Fetal Health Classifier

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Presentation

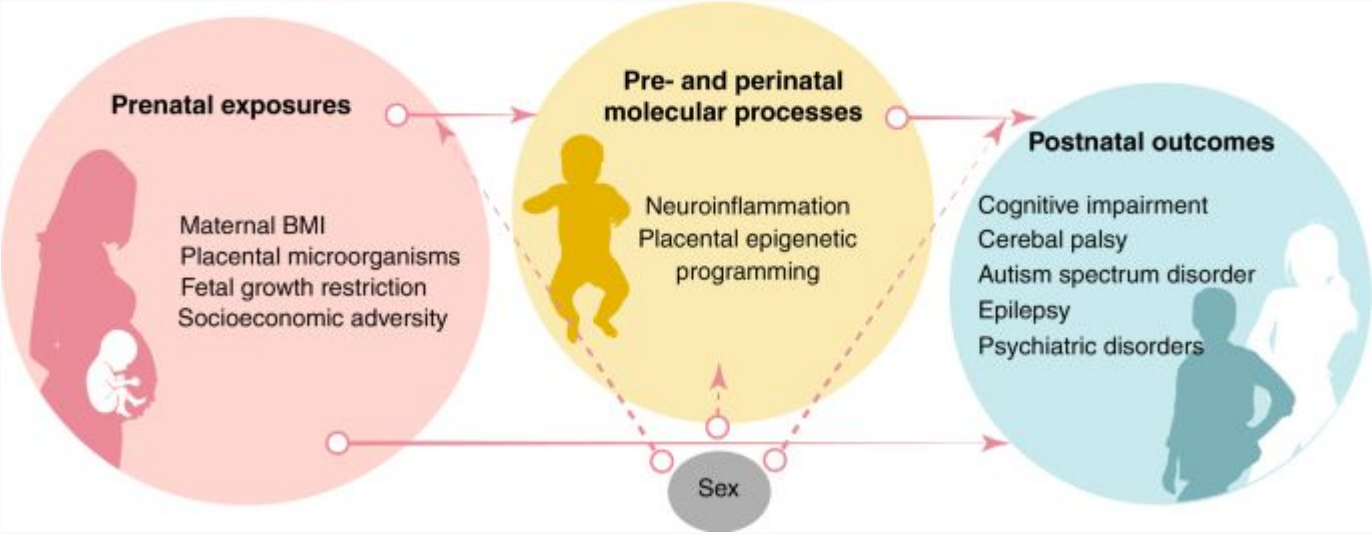
Contents

Introduction

Problem:
Fetal Health

- Fetal health of a baby in utero has an impact on child and maternal mortality.
- Child mortality is a concern in countries all over the world.
- By analyzing and classifying fetal health, countries can end preventable deaths of newborns and babies under the age of 5 years old.
- This issue of fetal health is something that affects both the fetus and the maternal health of its carrier. Thus, by solving this problem, we could save not just one life, but two.

Lifecycle of Fetal Health



Source: https://www.nature.com/articles/s41390-020-01236-1

Project Goals

Goal: We built machine learning models to predict fetal health using uterine contraction and other clinical features detectable by observing vitals for expectant mothers.

Plan: We built two supervised learning models to classify patients as having a fetus with normal health or at-risk health. We used pairwise correlation to find the most critical feature to use in our model as a predictor variable, prolonged_decelerations.

Random Forest Classifier Model   & Decision Tree Classifier Model

Metrics: Our model performance metrics included: accuracy, precision, recall, and F1-score to determine if our predictive models were successful and determine which model performed the best.

The Data

Dataset

2126

measurements

Variables included:

- baseline value
- accelerations
- fetal movement
- uterine contractions
- light decelerations
- severe decelerations
- prolonged decelerations
- abnormal short term variability
- mean value of short term variability
- percentage of time with abnormal long term variability

Data sourced from Kaggle. All variables were float numeric values, and there were no missing values.

Exploratory Data Analysis

Fetal Health Values

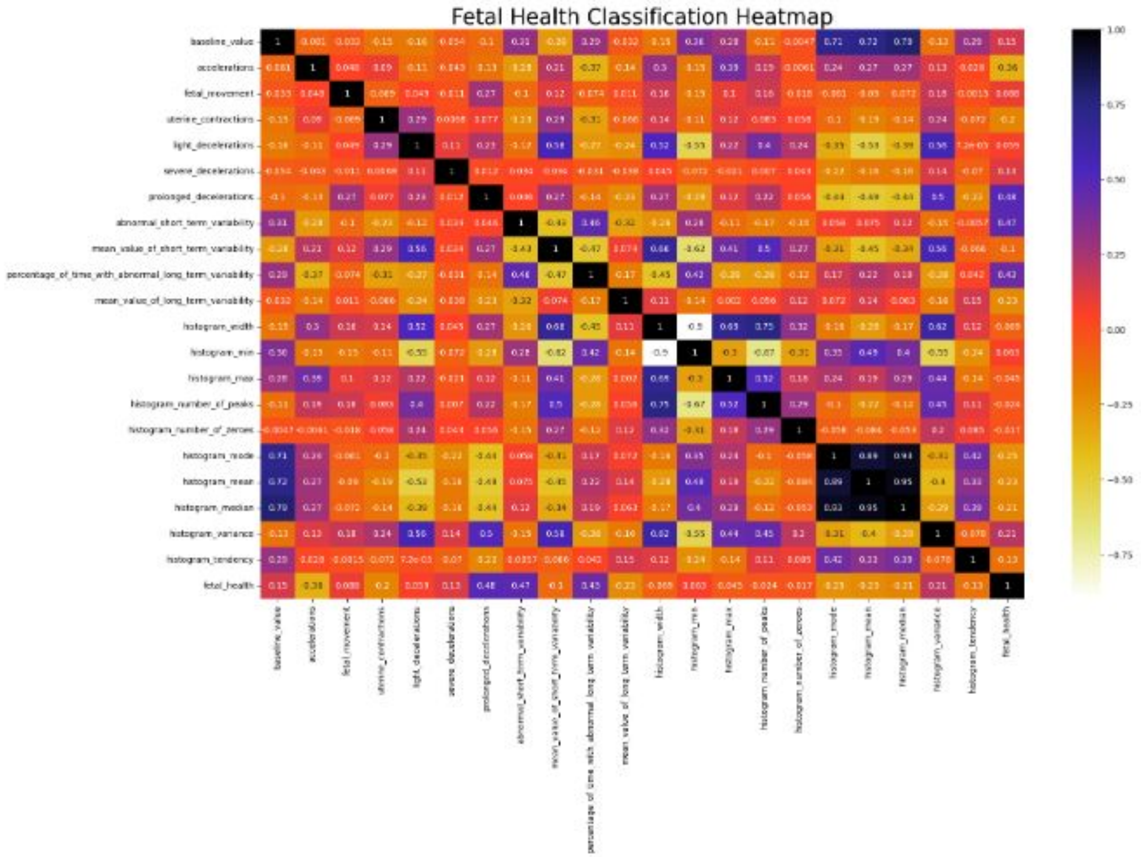
1 - Normal

2 - Suspect

3 - Pathological

	Normal	Suspicious	Pathological
Baseline	110–160 bpm	Lacking at least one characteristic of normality, but with no pathological features	< 100 bpm
Variability	5–25 bpm	Lacking at least one characteristic of normality, but with no pathological features	Reduced variability, increased variability, or sinusoidal pattern
Decelerations	No repetitive[b] decelerations	Lacking at least one characteristic of normality, but with no pathological features	Repetitive[b] late or prolonged decelerations during > 30 min or 20 min if reduced variability, or one prolonged deceleration with > 5 min

Source: https://obgyn.onlinelibrary.wiley.com/doi/10.1016/j.ijgo.2015.06.020



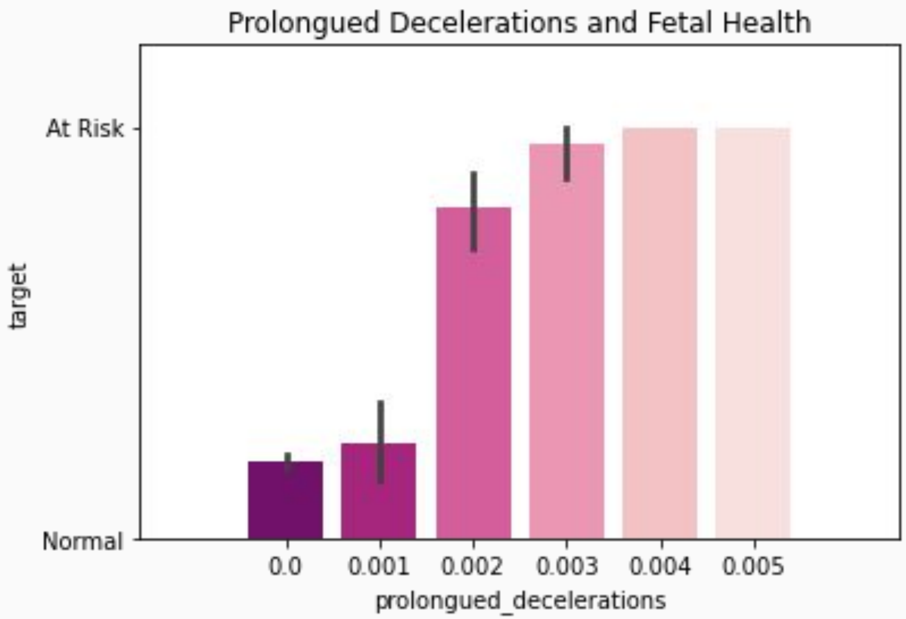
With any research using this dataset, we would drop the highly correlated features shown in this heatmap from the model. However, we will focus on prolonged decelerations for the purpose of group research.

Decision Tree Classifier

Fetal Health correlations

	baseline_value	accelerations	fetal_movement	uterine_contractions	light_decelerations	severe_decelerations	prolongued_decelerations	abno
baseline_value	1.000000	-0.080560	-0.033436	-0.146373	-0.159032	-0.053518	-0.104597	
accelerations	-0.080560	1.000000	0.048235	0.089674	-0.108615	-0.043018	-0.127749	
fetal_movement	-0.033436	0.048235	1.000000	-0.068779	0.049228	-0.010976	0.265922	
uterine_contractions	-0.146373	0.089674	-0.068779	1.000000	0.285079	0.006788	0.077036	
light_decelerations	-0.159032	-0.108615	0.049228	0.285079	1.000000	0.107573	0.225611	
severe_decelerations	-0.053518	-0.043018	-0.010976	0.006788	0.107573	1.000000	0.012395	
›ngued_decelerations	-0.104597	-0.127749	0.265922	0.077036	0.225611	0.012395	1.000000	
short_term_variability	0.305570	-0.279577	-0.103715	-0.232811	-0.119152	0.033949	0.046226	
short_term_variability	-0.279607	0.207170	0.121314	0.289679	0.562170	0.034130	0.267011	
_long_term_variability	0.285630	-0.373943	-0.074096	-0.306608	-0.271282	-0.030770	-0.137333	
_long_term_variability	-0.032091	-0.142363	0.011047	-0.066058	-0.242932	-0.037667	-0.226514	
histogram_width	-0.147679	0.298631	0.162790	0.142541	0.520467	0.044880	0.265391	
histogram_min	0.361619	-0.154286	-0.153917	-0.113323	-0.553534	-0.071974	-0.276764	
histogram_max	0.275110	0.394147	0.099853	0.122766	0.218043	-0.021135	0.120221	
ım_number_of_peaks	-0.113933	0.190452	0.164654	0.082693	0.397620	0.007024	0.222860	
m_number_of_zeroes	-0.004745	-0.006147	-0.017749	0.057894	0.235296	0.043441	0.056423	
histogram_mode	0.708993	0.243610	-0.061192	-0.104854	-0.347233	-0.215161	-0.436416	
histogram_mean	0.723121	0.270334	-0.089671	-0.187505	-0.527354	-0.158673	-0.488663	
histogram_median	0.789246	0.272849	-0.072329	-0.140287	-0.388586	-0.160451	-0.444778	
histogram_variance	-0.133938	0.125704	0.179340	0.238582	0.564289	0.136421	0.503301	
histogram_tendency	0.293503	0.028420	-0.001541	-0.072314	0.000072	-0.070483	-0.215405	
fetal_health	0.148151	-0.364066	0.088010	-0.204894	0.058870	0.131934	0.484859	

Examining relationship between Prolonged Decelerations and Fetal Health



Methodology

Preprocessing

- In preparation for building our chosen models, we found that we had no missing values to impute and that all values were numeric.
- However, we did need to classify Fetal Health ranges as Normal or At Risk with the scale given in our data set. We assigned 1 as Normal, and 2 or 3 values as At-Risk.
- Finally, we provided scalar standardization for the predictor variable, X.

Standardization of X variables

Standardization of the dataset is an common requirement for many machine learning algorithms implemented in scikit-learn.they might behave badly if the individual features do not more or less look like standard normally distributed data.Gaussian with zero mean and unit variance.

```
from sklearn.preprocessing import StandardScaler
sss=StandardScaler()
X=sss.fit_transform(X)
X.shape
```

```
(2126, 21)
```

Methodology Selection: Decision Trees

Decision Trees Classifier is a supervised machine learning algorithm, which uses labeled data sets to train algorithms that classify data or predict outcomes accurately. Decision trees uses a tree-like flowchart model of decisions and the corresponding possible consequences. A decision tree consists of three types of nodes:

1. Root Node - represents the feature all other nodes split from;

2. Decision Nodes - represent a test on a feature or attribute for a decision to be made on. As the tree depth increases, the loss entropy should decrease and the information gain should increase until we end up with a pure leaf or end node

3. Leaf/End Nodes - represents the outcome with reduced uncertainty

It is advantageous to use decision trees because they are interpretable and understandable after brief explanation.A disadvantage is that calculation can become complex if many values are uncertain. Since our data has no missing values, there is little to no uncertainty to impact decision trees as a selected model. Accuracy of the decision tree model is increased when the depth increases.

Methodology Selection: Random Forest

Random Forest Classifier is a supervised machine learning technique consisting of many decision trees.

Random Forest uses ensemble learning to combine many weak classifier to provide solutions for complex problems.

Random Forest is a bagging method that uses a subset of the original dataset to make predictions, which is an advantage to help to limit overfitting, and creates multiple decision trees with a different set of observations.

This classifier involves bootstrapping, which is row and feature sampling with a replacement before training the model.

A disadvantage in using this model is when using one feature, Low Bias and High Variance increases with the depth of the decision trees.

Methodology Comparison
Decision Tree vs. Random Forest

Decision Trees Classifier

- A single decision tree has faster computation
- Uses rules to predict from input that is a dataset with features
- May experience overfitting if maximum depth reached

Random Forest Classifier

- Computation is slower
- Randomly selects observations, builds decision trees and averages
- May experience overfitting if not enough features selected; otherwise, the bagging method that yields output based on majority vote/ranking fixes overfitting

Evaluation Metrics

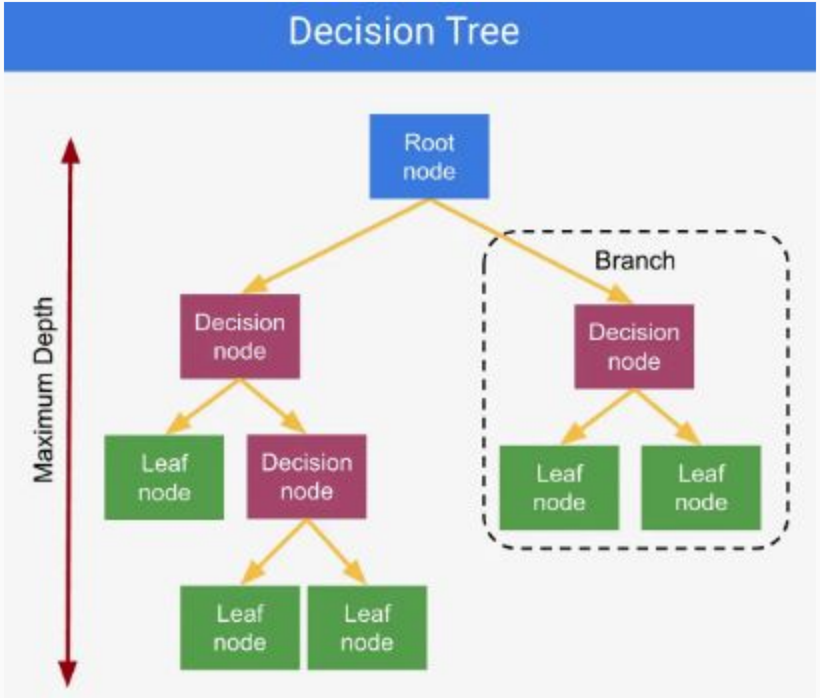
Method

Decision Tree Classifier

Accuracy & F-1: 0.87

Method

Decision Tree Classifier

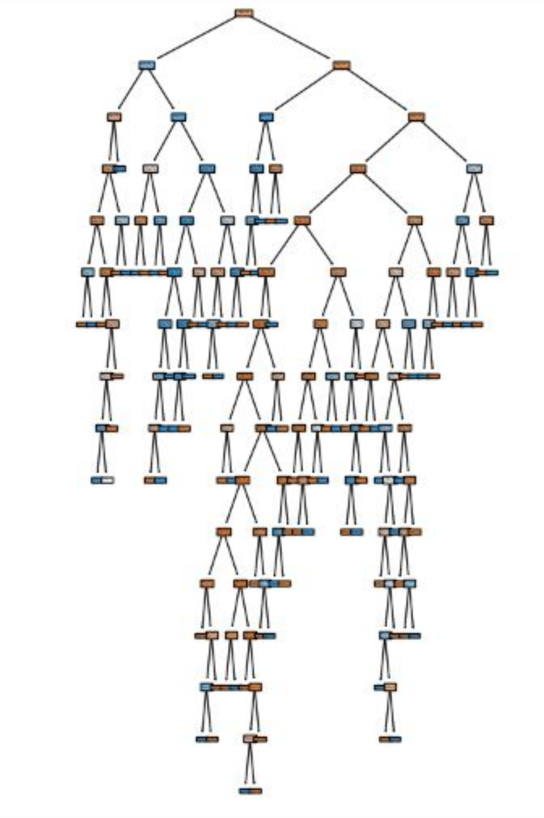


Source: https://www.jcchouinard.com/decision-trees-in-machine-learning/.

Showing illustration of Decision Tree structure. Now Let's see the full decision tree model plot for our data to check depth.

Method

Decision Tree Classifier



Showing illustration of Decision Tree model plot to show depth level of the Decision Tree Classifier was 15.
A greater depth number increases accuracy.

Method

Decision Tree Classifier

Decision Tree Classifier & Tuned DT	Actual Values	
	Actual Positive	Actual Negative
Predicted Positive	313 (TP)	23 (FP)
Predicted Negative	37 (FN)	53 (TN)

There were 313 true positives outcomes, and 23 false positive outcomes for predictions. There were 37 false negatives and 53 true negatives.

Decision Tree Classifier & Tuned DT	Evaluation Parameter		
	Precision	Recall	F1-score
0	0.89	0.93	0.91
1	0.70	0.59	0.64
Weighted Avg	0.85	0.86	0.85
		Accuracy:	0.86

The Decision Tree Classifier accuracy was 86%, pre and post hyperparameter tuning. Fetal Health Classification is binary, where Normal 0 and At-Risk = 1. The model performs better for Normal outcomes.

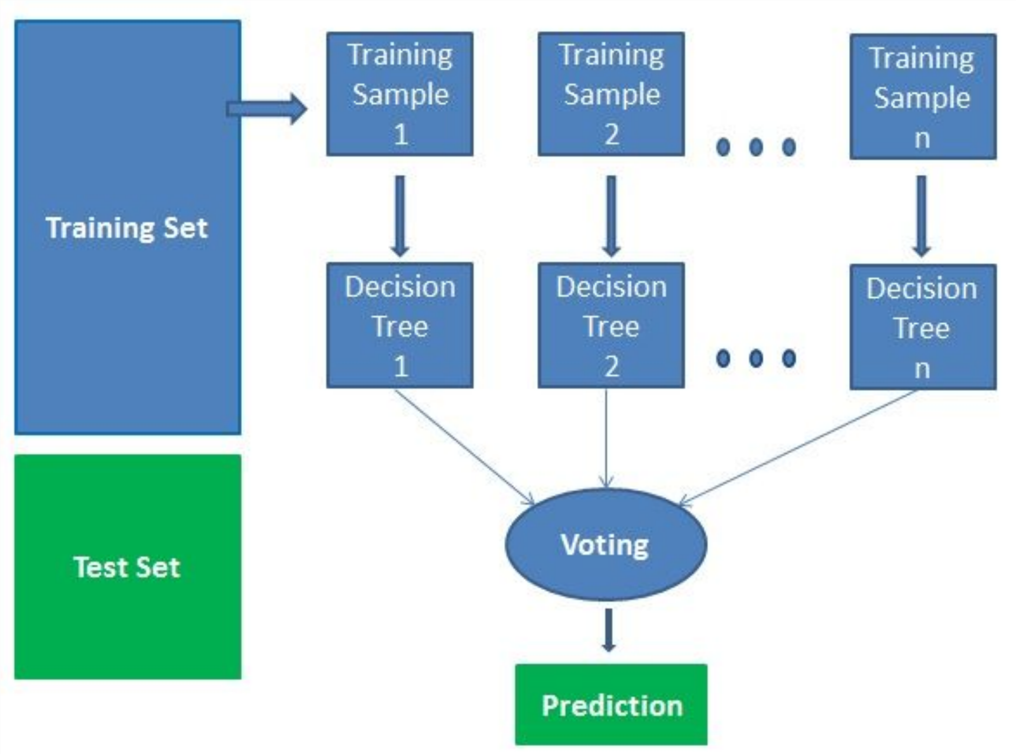
Method

Random Forest Classifier

Accuracy & F-1: 0.87

Method

Random Forest Classifier



Source: https://github.com/geekquad/Random-Forest-from-Scratch

Showing illustration of Random Forest Classifier structure. Now Let's see the full Random Forest Classifier model metrics.

Method

Random Forest Classifier

Random Forest Classifier	Actual Values	
	Actual Positive	Actual Negative
Predicted Positive	310 (TP)	26 (FP)
Predicted Negative	30 (FN)	60 (TN)

There were 310 true positives outcomes, and 26 false positive outcomes for positive predictions. There were 30 false negatives and 60 true negatives.

Random Forest Classifier	Evaluation Parameter		
	Precision	Recall	F1-score
0	0.91	0.92	0.92
1	0.70	0.67	0.68
Weighted Avg	0.87	0.87	0.87
		Accuracy:	0.87

The Random Forest Classifier accuracy was 87% and it has higher performance for the Normal health outcome than At Risk.

Future Work

Missing Information

- Demographics
- Stage of pregnancy during which measurements were taken
- Number of fetuses in utero
- Gender of fetus
- Lifestyle of mother
- Results of non-stress test
- Previous pregnancies or stillbirths of mother

These missing features could improve research and help with eliminating disparities in clinical practice.

Results

Model Performance Results Summary

- Performance for each model showed very good results (accuracy score):
  0.87 for the RF model | 0.87 for the DT model

- Random Forest predicted Fetal Health with 87% accuracy, recall, and precision.
- Decision Trees predicted Fetal Health with 87% accuracy and recall, but 86% precision.
- After hyperparameter tuning, Decision Trees modelling precision performance increased to 87%, but remained the same for the other metrics.
- Overall, Random Forest classification model was the best performing model in detecting fetal health and was 1% more precise than Decision Tree on the first run.

Conclusion

Concluding statements

- We need more patient data to drive the false positive and false negative ratios down, thus improving performance. Performance can be further improved for Random Forest with additional hyperparameter tuning.
- We find that the application of machine learning models like Decision Trees and Random Forest for the detection of at-risk fetal health is an effective method that with additional data collection and demographic features can easily be used in clinical settings.
- Although considerable advancements have been made in medical care, the rate of maternal mortality and morbidity and preterm birth have been rising in the United states of the past few years.
- We see that maternal and infant mortality rates in the US are much higher than their counterparts of similarly populated and wealthy countries.
- And of course the most at risk populations are those of people of color where they experience an increased risk for poor maternal and infant health outcomes in comparison to their American peers of European descent.
- It is imperative to close the gap on this disparity and collect data that includes demographic attributes. For we all know that race and ethnicity has correlating trends with family income, which correlates with lifestyle and health access and outcomes.

References

- Bangma, Jacqueline T., et al. "Placental Programming, Perinatal Inflammation, and Neurodevelopment Impairment among Those Born Extremely Preterm." *Nature News*, Nature Publishing Group, 12 Nov. 2020, https://www.nature.com/articles/s41390-020-01236-1.
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