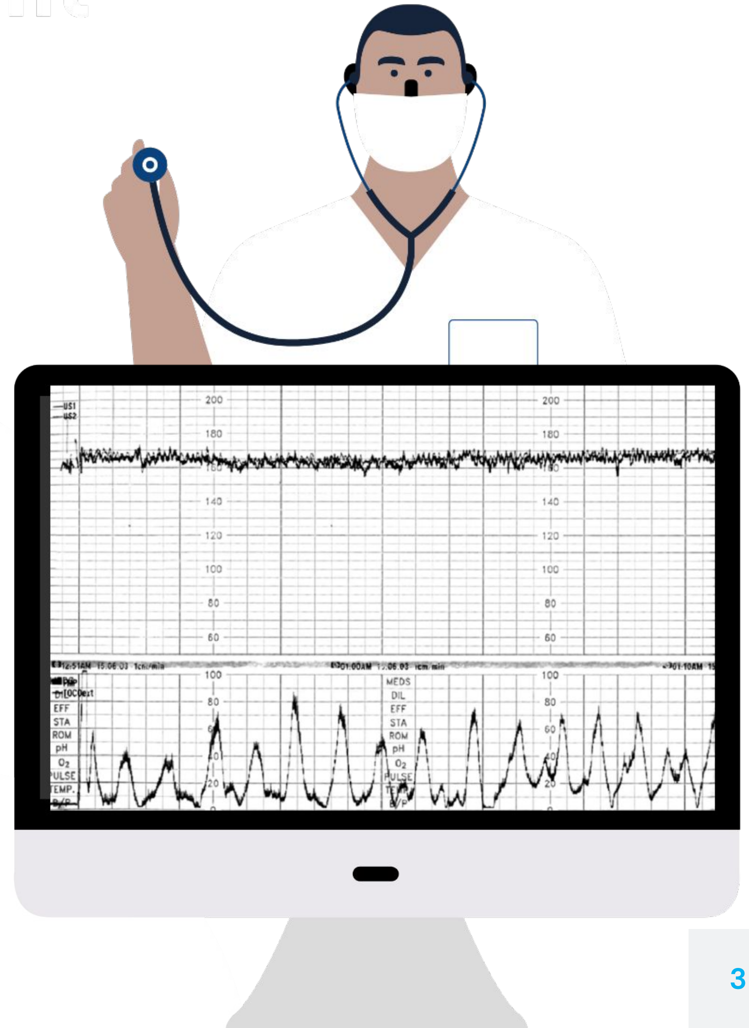
The Importance of this study

- Every day in 2017: 810 women die from preventable causes related to pregnancy and childbirth.
- Maternal mortality accounts for 295 000 deaths during and following pregnancy and childbirth
  - 94% in low-income countries

The Data

This dataset contains 2126 records of features extracted from Cardiotocogram (CTG) exams, which were then classified by three expert obstetricians into 3 classes:

- Normal (labeled as 1)
- Suspect (labeled as 2)
- Pathological (labeled as 3)



OBJECTIVE

Create a predictive model to classify CTG features into the three fetal health states to try and prevent child and maternal mortality.

Comparable Studies

[Fetal health status prediction based on maternal clinical history using machine learning techniques - ScienceDirect]

[Use of Machine Learning Algorithms for Prediction of Fetal Risk using Cardiotocographic Data - PubMed (nih.gov)]

1 Methodology

The Features

- Fetal Heart Rate
- Accelerations per second
- Fetal movements per second
- Uterine contractions per second
- LDs, SDs and PDs per second
- % of time with abnormal short term/long term variability
- Mean short term/long term variability
- Histograms made using all values from a record

Data Cleaning and Preprocessing

- Dropping duplicates
- Dropping Variables with no variance
- Scaling
- Determining outliers
- Dummification

Classification Metrics

Recall

Micro F1-score

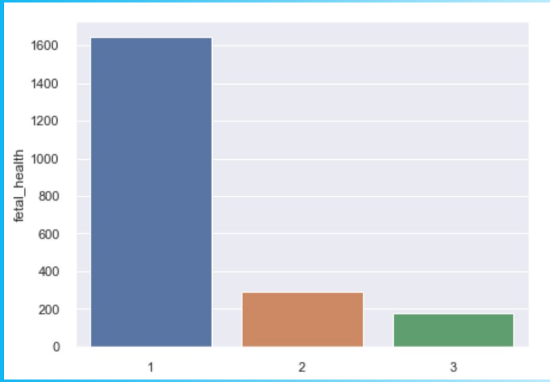
Feature Selection

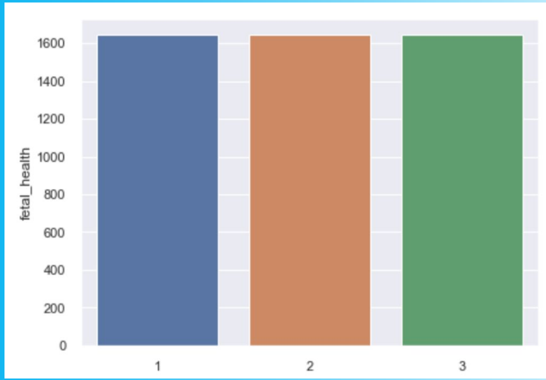
Recursive Feature Elimination with Cross-Validation (RFECV) to assign feature importance to each feature and selected only the ones which were supported based on a Random Forest Classifier.

	Features	Ranking	Support
0	baseline value	1	True
18	histogram_variance	1	True
17	histogram_median	1	True
16	histogram_mean	1	True
	...		
4	light_decelerations	2	False
20	histogram_tendency_1.0	3	False
14	histogram_number_of_zeroes	4	False
19	histogram_tendency_0.0	5	False

SMOTE Up-Sampling

Fix severe class imbalance in the dataset. Improving recall of pathological labels from 0.86 to 0.97!





2 Models & Results

Baseline Modeling Approach

- Different base models → Logistic Regression, KNN, Decision Tree, LDA / QDA, Gaussian NB
- Pipeline
  - To test different scaling methods / transformations
  - With feature selection vs with PCA

Ensemble Methods

Bagging Models

- Random Forest

Boosting Models

- Ada Boosting
- XGBoost
- **Gradient Boosting**

Other

- Support Vector Machine

Voting (Hard and Soft)

Recall for Pathological Class

Base Decision-Tree Model

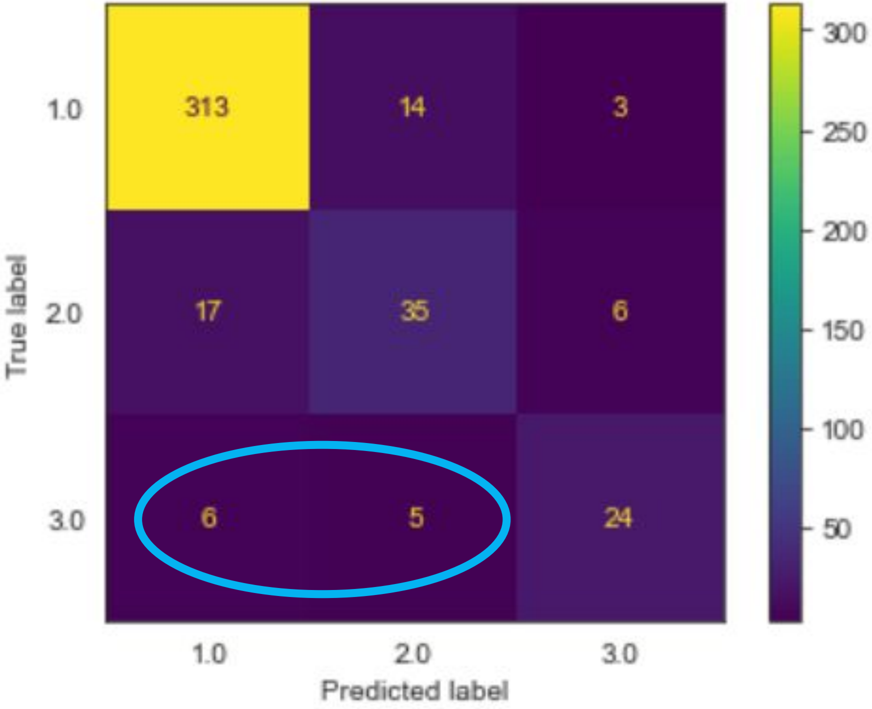
86%

Gradient Boosting Model

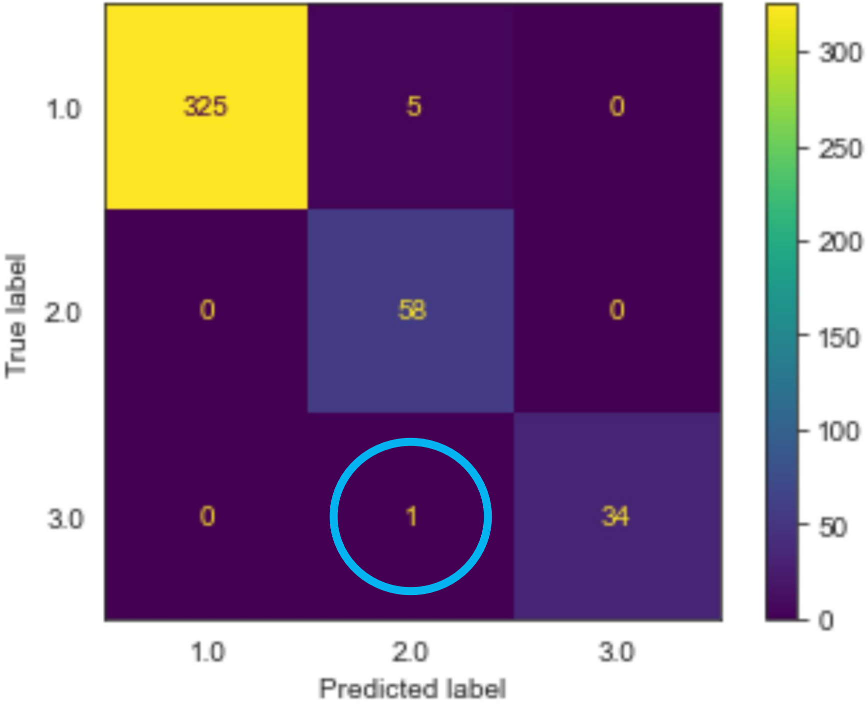
97%

Confusion Matrix

Base Model



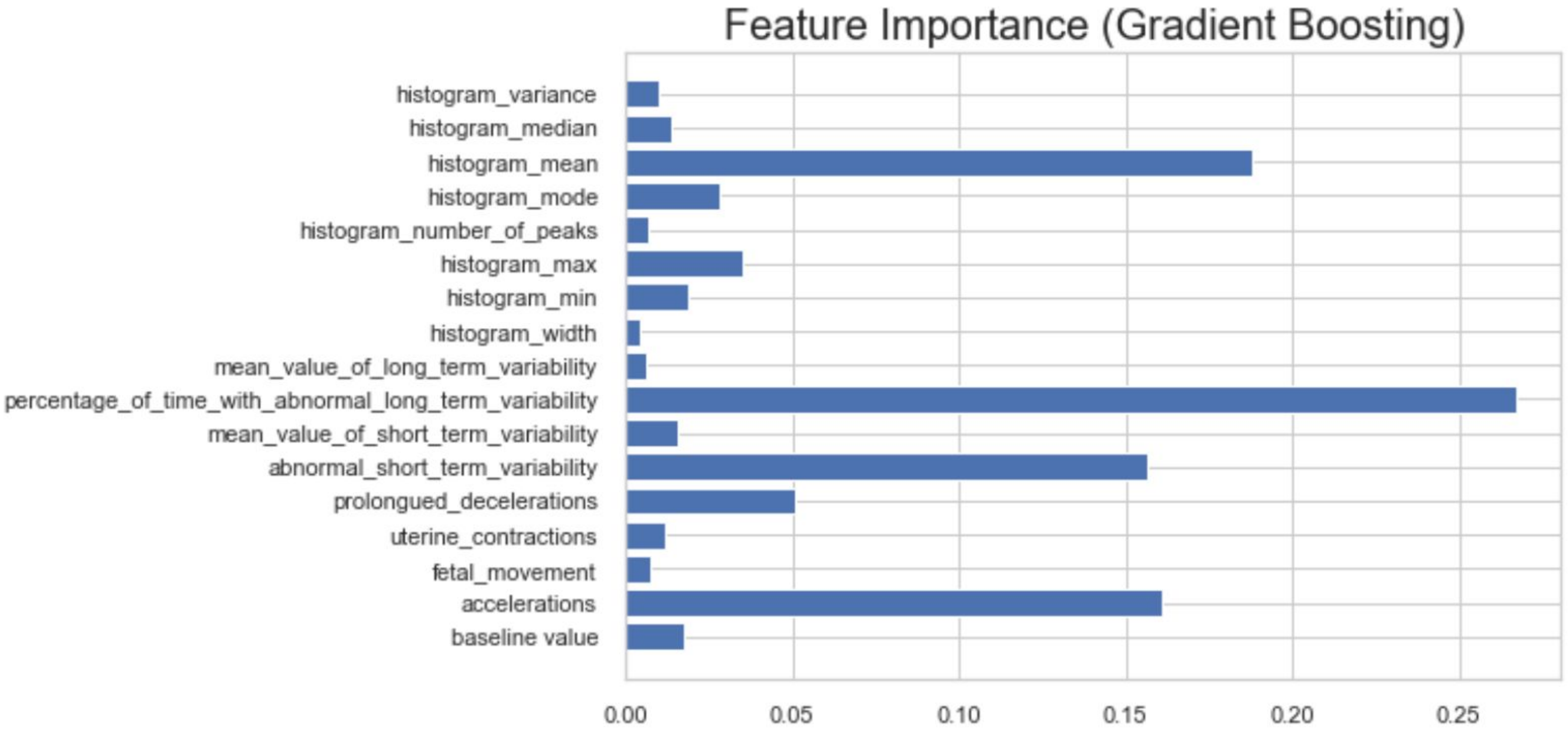
Final Model



0.986

Micro F-1 Score

– on test set –


Feature Importance (Gradient Boosting)
histogram_variance
histogram_median
histogram_mean
histogram_mode
histogram_number_of_peaks
histogram_max
histogram_min
histogram_width
mean_value_of_long_term_variability
percentage_of_time_with_abnormal_long_term_variability
mean_value_of_short_term_variability
abnormal_short_term_variability
prolongued_decelerations
uterine_contractions
fetal_movement
accelerations
baseline value
0.00
0.05
0.10
0.15
0.20
0.25

Clustering

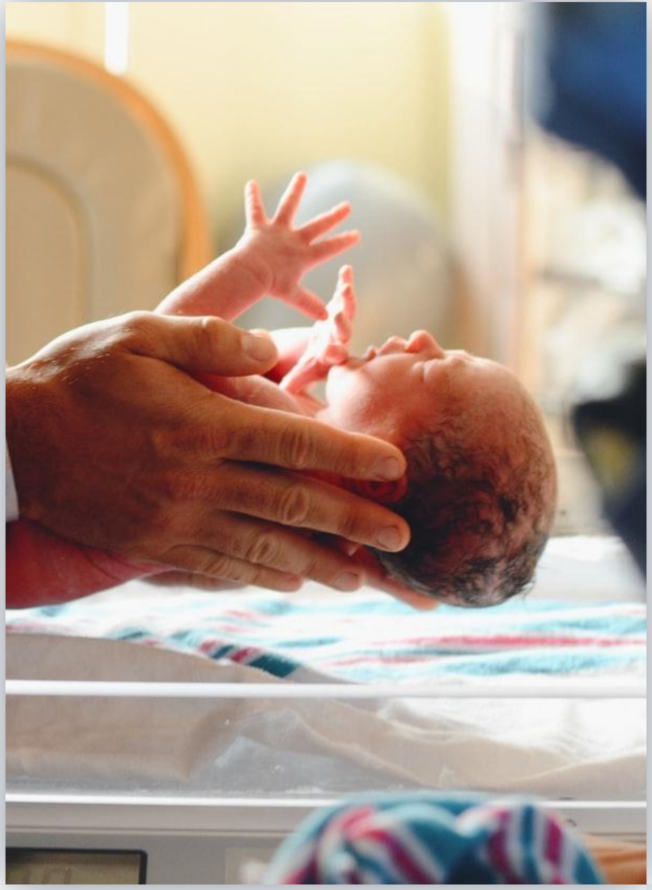
- Hierarchical, KMeans, DBSCAN
- All showed that dividing the CTG scans into two clusters was best (based on internal validation)
  - These did not correspond much to the original labels
  - However, hard to interpret...

Conclusion

Study with similar data only reached 92% precision on test set while we reached 97%

Implementation in LICs:

- Lack of knowledge on the significance of the tool
- Lack of training in the acquisition and interpretation.
- Equipment and maintenance cost
- Requirement of a qualified specialists



Thanks!

Any questions?

References

Fetal Health Classification | Kaggle

Automated Software Analysis of Fetal Movement Recorded during a Pregnant Woman's Sleep at Home (nih.gov)

Interpretation of the Electronic Fetal Heart Rate During Labor - American Family Physician (aafp.org)