FETAL CARDIOTOCOGRAPHY

Exploratory Analysis and Prediction of Fetal State

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08.09.2021

SPRINGBOARD CAPSTONE3

PROBLEM STATEMENT

Identify trends and patterns in fetal heart rate and uterine contractions and predict fetal state.

BACKGROUND

Cardiotocography is a technical means of recording the fetal heartbeat and the uterine contractions during pregnancy. In the project, we will perform a thorough exploratory analysis of the fetal cardiotocography data to uncover truths and patterns about the fetal state and how each feature affects the fetal state. We will further use classification models and deep learning procedures to predict fetal state given our data features.

The success of this project can help obstetricians and fetal cardiologists to make better decisions on expecting mothers' fetuses.

DATASETS

Over a period of 4 years 1995-1998, 2126 fetal cardiotocography(CTGs) were automatically processed and the respective diagnostic features measured. The CTGs were also classified by three expert obstetricians and a consensus classification label assigned to each of them. Classifications were both with respect to a morphologic pattern(A, B, C….) and to a fetal state(N,S,P). Therefore the database can be used for 10 class or 3 class experiments.

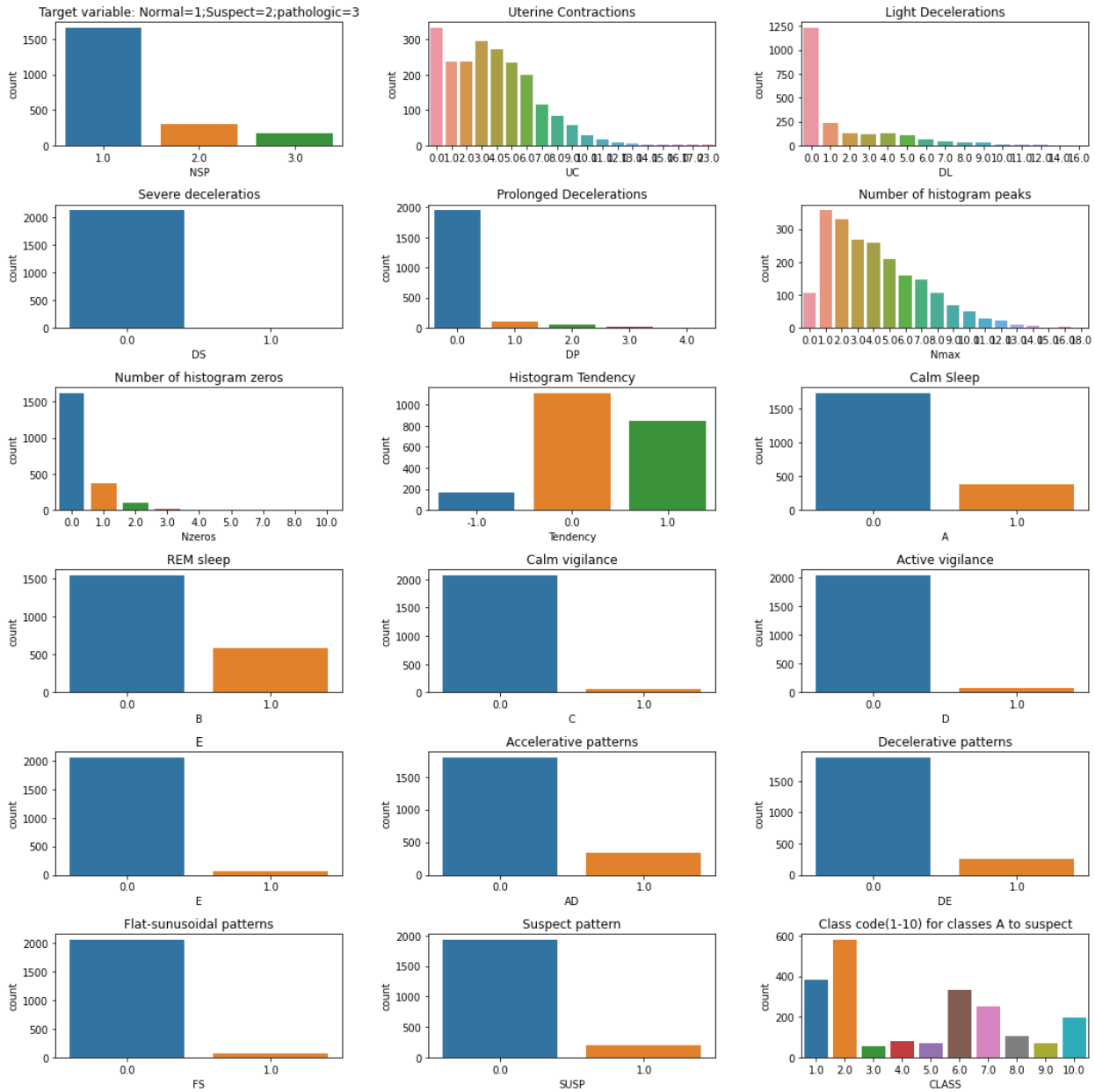
DATA WRANGLING

The dataset was retrieved from the UCI Machine Learning database. The data contained 41 features of 2126 records. I observed that multiple features were highly correlated with each other. Features “Mean”, “Median” and “Mode” had direct linear functional relationships with each other but were not dropped so they could be future explored . However, it was noted, so they would not be included in the training datasets. Negligible amount of null-values was observed in data, so we dropped them since we will not be losing tangible information.We also observed that the feature *“DR”* contained no info, as it contained just one unique value, 0.0. Thus, it was dropped. Further wrangling revealed we had 2 duplicated columns; *“LBE”* and *“LB”*, thus we dropped one of them. Using

histogram plots we got a general overview of the distributions of all features.

EXPLORATORY DATA ANALYSIS

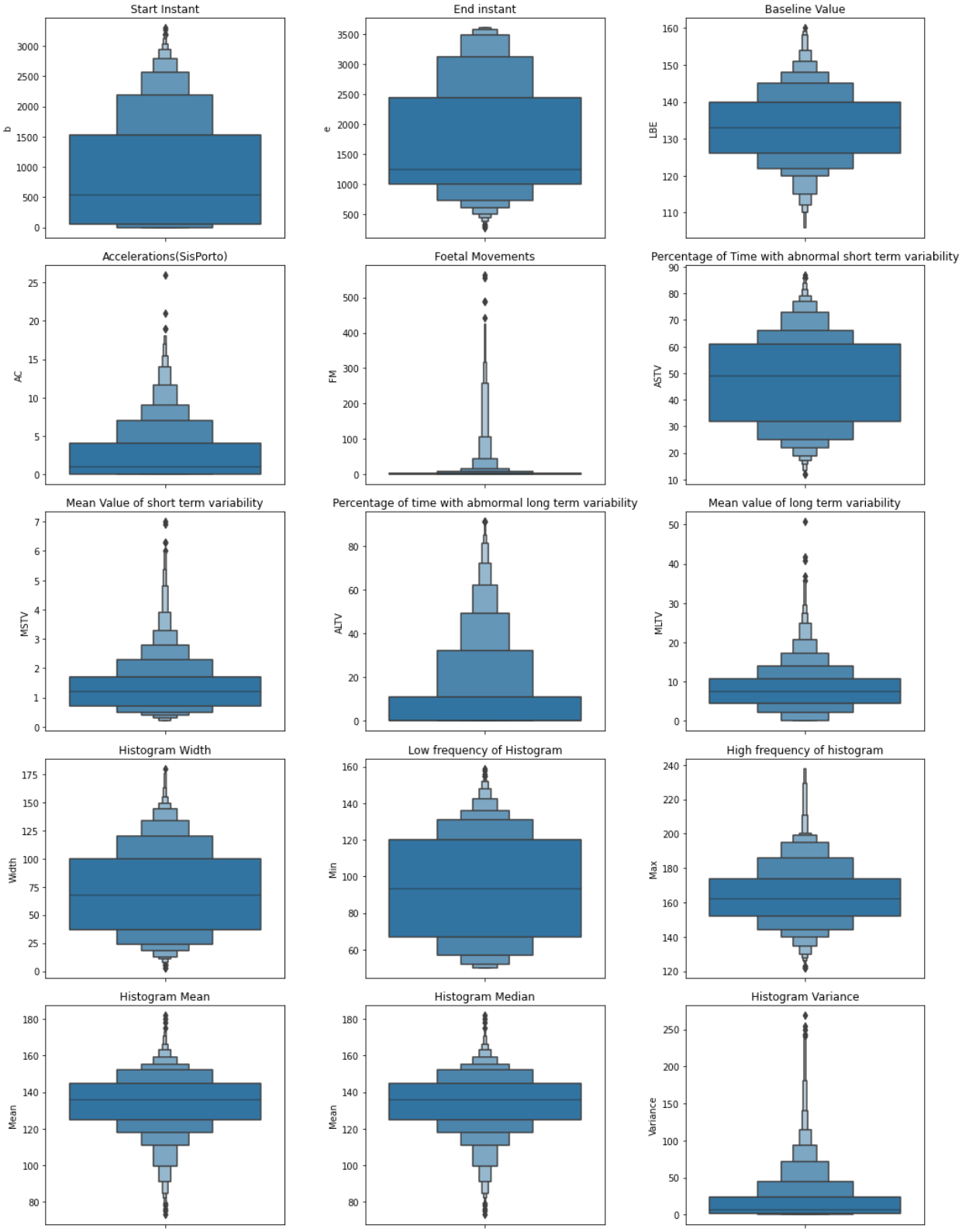
At this stage, we explored each feature independently and how they relate with the target variable *"NSP"*, and with each other for the purpose of gaining greater insights to data and problems using best fit visualizations from seaborn and matplotlib's pyplot libraries. We began with Univariate Analysis of all categorical features.



Observations:

- The Target variable "*NSP"* has majority of Normal fetus and less of Suspect and pathologic cases *Majority of the cases has Uterine contractions ranging from 1- 6
- Most cases had Light decelerations of zero
- Almost no cases had severe or prolonged decelerations of the fetal heartbeat
- about 1500 of our fetus has 0 value for Calm and Rem sleep
- Fetal heartbeat rate for about 2000 of our fetal data has 0 value for Accelerative/Decelerative and flat-sinusoidal patterns
- Most of our fetal had zero for value of Calm and Active vigilance

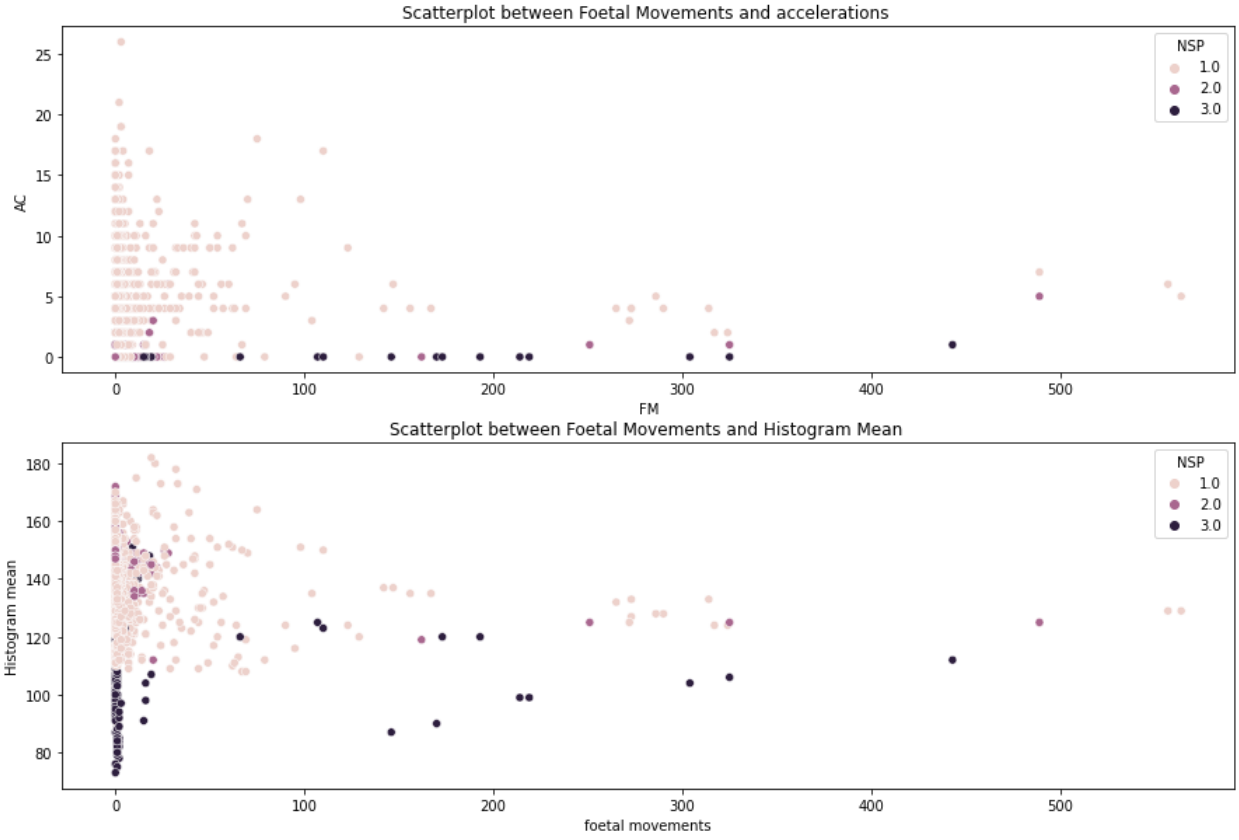
Next, we further performed a univariate analysis on all numerical features in our data.


Start Instant
b
End instant
e
Baseline Value
LBE
Accelerations(SisPorto)
AC
Foetal Movements
FM
Percentage of Time with abnormal short term variability
ASTV
Mean Value of short term variability
MSTV
Percentage of time with abmormal long term variability
ALTV
Mean value of long term variability
MLTV
Histogram Width
Width
Low frequency of Histogram
Min
High frequency of histogram
Max
Histogram Mean
Mean
Histogram Median
Mean
Histogram Variance
Variance

Observations:

- Majority of our data points has Start Instant between 1-1500
- Majority of our data points has End Instant between 1000-2500
- Majority of our data points has Baseline Value between 125-140
- The number of datapoints dropped with an increased Acceleration(SisPorto)
- Most of the data points had a Percentage of time with short term abnormal variability value between 30-60%
- Histogram width was between 25 and 100
- Histogram variance range between 0-50 and had outliers between 200 and 250
- Foetal Movements for most data points range between 0 and 100, with outliers 500

To further understand the relationships between features in relation to the target variable “NSP”, I performed a multivariate analysis using scatterplots and kdeplots on some important features.

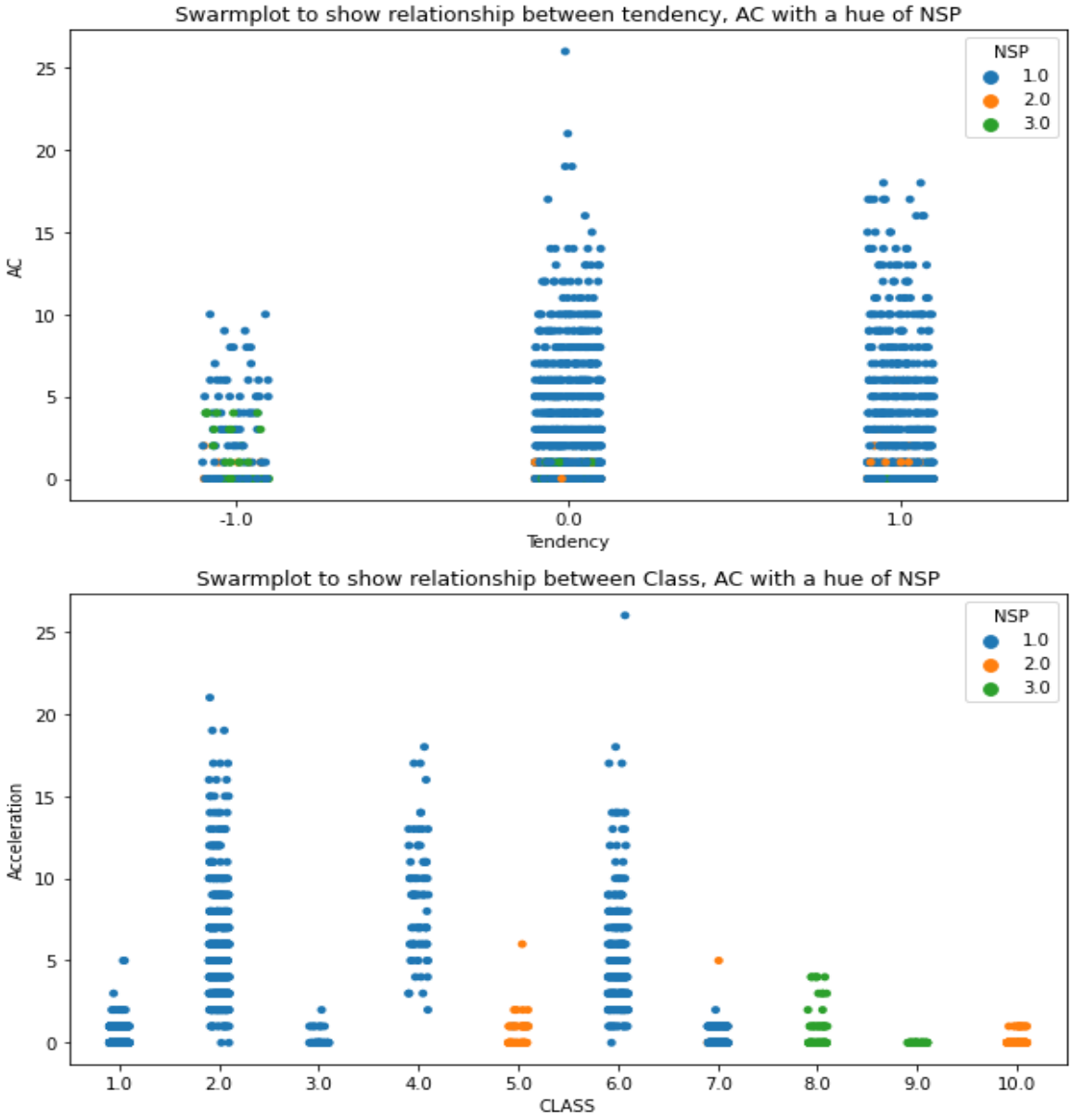


Observations:

- While there is no clear strong correlations there exist clusters of foetal states

- Observe that most of fetals in Normal state had high accelerations
- Also, observe that low accelerations and high foetal movements does not necessarily imply NOT Normal foetus.
- Pathologic Fetal states tends to have higher foetal movements with low or no accelerations
- Observe that most pathologic fetus have lower histogram means and lower foetal movements

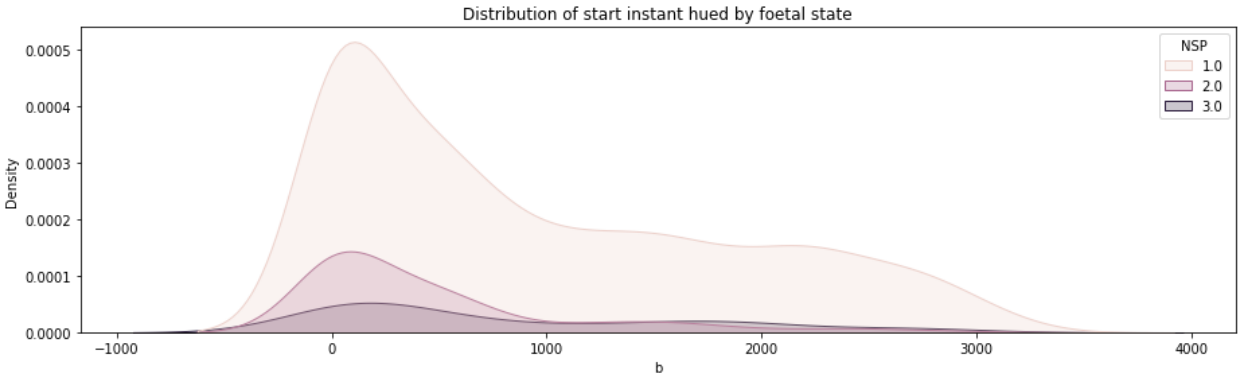
Furthermore, we investigated the relationship between features Tendency, Class and acceleration with a hue on the foetal state.

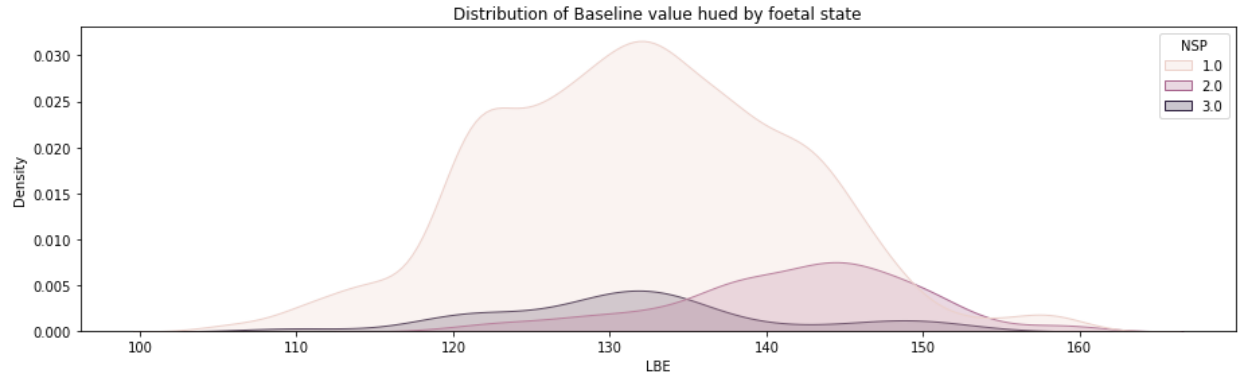


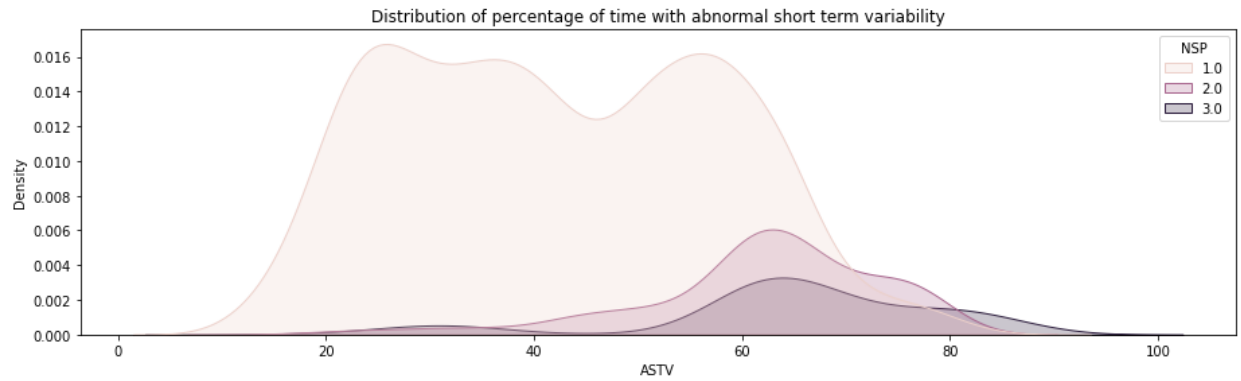
Observations:

- Observe accelerations was low for all but present in all different tendencies for all foetal states
- Normal foetal states seemed to be least in Tendency=-1
- Observe Classes 1,2,3,4,6 and 7 has Normal foetal states
- Classes 5 and 10 has Suspects foetal states
- Classes 8 and 9 has pathologic foetal states

Finally at this stage we observed the distribution of some features with a hue on foetal state.







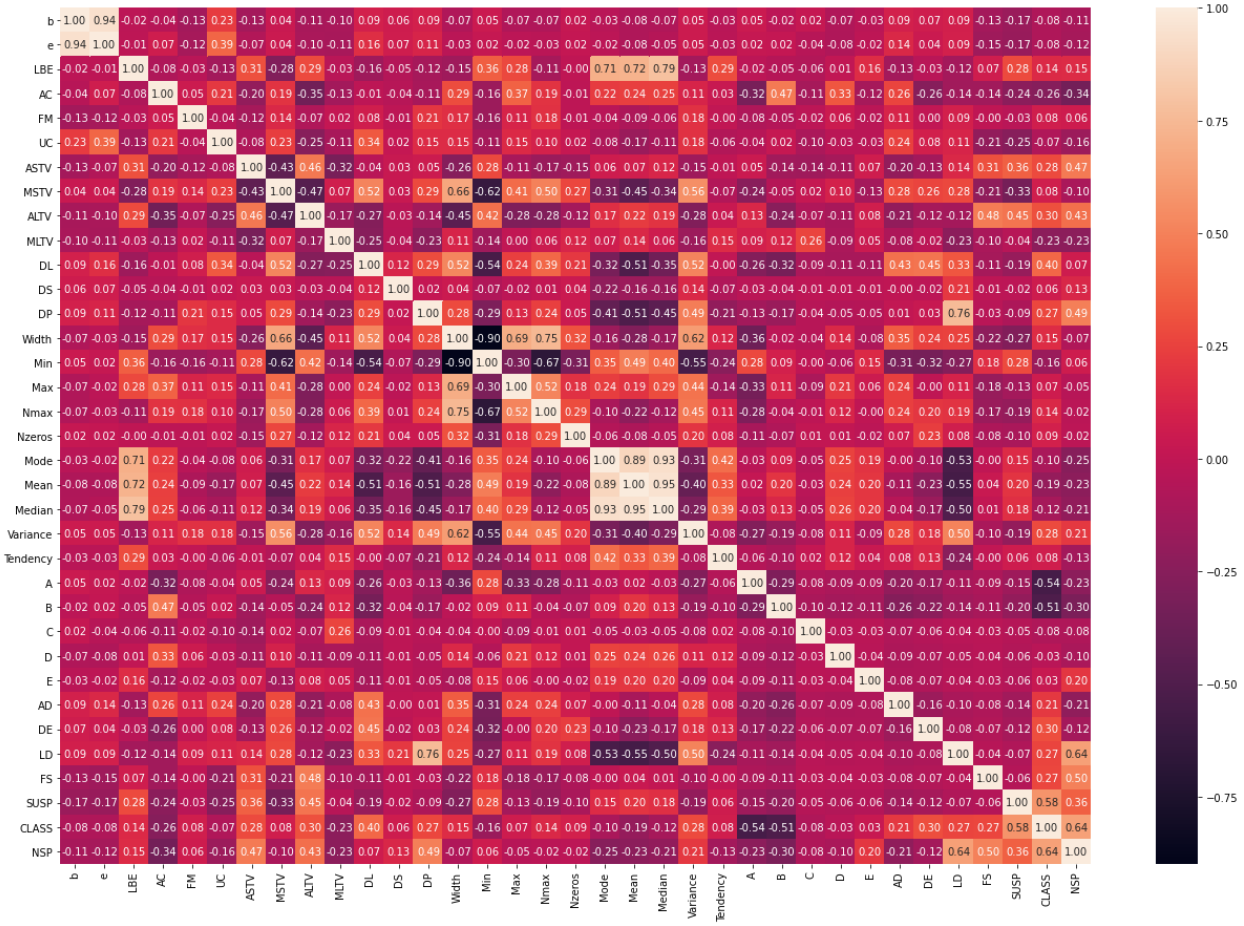
Observations:

- Observe the distributions for all foetal states are skewed to the right
- The mean for Baseline value differs for each foetal states
- Normal State NSP averagely has a lower percentage of time with abnormal short term variability to pathologic and suspect states

PRE-PROCESSING

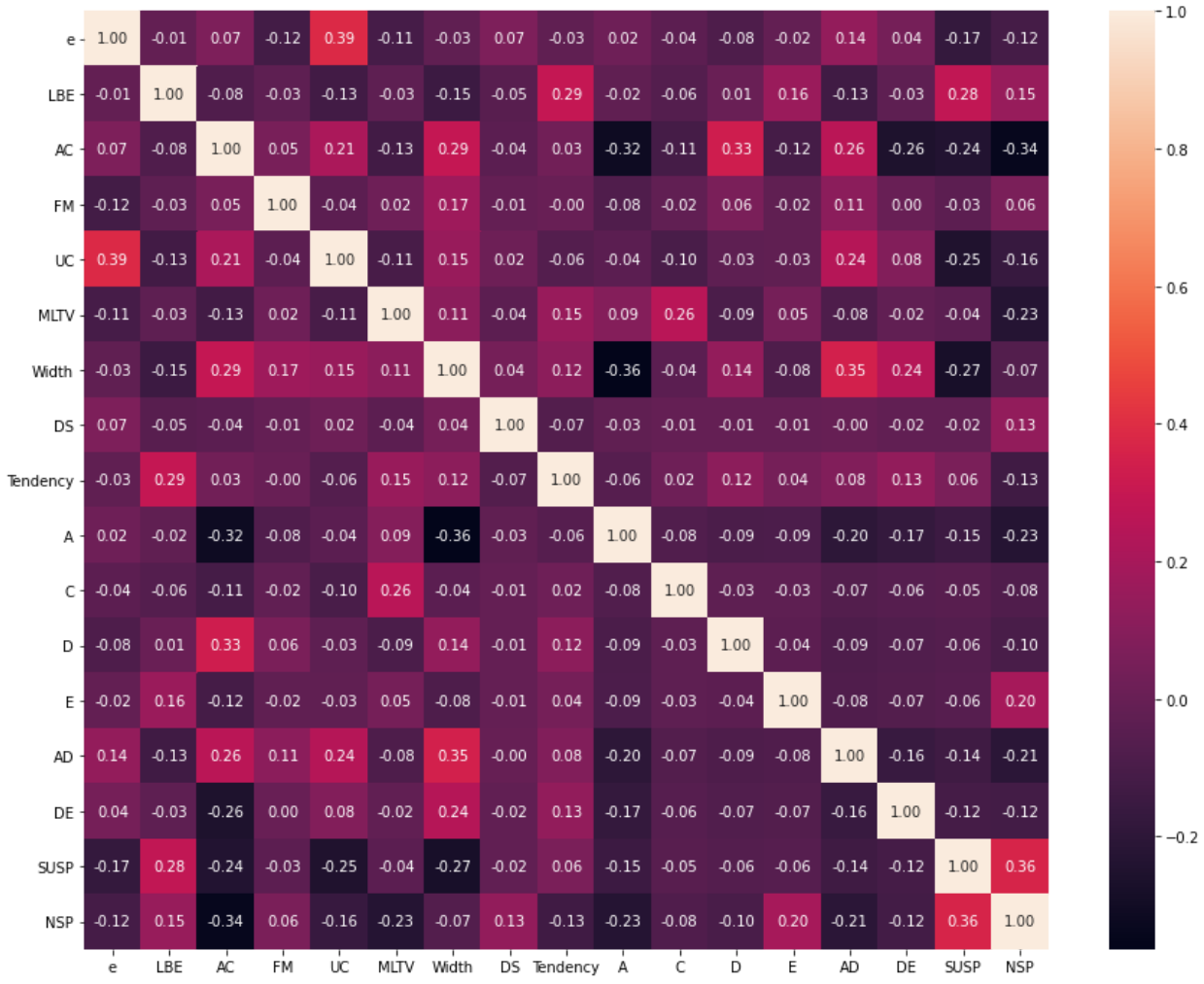
At this stage, we prepared the data to be trained by scaling and managing collinearity to make trained models result consistent and clear of errors.

To scale our independent numerical features, we used sklearn StanardScaler. Furthermore, we observed multicollinearity using heatmaps as below:



Observe that, the lighter colors implies high collinearity. Using sklearn's

SelectNonCOllinear library to drop all features with collinearity threshold greater than 0.4. The resulting heatmap is:

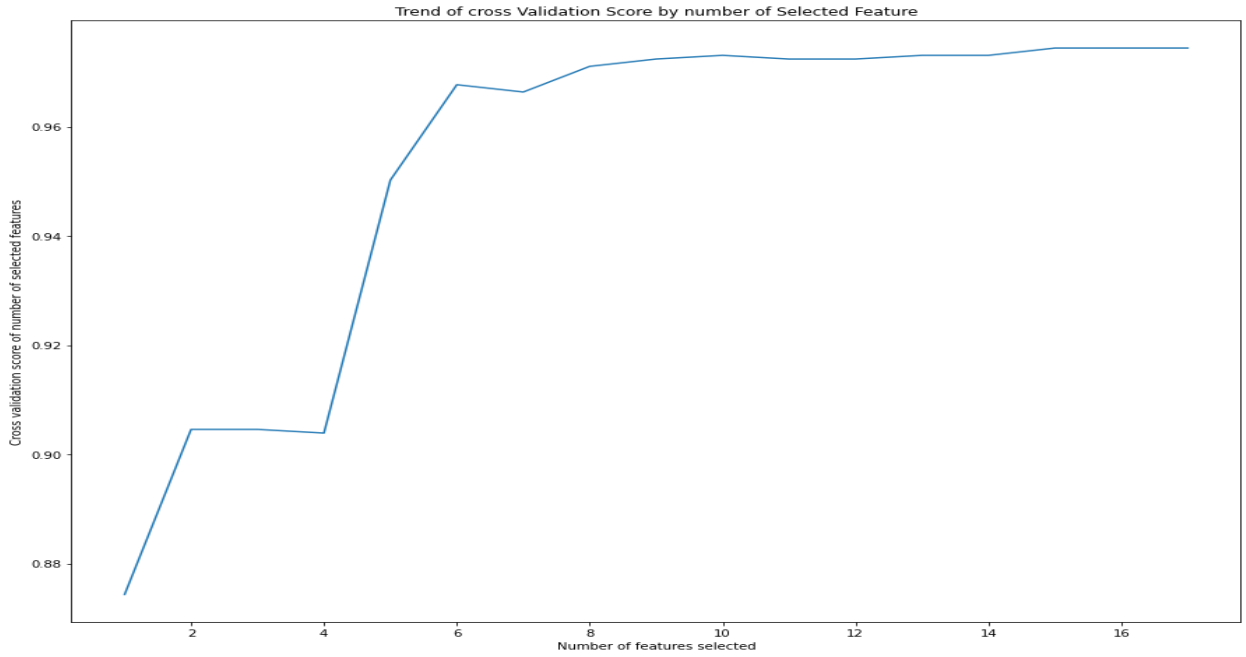


Thereafter, we trained our data on a dummy RandomForestClassifier model. It revealed, some features still are of negligible importance to training. In an attempt to build an efficient and fast model, we performed FeatureSelection using sklearn's SelectKBest. We obtained a the ranks for each feature:

	Feature	Scores
16	SUSP	242.366532
2	AC	191.741055
10	A	81.692933

5	MLTV	76.813624
14	AD	67.099501
13	E	58.955572
4	UC	40.228658
9	Tendency	38.745541
7	DS	31.178942
15	DE	26.284907
0	e	25.775629
1	LBE	22.315388
12	D	16.051565
6	Width	8.914485
11	C	8.070867
3	FM	7.445033
8	Nzeros	1.925993

Finally, we scored feature using recursive feature elimination with cross validation technique

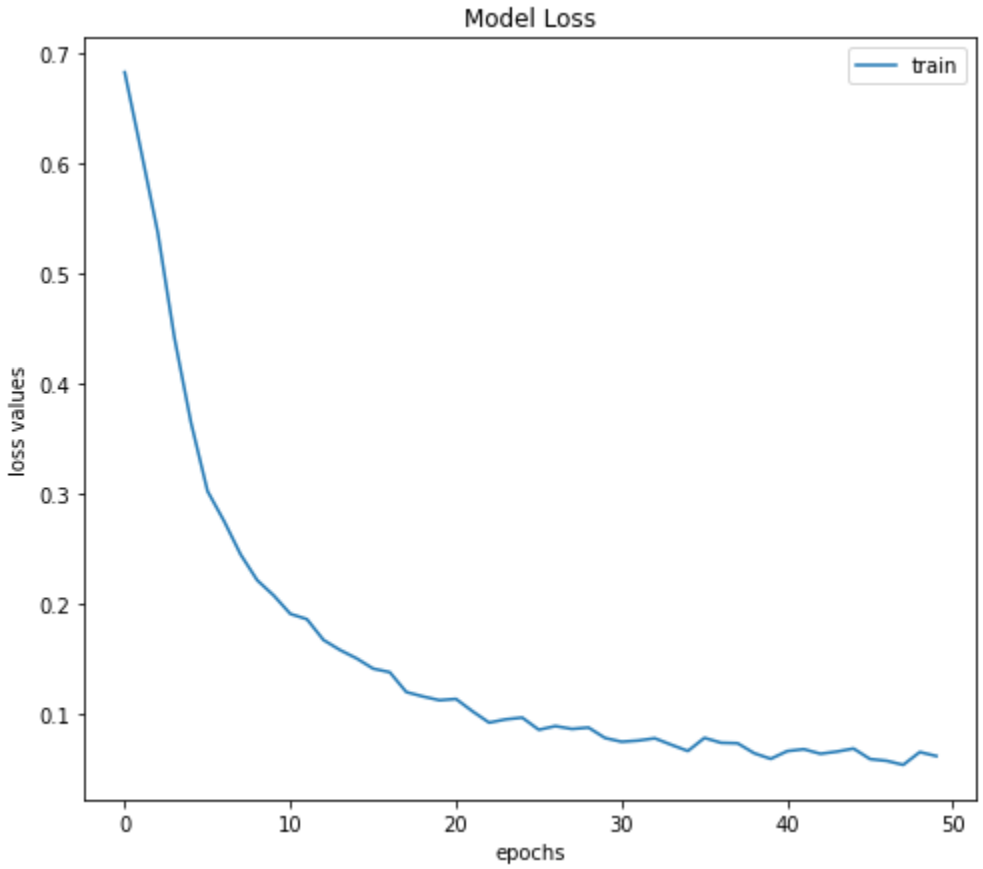


Observe that the minimum number of features for optimum results is 16 and our model learning rate drops critically after 9 features

MODELLING

Having thoroughly cleaned and prepped data, we are ready to build a classification model to predict foetal state based on our independent features. The metrics for evaluation of our classifiers would be Accuracy, Recall and F1-Score. Note that Precision is less important than Recall in this project because the cost of false negatives is more costly than false positives. False negatives could lead to fetal distress or death.

Our approach was to use out-of-the-box classifiers and optimize the best performing one. The models attempted were; Decision Tree, Logistic Regression, RandomForest and XGBoost. In search of better results based on our metrics we attempted Deep learning, We defined our Neural Network and fit our data, and got even better results than all ML models attempted. The loss function was impressively steep as the epoch increased.



To optimize the best performing model which is the Neural Network, we built a gridsearchcv neural network model which performed even better with the results.

Results and Key Takeaway:

In this project, we have attempted to build a model to predict fetal state given the cardiotocography dataset. We have learnt that the best performing model of all attempts is the optimised gridsearchcv neural network as seen below.

ML Classifier	Training Score	Accuracy	Recall	F1-SCore
Logistic Regression	0.97513	0.97492	0.97492	0.97426
Decision Tree	1.0	0.97178	0.97178	0.97142
RandomForest Classifier	1.0	0.97648	0.97648	0.97605
Gradient Boosting Classifier	0.99865	0.97649	0.97649	0.97606
Optimised Neural Network	0.99756	0.98746	0.98746	0.98739

Future Works:

This work can be further extended with the following ideas:

- Analysis and prediction of the same data used in this project on the feature "*CLASS*"
- Exploratory analysis and prediction of cardiotocography and fetal ejection
- Exploratory analysis of cardiotocography data and maternal mortality and complications in high risk pregnancy.