

Improving Fetal Health Outcomes: Data Cleaning Process and Exploratory Data Analysis

A closer look into the
technical process..

Fetal Health Data Set

“Reduction of child mortality is reflected in several of the United Nations' Sustainable Development Goals and is a key indicator of human progress.

The UN expects that by 2030, countries end preventable deaths of newborns and children under 5 years of age, with all countries aiming to reduce under 5 mortality to at least as low as 25 per 1,000 live births.

Parallel to notion of child mortality is of course maternal mortality, which accounts for 295,000 deaths during and following pregnancy and childbirth (as of 2017). The vast majority of these deaths (94%) occurred in low-resource settings, and most could have been prevented.

In light of what was mentioned above, Cardiotocograms (CTGs) are a simple and cost accessible option to assess fetal health, allowing healthcare professionals to take action in order to prevent child and maternal mortality. The equipment itself works by sending ultrasound pulses and reading its response, thus shedding light on fetal heart rate (FHR), fetal movements, uterine contractions and more.”

External Fetal Monitor

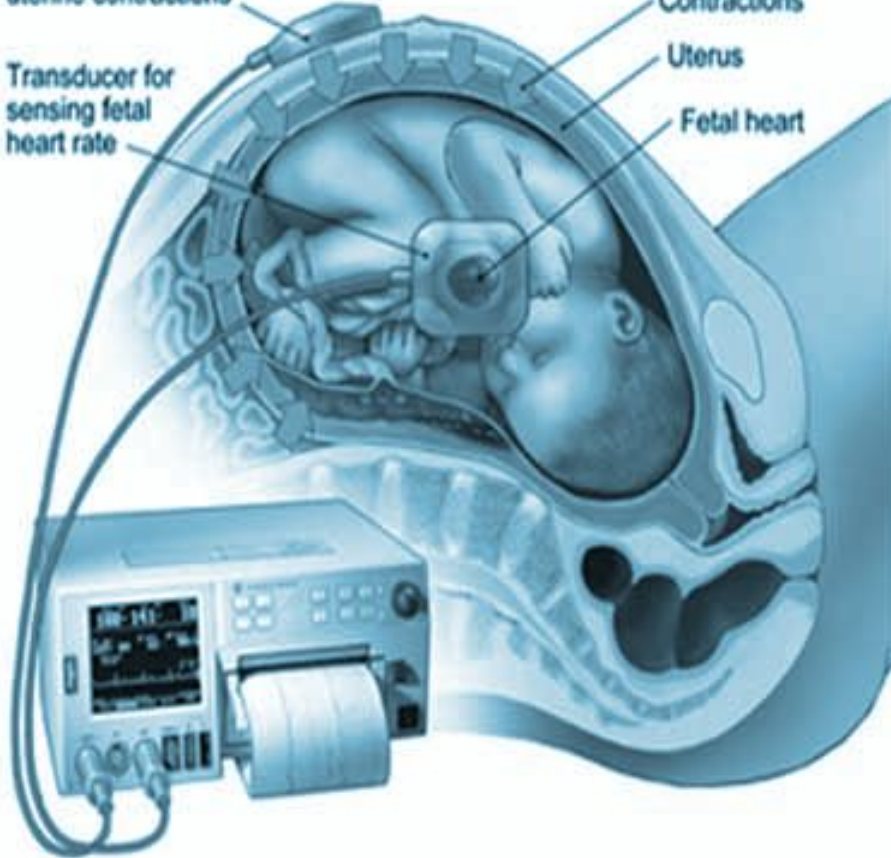
Transducer for sensing
uterine contractions

Transducer for sensing fetal
heart rate

Contractions

Uterus

Fetal heart



Cardiotocogram (CTGs)

Fetal Health Dataset

```
filename = '/content/fetal_health.csv'  
df = pd.read_csv(filename)  
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 2126 entries, 0 to 2125
```

```
Data columns (total 22 columns):
```

#	Column	Non-Null Count	Dtype
0	baseline value	2126 non-null	float64
1	accelerations	2126 non-null	float64
2	fetal_movement	2126 non-null	float64
3	uterine_contractions	2126 non-null	float64
4	light_decelerations	2126 non-null	float64
5	severe_decelerations	2126 non-null	float64
6	prolongued_decelerations	2126 non-null	float64
7	abnormal_short_term_variability	2126 non-null	float64
8	mean_value_of_short_term_variability	2126 non-null	float64
9	percentage_of_time_with_abnormal_long_term_variability	2126 non-null	float64
10	mean_value_of_long_term_variability	2126 non-null	float64
11	histogram_width	2126 non-null	float64
12	histogram_min	2126 non-null	float64
13	histogram_max	2126 non-null	float64
14	histogram_number_of_peaks	2126 non-null	float64
15	histogram_number_of_zeroes	2126 non-null	float64
16	histogram_mode	2126 non-null	float64
17	histogram_mean	2126 non-null	float64
18	histogram_median	2126 non-null	float64
19	histogram_variance	2126 non-null	float64
20	histogram_tendency	2126 non-null	float64
21	fetal_health	2126 non-null	float64

```
dtypes: float64(22)
```

```
memory usage: 365.5 KB
```

Data Cleaning

```
✓ 0s ▶ df.isnull().sum()

#No missing values

baseline value 0
accelerations 0
fetal_movement 0
uterine_contractions 0
light_decelerations 0
severe_decelerations 0
prolonged_decelerations 0
abnormal_short_term_variability 0
mean_value_of_short_term_variability 0
percentage_of_time_with_abnormal_long_term_variability 0
mean_value_of_long_term_variability 0
fetal_health 0
dtype: int64
```

Resolving duplicated rows

```
✓ [11] df.duplicated().sum()  
0s
```

13

```
✓ [12] #13 Duplicated rows will be dropped  
0s
```

```
✓ [13] df.drop_duplicates(inplace = True)  
0s
```

```
✓ [14] df.duplicated().sum()  
0s
```

0

Eliminating unnecessary columns

Removing unnecessary columns

```
[15] df.drop(columns = ['histogram_width', 'histogram_min', 'histogram_max', 'histogram_number_of
```

```
df.head().T
```

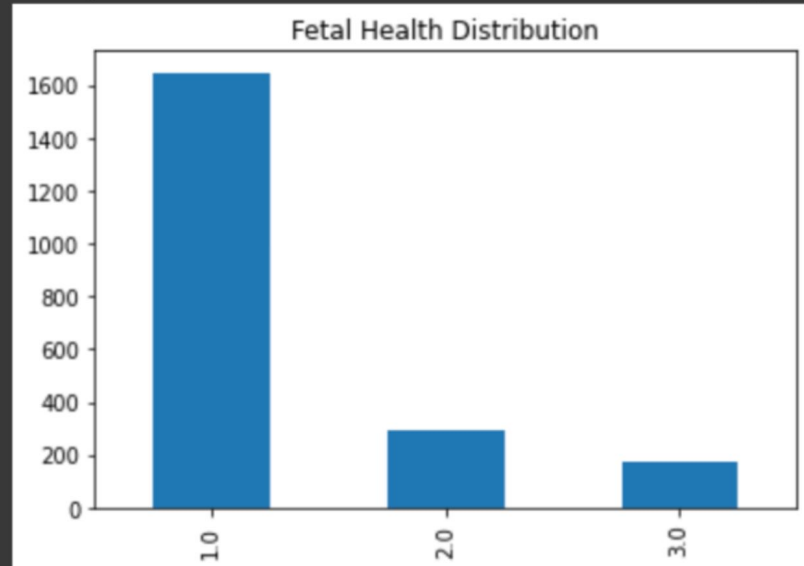
	0	1	2	3	4
baseline value	120.0	132.000	133.000	134.000	132.000
accelerations	0.0	0.006	0.003	0.003	0.007
fetal_movement	0.0	0.000	0.000	0.000	0.000
uterine_contractions	0.0	0.006	0.008	0.008	0.008
light_decelerations	0.0	0.003	0.003	0.003	0.000
severe_decelerations	0.0	0.000	0.000	0.000	0.000
prolongued_decelerations	0.0	0.000	0.000	0.000	0.000
abnormal_short_term_variability	73.0	17.000	16.000	16.000	16.000
mean_value_of_short_term_variability	0.5	2.100	2.100	2.400	2.400
percentage_of_time_with_abnormal_long_term_variability	43.0	0.000	0.000	0.000	0.000
mean_value_of_long_term_variability	2.4	10.400	13.400	23.000	19.900
fetal_health	2.0	1.000	1.000	1.000	1.000

Visualizing Fetal Health Distribution in this dataset:

```
✓ [17] df['fetal_health'].value_counts()  
0s  
  
1.0    1646  
2.0     292  
3.0     175  
Name: fetal_health, dtype: int64
```

```
✓ [18] df['fetal_health'].value_counts().plot(kind='bar');  
0s  
plt.title('Fetal Health Distribution')
```

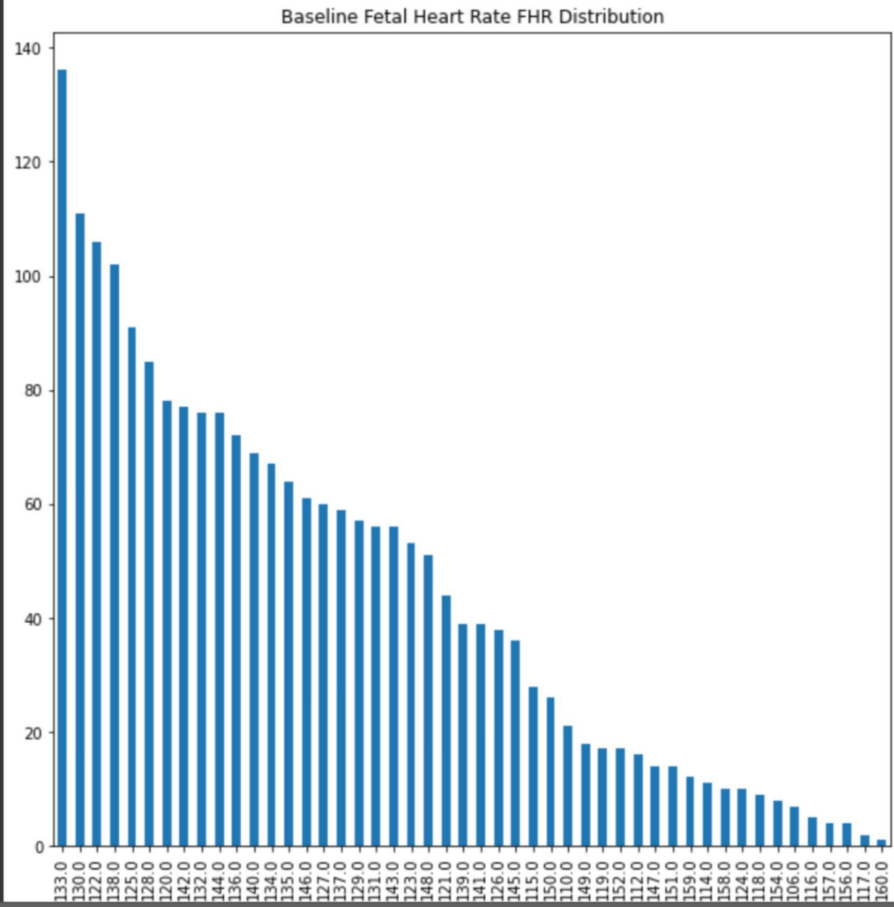
```
Text(0.5, 1.0, 'Fetal Health Distribution')
```



Visualizing the Baseline Fetal Heart Rate bpm Distribution:

```
[19] df['baseline value'].value_counts().plot(kind='bar');  
plt.title('Baseline Fetal Heart Rate FHR Distribution')  
#Baseline Fetal Heart Rate (FHR)
```

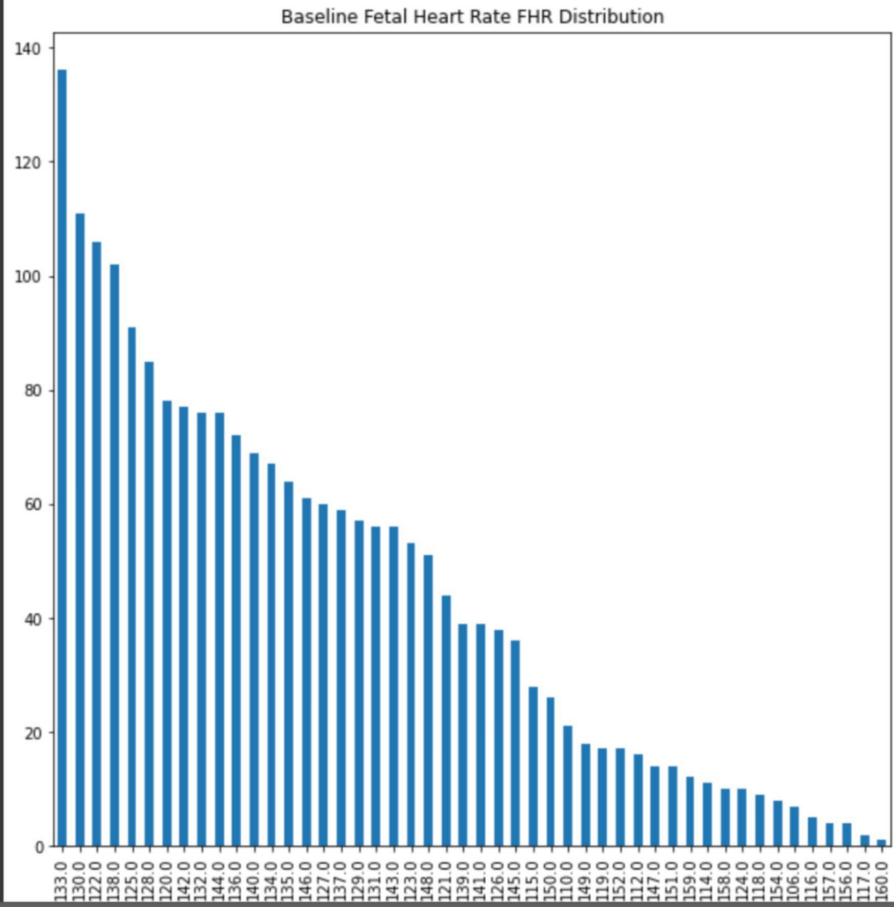
```
Text(0.5, 1.0, 'Baseline Fetal Heart Rate FHR Distribution')
```



Visualizing the Baseline Fetal Heart Rate bpm Distribution:

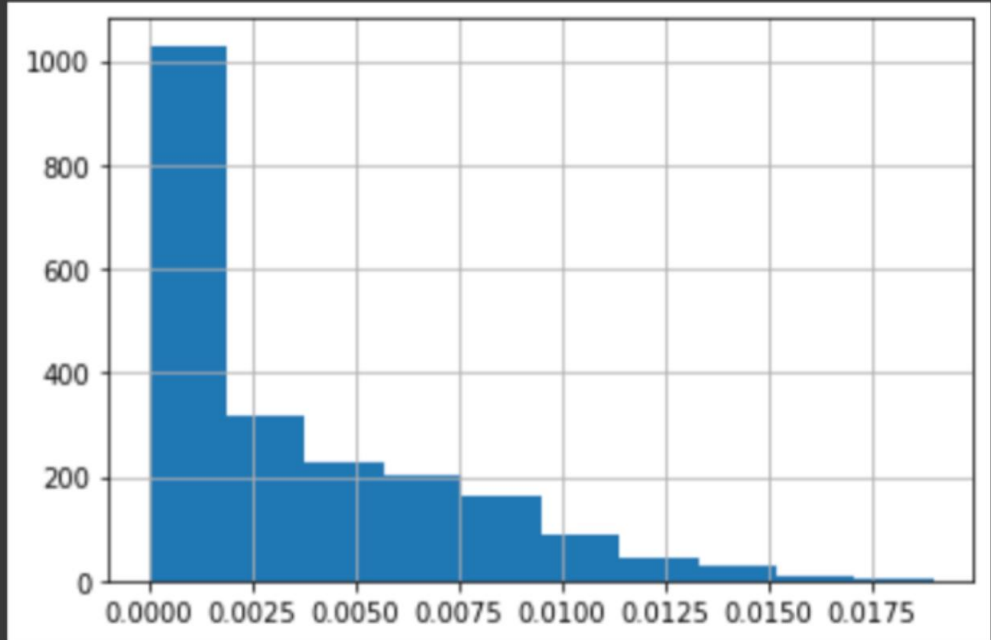
```
[19] df['baseline value'].value_counts().plot(kind='bar');  
plt.title('Baseline Fetal Heart Rate FHR Distribution')  
#Baseline Fetal Heart Rate (FHR)
```

```
Text(0.5, 1.0, 'Baseline Fetal Heart Rate FHR Distribution')
```



Distribution of FHR accelerations per second:

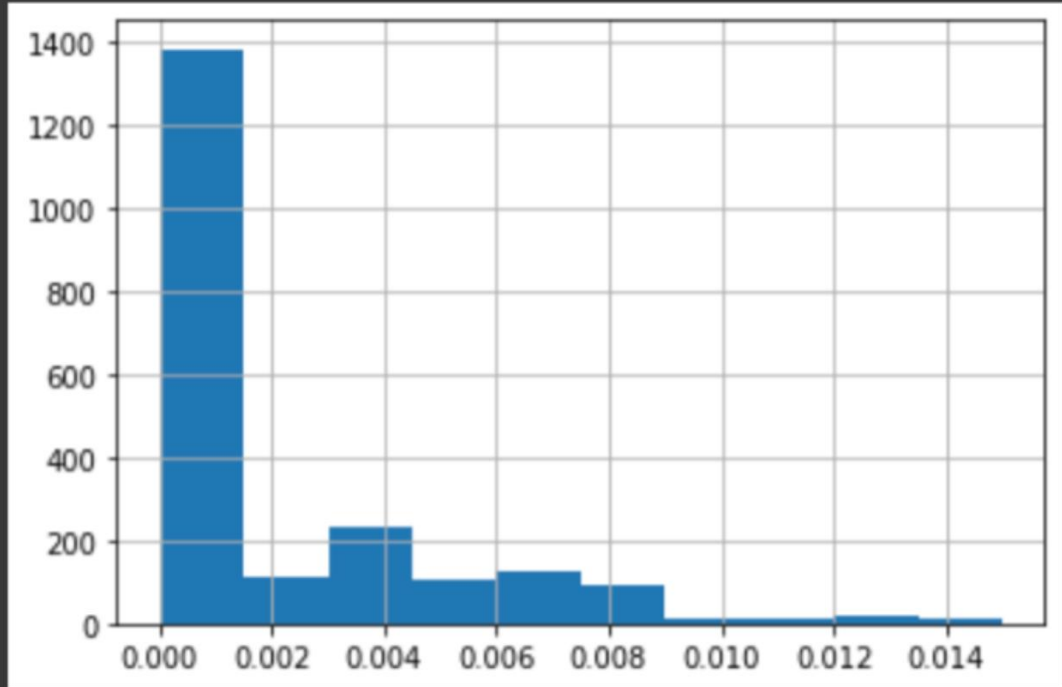
```
✓ [22] df['accelerations'].hist();  
0s
```



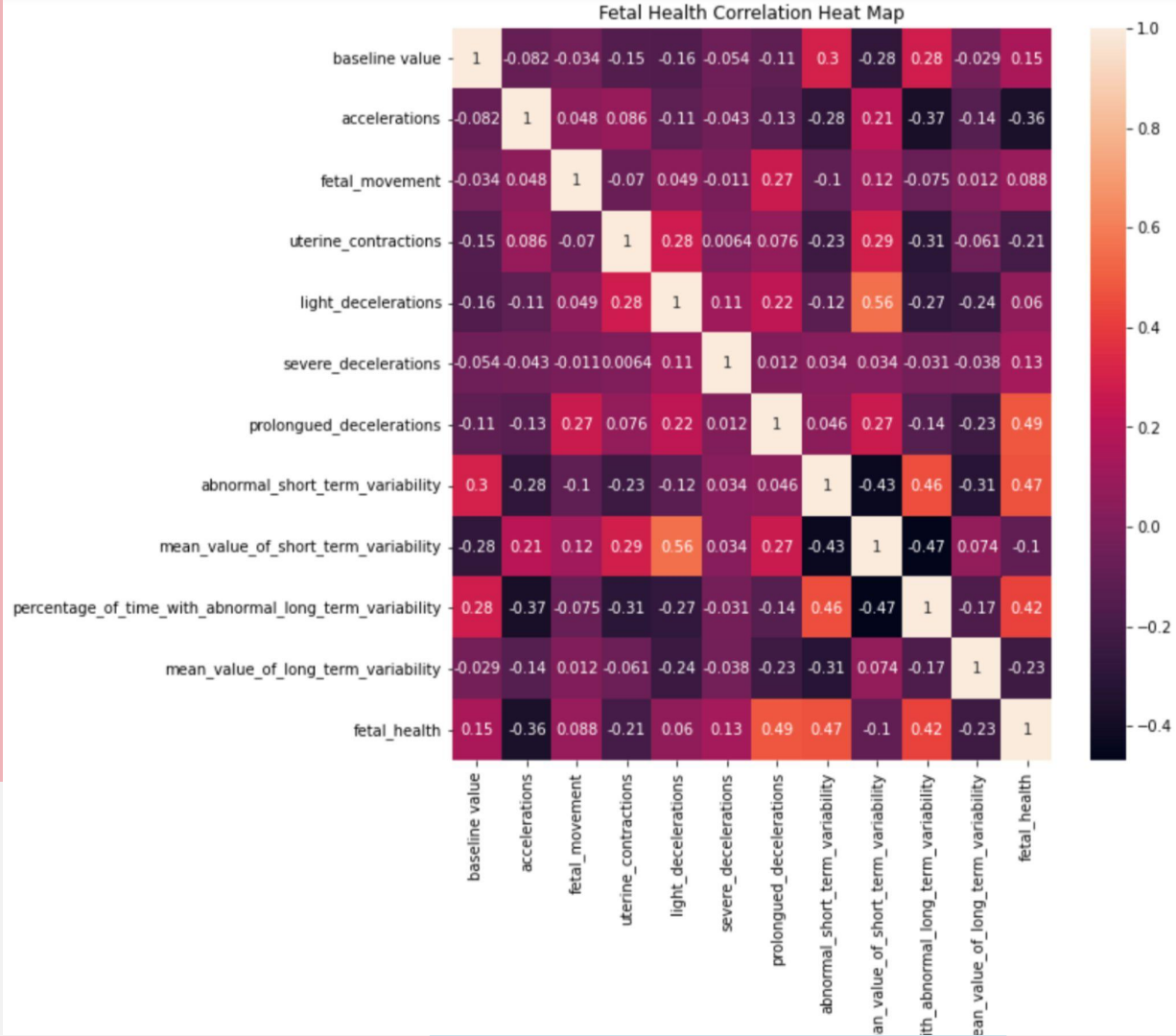
Distribution of FHR decelerations per second:

✓
0s

```
[28] df['light_decelerations'].hist();
```



Visualizing correlations of Fetal Health Data and emerging Fetal Health Predictors



Possible next steps..

01

Supervised Machine Learning

Fetal Health as target vector

02

Unsupervised Machine Learning

Cluster Fetal Health Indicators to identify essential health data for outcome prediction

03

Deliver results

Analyse machine learning models and deliver results to providers

Thank you!

Email questions:

eva.vukich@gmail.com