



# FETAL HEALTH CLASSIFICATION USING RANDOM FOREST

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# **OBJECTIVE**

This project uses the Fetal Health dataset from Kaggle to build a classification model that classifies fetal health status into three target classes: Normal, Suspicious, and Pathological. The dataset is made up of 2126 records and 22 features.

Dataset: https://www.kaggle.com/datasets/andrewmvd/fetal-health-classification



# TECH STACK













#### LOAD DATASET

```
#Load dataset
import pandas as pd

fetal_health = pd.read_csv('fetal_health.csv')

print('Dataframe: ', fetal_health.shape)
fetal_health.head(10)
```



Dataf	rame: (	(2126, 22)						
b	aseline value	accelerations	fetal_movement	uterine_contractions	light_decelerations	severe_decelerations	prolongued_decelerations	abnormal_short_term_variability
0	120.0	0.000	0.0	0.000	0.000	0.0	0.000	73.0
1	132.0	0.006	0.0	0.006	0.003	0.0	0.000	17.0
2	133.0	0.003	0.0	0.008	0.003	0.0	0.000	16.0
3	134.0	0.003	0.0	0.008	0.003	0.0	0.000	16.0
4	132.0	0.007	0.0	0.008	0.000	0.0	0.000	16.0
5	134.0	0.001	0.0	0.010	0.009	0.0	0.002	26.0
6	134.0	0.001	0.0	0.013	0.008	0.0	0.003	29.0
7	122.0	0.000	0.0	0.000	0.000	0.0	0.000	83.0
8	122.0	0.000	0.0	0.002	0.000	0.0	0.000	84.0
9	122.0	0.000	0.0	0.003	0.000	0.0	0.000	86.0

10 rows × 22 columns



#### DATASET OVERVIEW

fetal\_health.info()

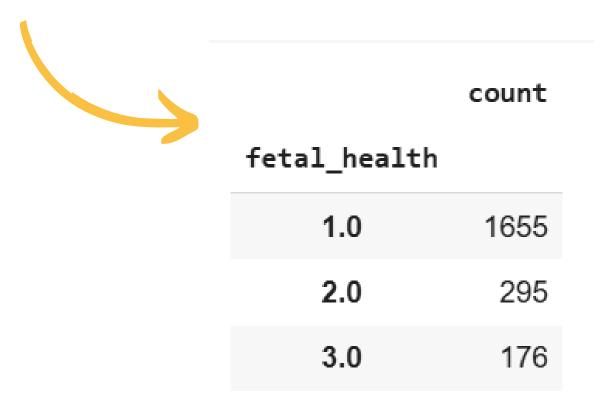


```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2126 entries, 0 to 2125
Data columns (total 22 columns):
    Column
                                                            Non-Null Count Dtype
                                                            -----
     baseline value
                                                            2126 non-null
                                                                           float64
     accelerations
                                                            2126 non-null
                                                                           float64
    fetal movement
                                                            2126 non-null
                                                                           float64
     uterine contractions
                                                            2126 non-null
                                                                           float64
    light decelerations
                                                            2126 non-null
                                                                           float64
     severe_decelerations
                                                            2126 non-null
                                                                           float64
     prolongued_decelerations
                                                            2126 non-null
                                                                           float64
     abnormal short term variability
                                                            2126 non-null
                                                                            float64
    mean value of short term variability
                                                            2126 non-null
                                                                           float64
     percentage of time with abnormal long term variability 2126 non-null
                                                                           float64
    mean_value_of_long_term_variability
                                                            2126 non-null
                                                                           float64
11 histogram width
                                                            2126 non-null
                                                                           float64
12
    histogram min
                                                            2126 non-null
                                                                           float64
    histogram max
                                                            2126 non-null
                                                                           float64
    histogram_number_of_peaks
                                                                           float64
                                                            2126 non-null
    histogram_number_of_zeroes
                                                            2126 non-null
                                                                           float64
    histogram mode
                                                            2126 non-null
                                                                           float64
17 histogram mean
                                                            2126 non-null
                                                                           float64
    histogram median
                                                            2126 non-null
                                                                           float64
    histogram variance
                                                                           float64
                                                            2126 non-null
20 histogram tendency
                                                            2126 non-null
                                                                           float64
21 fetal health
                                                            2126 non-null
                                                                           float64
dtypes: float64(22)
memory usage: 365.5 KB
```



#### DATASET OVERVIEW

fetal\_health['fetal\_health'].value\_counts()



dtype: int64

1.0 - Normal

2.0 - Suspicious

3.0 - Pathological



#### STATISTICAL SUMMARY

fetal\_health.describe()



	baseline value	accelerations	fetal_movement	uterine_contractions	light_decelerations	severe_decelerations	prolongued_decelerations	abnormal_short_term_variability	mean_value_of_short_term_variability	percentage_of_time_wit
count	2126.000000	2126.000000	2126.000000	2126.000000	2126.000000	2126.000000	2126.000000	2126.000000	2126.000000	
mean	133.303857	0.003178	0.009481	0.004366	0.001889	0.000003	0.000159	46.990122	1.332785	
std	9.840844	0.003866	0.046666	0.002946	0.002960	0.000057	0.000590	17.192814	0.883241	
min	106.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	12.000000	0.200000	
25%	126.000000	0.000000	0.000000	0.002000	0.000000	0.000000	0.000000	32.000000	0.700000	
50%	133.000000	0.002000	0.000000	0.004000	0.000000	0.000000	0.000000	49.000000	1.200000	
75%	140.000000	0.006000	0.003000	0.007000	0.003000	0.000000	0.000000	61.000000	1.700000	
max	160.000000	0.019000	0.481000	0.015000	0.015000	0.001000	0.005000	87.000000	7.000000	

8 rows x 22 columns



#### **NULL VALUE CHECK**

#Check for null values
fetal\_health.isnull().sum()



	U
baseline value	0
accelerations	0
fetal_movement	0
uterine_contractions	0
light_decelerations	0
severe_decelerations	0
prolongued_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
histogram_width	0
histogram_min	0
histogram_max	0
histogram_number_of_peaks	0
histogram_number_of_zeroes	0
histogram_mode	0
histogram_mean	0
histogram_median	0
histogram_variance	0
histogram_tendency	0
fetal_health	0

No null values in this dataset

dtype: int64



#### DUPLICATE VALUE CHECK

```
#Check for duplicates
fetal_health.duplicated().sum()
```

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```
#Drop duplicates
fetal_health.drop_duplicates(inplace=True)
fetal_health.duplicated().sum()
```

0



#### STANDARIZE DATA

```
from sklearn.preprocessing import StandardScaler, LabelEncoder

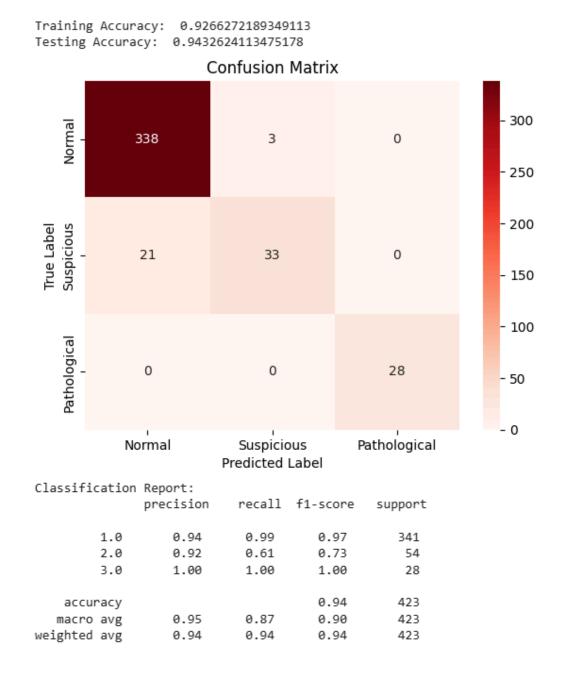
#Standarize data
x = fetal_health.drop(['fetal_health'], axis=1) #features
y = fetal_health['fetal_health'] #target class
scaler = StandardScaler()
scaler.fit(x)
standarized = scaler.transform(x)
x = standarized
```



#### MODEL TRAINING, TESTING & EVALUATION

```
#Split Data
from sklearn.model selection import train test split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)
from sklearn.ensemble import RandomForestClassifier
#training & tuning
model = RandomForestClassifier(n estimators=100, max depth=5, random state=42)
model.fit(x train, y train)
#testing
y test predict = model.predict(x test)
from sklearn.metrics import accuracy score, confusion_matrix, classification_report
y_train_predict = model.predict(x_train)
training_acc = accuracy_score( y_train_predict, y_train)
print('Training Accuracy: ', training_acc)
testing acc = accuracy score(y test predict, y test)
print('Testing Accuracy: ', testing_acc)
sns.heatmap(confusion_matrix(y_test, y_test_predict), annot=True, fmt='d', cmap='Reds',
           xticklabels=['Normal', 'Suspicious', 'Pathological'],
           yticklabels=['Normal', 'Suspicious', 'Pathological'])
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

print('Classification Report: \n', classification\_report(y\_test, y\_test\_predict))

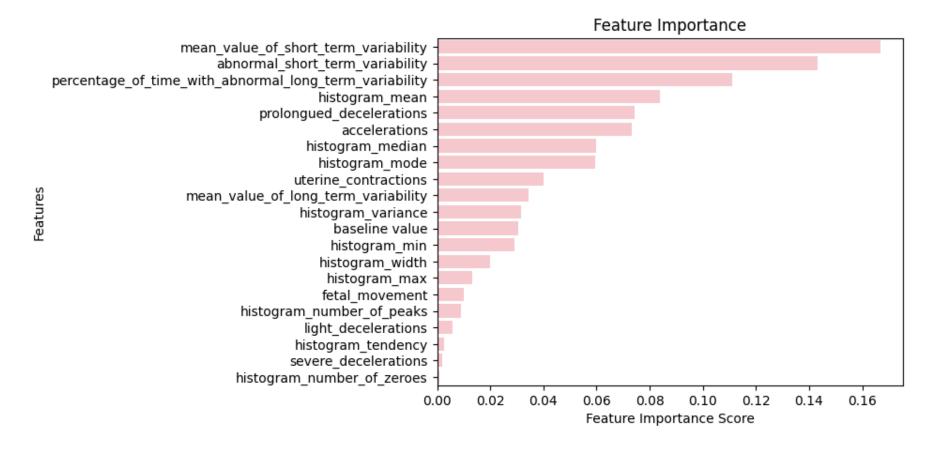




#### MODEL TRAINING, TESTING & EVALUATION

```
feature_importance = model.feature_importances_
features = fetal_health.drop(['fetal_health'], axis=1).columns
importance = pd.Series(feature_importance, index=features).sort_values(ascending=False)
sns.barplot(x=importance, y=importance.index, color='pink')
plt.xlabel('Feature Importance Score')
plt.ylabel('Features')
plt.title("Feature Importance")
plt.show()
```





Feature Importance refers to how valuable each feature is in predicting the target variable. Higher feature importance score means that the feature strongly impacts the prediction model.

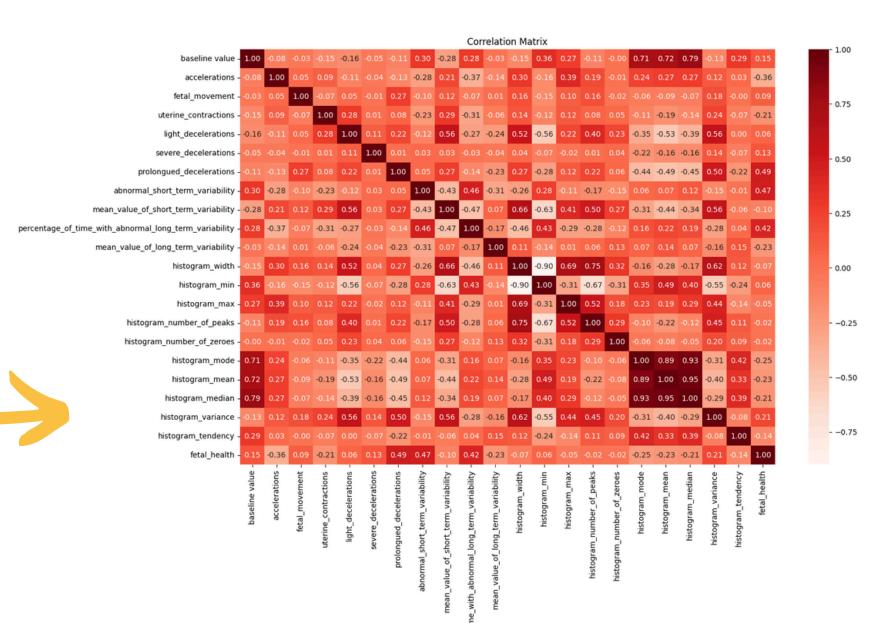


#### MODEL TRAINING, TESTING & EVALUATION

```
import seaborn as sns
import matplotlib.pyplot as plt

#Correlation Matrix
plt.figure(figsize=(16, 10))
sns.heatmap(fetal_health.corr(), annot=True, fmt='.2f', cmap='Reds')
plt.title('Correlation Matrix')
plt.show()
```

Correlation Matrix shows the relationships between a feature with another feature.





### CONCLUSION

Result shows that there are 399 correctly predicted value out of 423 testing data:

- 338 data predicted as normal,
- 33 data predicted as suspicious, and
- 28 data predicted as pathological.

The Random Forest model achieved 92.7% for training accuracy and 94.3% for testing accuracy.

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# THANKYOU

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