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CHAPTER 1
INTRODUCTION

Fetal health refers to the well-being of a developing fetus during pregnancy. It encompasses a variety of factors including fetal growth and development, fetal organ function, and fetal response to stressors.

Foetal movement, foetal heart rate, and amniotic fluid content are three crucial aspects to consider while evaluating the health of the foetus. Foetal movement is a sign of the health and neurologic function of the developing foetus. Foetal distress or compromise may be indicated by a decrease in foetal movement. Another crucial sign of foetal health is the heart rate, with fluctuations in the heart rate revealing the level of stress experienced by the foetus. The amount of amniotic fluid is also measured since low amounts of amniotic fluid may be a sign of foetal impairment.

Throughout pregnancy, foetal health can be monitored using a variety of medical tests and procedures. Medical experts can track foetal growth and development by using ultrasound exams to provide fine-grained images of the growing foetus. Additionally, non-invasive techniques like the non-stress test or more invasive techniques like foetal scalp electrode monitoring can be used to monitor the foetal heart rate.

Healthy foetal development is crucial for a healthy pregnancy and delivery. Regular check-ups with medical specialists as part of prenatal care can help identify potential issues early on and enable rapid medical action when necessary. This can increase the likelihood of a healthy pregnancy and birth as well as help assure the new-born’s long-term wellbeing.

There are several machine learning algorithms and models that can be used to predict **fetal health**, including ***decision trees, support vector machines (SVM), neural networks, and random forests***. These algorithms use various features and input data to make predictions about fetal health and can assist in identifying potential risks or complications during pregnancy.

CHAPTER 2
OBJECTIVE

The objectives of fetal health are primarily centered around ensuring the well-being of the developing fetus during pregnancy. These objectives can be broken down into three main categories: identifying potential risks to fetal health, managing identified risks, and promoting overall fetal development and health.

Identifying potential risks to fetal health involves monitoring the mother and fetus for any signs of potential complications. This may involve regular check-ups with healthcare professionals, as well as various medical tests and procedures to assess fetal health. These tests can help identify potential risks such as fetal distress, intrauterine growth restriction, and preterm labor, which can be managed to ensure the best possible outcome for mother and baby.

Managing identified risks involves taking appropriate steps to mitigate any risks that have been identified. This may involve medical intervention, such as medication or surgery, or lifestyle changes such as reducing stress or improving nutrition. Proper management of identified risks can help reduce the risk of complications during pregnancy and improve the overall health of the developing fetus.

Promoting overall fetal development and health involves ensuring that the fetus is receiving adequate nutrition and is developing normally. This may involve encouraging healthy lifestyle choices in the mother, such as maintaining a healthy diet and exercise regimen, as well as monitoring fetal growth and development through regular medical check-ups. Promoting overall fetal health can help reduce the risk of complications during pregnancy and can improve the long-term health outcomes for the developing fetus.

CHAPTER 3
DATASET

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.

This dataset contains **2126** records of features extracted from Cardiotocogram exams, which were then classified by three expert obstetritians into **3 classes**:

- Normal
- Suspect
- Pathological

#	Column	Non-Null Count	Dtype
0	accelerations	2112 non-null	float64
1	fetal_movement	2112 non-null	float64
2	uterine_contractions	2112 non-null	float64
3	light_decelerations	2112 non-null	float64
4	severe_decelerations	2112 non-null	float64
5	prolongued_decelerations	2112 non-null	float64
6	abnormal_short_term_variability	2112 non-null	float64
7	mean_value_of_short_term_variability	2112 non-null	float64
8	percentage_of_time_with_abnormal_long_term_variability	2112 non-null	float64
9	mean_value_of_long_term_variability	2112 non-null	float64

```
10  histogram_width                                  2112 non-null
    float64
11  histogram_min                                    2112 non-null
    float64
12  histogram_max                                    2112 non-null
    float64
13  histogram_number_of_peaks                        2112 non-null
    float64
14  histogram_number_of_zeroes                       2112 non-null
    float64
15  histogram_mode                                   2112 non-null
    float64
16  histogram_mean                                   2112 non-null
    float64
17  histogram_median                                 2112 non-null
    float64
18  histogram_variance                               2112 non-null
    float64
19  histogram_tendency                               2112 non-null
    float64
20  fetal_health                                     2112 non-null
```

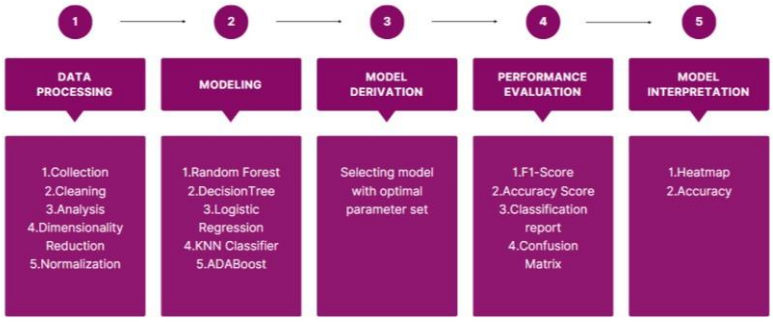
The Fetal Health Classification dataset is a medical dataset that contains features extracted from Cardiotocogram (CTG) measurements, which are used to monitor the fetal heart rate (FHR) and uterine contractions during pregnancy. The dataset contains 2,126 records of fetal health and consists of 21 features, which are described below:

1. baseline value: The FHR baseline value in beats per minute (bpm)
2. accelerations: The number of accelerations per second
3. fetal_movement: The number of fetal movements per second
4. uterine_contractions: The number of uterine contractions per second
5. light_decelerations: The number of light decelerations per second
6. severe_decelerations: The number of severe decelerations per second
7. prolongued_decelerations: The number of prolonged decelerations per second
8. abnormal_short_term_variability: The percentage of time with abnormal short-term variability
9. mean_value_of_short_term_variability: The mean value of short-term variability
10. percentage_of_time_with_abnormal_long_term_variability: The percentage of time with abnormal long-term variability
11. mean_value_of_long_term_variability: The mean value of long-term variability
12. histogram_width: The width of FHR histogram
13. histogram_min: The minimum value of FHR histogram
14. histogram_max: The maximum value of FHR histogram
15. histogram_number_of_peaks: The number of histogram peaks
16. histogram_number_of_zeroes: The number of histogram zeroes
17. histogram_mode: The histogram mode value
18. histogram_mean: The histogram mean value
19. histogram_median: The histogram median value
20. histogram_variance: The histogram variance value
21. histogram_tendency: The histogram tendency value

The dataset is labeled with three classes, namely, Normal (N), Suspect (S), and Pathological (P), which represent the fetal health status. The aim is to use the features to predict the fetal health status accurately. This dataset can be useful in developing decision support systems for fetal health monitoring during pregnancy

CHAPTER 4

METHODOLOGY


1
2
3
4
5
DATA PROCESSING
MODELING
MODEL DERIVATION
PERFORMANCE EVALUATION
MODEL INTERPRETATION
1.Collection
2.Cleaning
3.Analysis
4.Dimensionality Reduction
5.Normalization
1.Random Forest
2.DecisionTree
3.Logistic Regression
4.KNN Classifier
5.ADABoost
Selecting model with optimal parameter set
1.F1-Score
2.Accuracy Score
3.Classification report
4.Confusion Matrix
1.Heatmap
2.Accuracy

CHAPTER 5

CODE AND RESULT

```
# This Python 3 environment comes with many helpful analytics libraries
installed
# It is defined by the kaggle/python Docker image:
https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory #
For example, running this (by clicking run or pressing Shift+Enter) will
list all files under the input directory

import os for dirname, _, filenames in
os.walk('/kaggle/input'):     for filename in
filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that
gets preserved as output when you create a version using "Save & Run All"  #
You can also write temporary files to /kaggle/temp/, but they won't be
saved outside of the current session
```

```
/kaggle/input/fetal-health-classification/fetal_health.csv
```

```
import pandas as pd import
numpy as np import
matplotlib.pyplot as plt
import seaborn as sns from
sklearn.preprocessing
import StandardScaler from
sklearn.model_selection
import train_test_split
from sklearn.ensemble
import
RandomForestClassifier
from sklearn.metrics
import confusion_matrix,
accuracy_score from
tensorflow.keras.callback
s import EarlyStopping
early_stop =
```

```
EarlyStopping(monitor='va
l_loss', patience=10)
```

Loading the dataset

```
df = pd.read_csv('/kaggle/input/fetal-
healthclassification/fetal_health.csv')
df=df.iloc[:,1:]

df=df.drop_duplicates() df.head()
```

```
   accelerations  fetal_movement  uterine_contractions  light_decelerations
\
0          0.000             0.0                 0.000                0.000
1          0.006             0.0                 0.006                0.003
2          0.003             0.0                 0.008                0.003
3          0.003             0.0                 0.008                0.003
           4          0.007             0.0                 0.008
           0.000

   severe_decelerations  prolongued_decelerations  \0
0.0                       0.0
1                   0.0                       0.0
2                   0.0                       0.0
3                   0.0                       0.0
4                   0.0                       0.0

   abnormal_short_term_variability  mean_value_of_short_term_variability  \0
73.0                                    0.5
1                            17.0                                   2.1
2                            16.0                                   2.1
3                            16.0                                   2.4   4
                             16.0                                   2.4

   percentage_of_time_with_abnormal_long_term_variability  \0
43.0
1                                                   0.0
2                                                   0.0
3                                                   0.0        4
                                                    0.0

   mean_value_of_long_term_variability  ...  histogram_min  histogram_max  \
0                                  2.4  ...           62.0          126.0
1                                 10.4  ...           68.0          198.0
2                                 13.4  ...           68.0          198.0
3                                 23.0  ...           53.0          170.0
                                  4                                 19.9
                                  ...           53.0          170.0
```

```
   histogram_number_of_peaks  histogram_number_of_zeroes  histogram_mode  \0
2.0                          0.0                        120.0
1                          6.0                          1.0           141.0
2                          5.0                          1.0           141.0
3                          11.0                          0.0           137.0
                           4                          9.0
                           0.0           137.0

   histogram_mean  histogram_median  histogram_variance  histogram_tendency
\
0           137.0             121.0                73.0                 1.0
1           136.0             140.0                12.0                 0.0
2           135.0             138.0                13.0                 0.0
3           134.0             137.0                13.0                 1.0
            4           136.0             138.0                11.0
            1.0

   fetal_health   0
2.0
1           1.0
2           1.0
3           1.0
4           1.0

[5 rows x 21 columns]
```

Exploratory Data Analysis

```
df.shape  (2112,   21)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2112 entries, 0 to 2125 Data
columns (total 21 columns):
 #   Column                                                Non-Null Count
Dtype
---  ------                                                --------------
-----
0   accelerations                                        2112 non-null
float64
1   fetal_movement                                       2112 non-null
float64
2   uterine_contractions                                 2112 non-null
float64
3   light_decelerations                                  2112 non-null
float64
4   severe_decelerations                                 2112 non-null
float64
```

```
5   prolongued_decelerations                                2112 non-null
float64
6   abnormal_short_term_variability                         2112 non-null
float64
7   mean_value_of_short_term_variability                    2112 non-null
float64
8   percentage_of_time_with_abnormal_long_term_variability  2112 non-null
float64
9   mean_value_of_long_term_variability                     2112 non-null
float64
10  histogram_width                                         2112 non-null
float64
11  histogram_min                                           2112 non-null
float64
12  histogram_max                                           2112 non-null
float64
13  histogram_number_of_peaks                               2112 non-null
float64
14  histogram_number_of_zeroes                              2112 non-null
float64
15  histogram_mode                                          2112 non-null
float64
16  histogram_mean                                          2112 non-null
float64
17  histogram_median                                        2112 non-null
float64
18  histogram_variance                                      2112 non-null
float64
19  histogram_tendency                                      2112 non-null
float64
20  fetal_health                                            2112 non-null
int64   dtypes: float64(20), int64(1) memory usage: 363.0 KB df.isnull().sum()

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
```

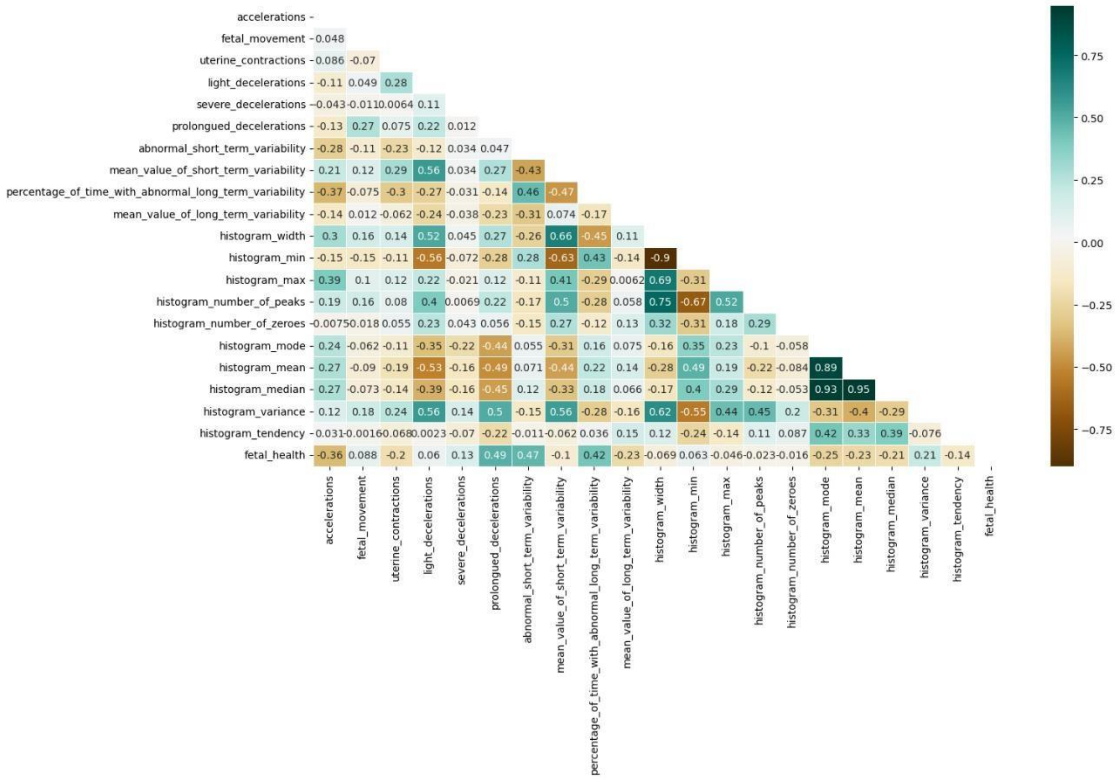
```
histogram_mean                                          0
histogram_median                                        0
histogram_variance                                      0
histogram_tendency                                      0 fetal_health
0 dtype: int64 df.describe()

       accelerations  fetal_movement  uterine_contractions  \
count    2112.000000     2112.000000           2112.000000
mean        0.003190        0.009511              0.004389    std
0.003872        0.046814              0.002940    min
0.000000        0.000000              0.000000    25%
0.000000        0.000000              0.002000
50%         0.002000        0.000000              0.005000    75%
0.006000        0.003000              0.007000    max
0.019000        0.481000              0.015000

       light_decelerations  severe_decelerations  prolongued_decelerations  \
count           2112.000000           2112.000000               2112.000000
mean               0.001902              0.000003                  0.000160
std                0.002966              0.000057                  0.000592
min                0.000000              0.000000                  0.000000
25%                0.000000              0.000000                  0.000000
50%                0.000000              0.000000                  0.000000
75%                0.003000              0.000000                  0.000000
max                0.015000              0.001000                  0.005000

       abnormal_short_term_variability  mean_value_of_short_term_variability
\
count                      2112.000000                             2112.000000
mean                         46.981061                                1.335511
std                          17.171788                                0.884290
min                          12.000000                                0.200000
25%                          32.000000                                0.700000
50%                          49.000000                                1.200000
75%                          61.000000                                1.700000
max                          87.000000                                7.000000

       percentage_of_time_with_abnormal_long_term_variability  \
count                                          2112.000000
mean                                              9.773201        std
18.313812         min
0.000000         25%
0.000000         50%
0.000000         75%
11.000000         max
91.000000

       mean_value_of_long_term_variability  ...  histogram_min
histogram_max
```

```
\
count                          2112.000000  ...    2112.000000    2112.000000
mean                              8.167472  ...      93.546875     164.103693
std                               5.634115  ...      29.558037      17.948559
min                               0.000000  ...      50.000000     122.000000
25%                               4.600000  ...      67.000000     152.000000
50%                               7.400000  ...      93.000000     162.000000
75%                              10.800000  ...     120.000000     174.000000
max                              50.700000  ...     159.000000     238.000000

       histogram_number_of_peaks  histogram_number_of_zeroes  histogram_mode
\
count                2112.000000                 2112.000000     2112.000000
mean                    4.077178                    0.325758      137.448390
std                     2.952363                    0.707903       16.403636
min                     0.000000                    0.000000       60.000000
25%                     2.000000                    0.000000      129.000000
50%                     4.000000                    0.000000      139.000000
75%                     6.000000                    0.000000      148.000000
max                    18.000000                   10.000000      187.000000

       histogram_mean  histogram_median  histogram_variance  \
count     2112.000000       2112.000000         2112.000000
mean       134.592330        138.083333           18.916193    std
15.610519         14.479658           29.042726    min
73.000000         77.000000            0.000000    25%
125.000000        129.000000            2.000000
50%        136.000000        139.000000            7.000000    75%
145.000000        148.000000           24.000000    max
182.000000        186.000000          269.000000

       histogram_tendency  fetal_health
count         2112.000000   2112.000000
mean             0.318182      1.303504   std
0.611039      0.614237   min             -
1.000000      1.000000   25%
0.000000      1.000000
50%              0.000000      1.000000   75%
1.000000      1.000000   max
1.000000      3.000000

[8 rows x 21 columns]
```

Correlation plot

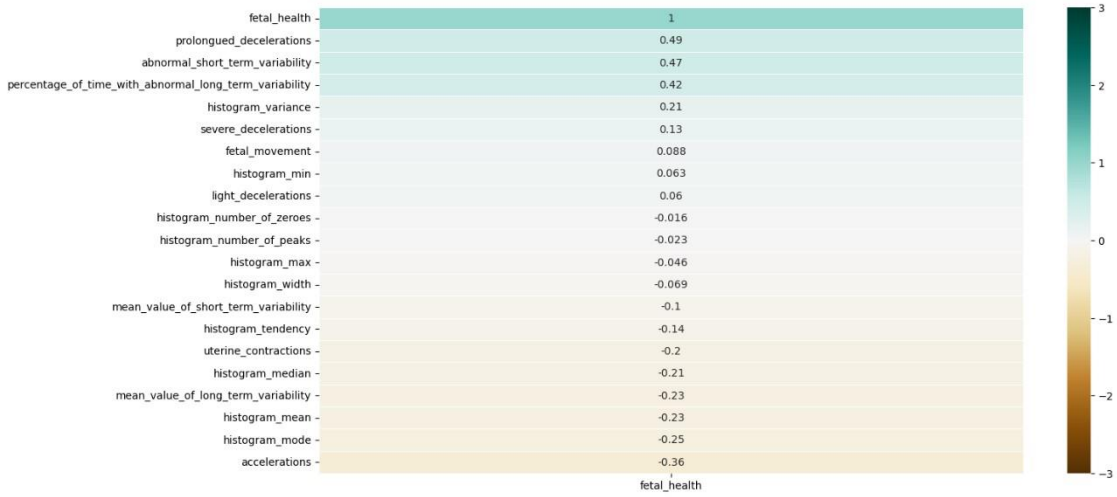
```
corr = df.corr()
plt.figure(figsize=(15,8))
```

```
mask = np.triu(np.ones_like(corr, dtype=bool))
sns.heatmap(corr,mask=mask,cmap='BrBG',annot=True,linewidth=.5,square=False)
<AxesSubplot:>
```



Correlation of all columns with respect to class

```
plt.figure(figsize=(15,8))

sns.heatmap(df.corr()[['fetal_health']].sort_values(by='fetal_health',
ascending=False),cmap='BrBG', vmin=-3, vmax= 3 , center=0,
annot=True,linewidth=.5,square=False)

<AxesSubplot:>
```




```
x=df.drop('fetal_health',axis=1) y=df['fetal_health']

from sklearn.preprocessing import LabelEncoder le=LabelEncoder()
df['fetal_health']=le.fit_transform(df['fetal_health'])

for column in x.columns:    x[column] = (x[column] -
x[column].min()) / (x[column].max() - x[column].min())  x.head()

   accelerations  fetal_movement  uterine_contractions  light_decelerations
\
0       0.000000             0.0              0.000000                  0.0
1       0.315789             0.0              0.400000                  0.2
2       0.157895             0.0              0.533333                  0.2
3       0.157895             0.0              0.533333                  0.2
        4       0.368421             0.0              0.533333
        0.0

   severe_decelerations  prolongued_decelerations  \0
0.0                      0.0
1                   0.0                      0.0
2                   0.0                      0.0
3                   0.0                      0.0
4                   0.0                      0.0

   abnormal_short_term_variability  mean_value_of_short_term_variability  \0
0.813333                                 0.044118
1                         0.066667                                0.279412
2                         0.053333                                0.279412
3                         0.053333                                0.323529   4
                          0.053333                                0.323529

   percentage_of_time_with_abnormal_long_term_variability  \
0                                           0.472527
1                                           0.000000
```

```
2                                          0.000000
3                                          0.000000
4                                          0.000000

   mean_value_of_long_term_variability  histogram_width  histogram_min  \0
0.047337         0.344633       0.110092
1                              0.205128         0.717514       0.165138
2                              0.264300         0.717514       0.165138
3                              0.453649         0.644068       0.027523    4
                               0.392505         0.644068       0.027523

   histogram_max  histogram_number_of_peaks  histogram_number_of_zeroes  \0
0.034483                    0.111111                           0.0
1       0.655172                    0.333333                           0.1
2       0.655172                    0.277778                           0.1
3       0.413793                    0.611111                           0.0    4
        0.413793                    0.500000                           0.0

   histogram_mode  histogram_mean  histogram_median  histogram_variance  \0
0.472441        0.587156          0.403670            0.271375
1        0.637795        0.577982          0.577982            0.044610
2        0.637795        0.568807          0.559633            0.048327
3        0.606299        0.559633          0.550459            0.048327    4
         0.606299        0.577982          0.559633            0.040892

   histogram_tendency   0
1.0
1                 0.5
2                 0.5
3                 1.0   4                1.0
```

```
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest= train_test_split(x,y,test_size=0.1,stratify=y)
print(xtrain.shape) print(xtest.shape) print(ytrain.shape)
print(ytest.shape)
```

```
(1900, 20)
(212, 20)
(1900,) (212,)
```

```
from sklearn.decomposition import PCA

pca = PCA()
x_train = pca.fit_transform(X_train) x_test
= pca.transform(X_test)

explained_variance = pca.explained_variance_ratio_ explained_variance
```

```
array([5.98047433e-01, 1.57319290e-01, 9.60723218e-02, 7.17305287e-02,
       3.61564735e-02, 2.83195995e-02, 5.99169535e-03, 3.95019578e-03,
       1.47454710e-03, 7.61650212e-04, 9.17104053e-05, 5.74755426e-05,
       2.66198715e-05, 4.55371086e-07, 1.71858342e-09, 1.40774917e-09,
       5.79359987e-10, 3.70914199e-11, 7.46480149e-13, 3.24768840e-32])
```

Decision Tree

```
from sklearn.tree import DecisionTreeClassifier

dtc = DecisionTreeClassifier(random_state=42, max_depth=7)
dtc = dtc.fit(X_train, y_train) y_pred_dtc = dtc.predict(X_test)

from sklearn.metrics import *

dtc_acc = accuracy_score(y_test, y_pred_dtc) dtc_acc

0.9290780141843972 print(classification_report(y_test,

y_pred_dtc))

              precision    recall  f1-score   support

         1.0       0.94      0.97      0.96       330
2.0       0.79      0.72      0.76        58
         3.0       1.00      0.89      0.94        35

    accuracy                           0.93       423
macro avg       0.91      0.86      0.88       423 weighted
avg       0.93      0.93      0.93       423


print(confusion_matrix(y_test, y_pred_dtc))

[[320  10   0]
 [ 16  42   0]
 [  3   1  31]]

f1_micro = f1_score(y_test, y_pred_dtc, average='micro')
print("F1-Score:       ",       f1_micro)      F1-Score:
0.9290780141843973

f1_macro = f1_score(y_test, y_pred_dtc, average='macro') print("F1-Score:
", f1_macro)
F1-Score:  0.8842674717114178

f1_weighted = f1_score(y_test, y_pred_dtc,average='weighted')
print("F1-Score: ", f1_weighted) F1-Score:
0.9278150048114746
```

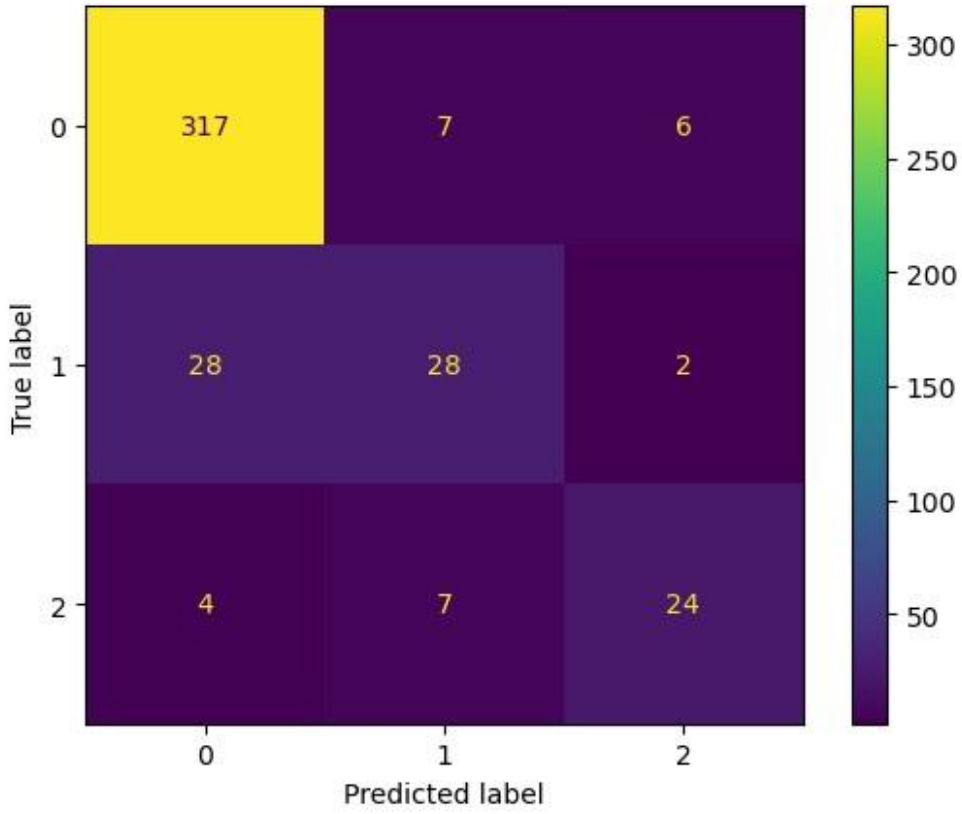
Random Forest Classifier

```
from sklearn.ensemble import RandomForestClassifier rfc =
RandomForestClassifier(n_estimators=100, random_state=42) rfc =
rfc.fit(X_train, y_train) y_pred_rfc = rfc.predict(X_test)
f1_rfc = f1_score(y_test, y_pred_rfc,average='weighted')

from sklearn.ensemble import RandomForestClassifier rfc =
RandomForestClassifier(n_estimators=100, random_state=42) rfc =
rfc.fit(X_train, y_train) y_pred_rfc = rfc.predict(X_test)
f1_micro = f1_score(y_test, y_pred_rfc,average='micro')

from sklearn.ensemble import RandomForestClassifier rfc =
RandomForestClassifier(n_estimators=100, random_state=42) rfc =
rfc.fit(X_train, y_train) y_pred_rfc = rfc.predict(X_test)
f1_macro = f1_score(y_test, y_pred_rfc,average='macro')

print("F1-Score: ", f1_weighted) print("Accuracy: ",
accuracy_score(y_test, y_pred_rfc))

F1-Score:  0.9278150048114746
Accuracy:  0.9527186761229315

print("F1-Score: ", f1_micro) print("Accuracy: ",
accuracy_score(y_test, y_pred_rfc))

F1-Score:  0.9527186761229315
Accuracy:  0.9527186761229315

print("F1-Score: ", f1_macro) print("Accuracy: ",
accuracy_score(y_test, y_pred_rfc))

F1-Score:         0.9116546866393908    Accuracy:
0.9527186761229315
print(classification_report(y_test, y_pred_rfc))

              precision    recall  f1-score   support

         1.0       0.96      0.99      0.97       330
2.0       0.91      0.74      0.82        58
         3.0       0.97      0.91      0.94        35

    accuracy                           0.95       423
macro avg       0.95      0.88      0.91       423 weighted
avg       0.95      0.95      0.95       423


print(confusion_matrix(y_test, y_pred_rfc))

[[328   2   0]
 [ 14  43   1]
 [  1   2  32]]
```

LOGISTIC REGRESSION

```
from sklearn.linear_model import LogisticRegression size
= X_train.shape[0]

model = LogisticRegression(max_iter=1000, C=0.009, penalty="l2",
solver="newton-cg") model.fit(X_train, y_train)
print("For the amounts of training data is: ",size)
print("Accuracy of LogisticRegression: ",model.score(X_test,y_test))
y_pred = model.predict(X_test) cm = confusion_matrix(y_test, y_pred)
cm_display = ConfusionMatrixDisplay(cm).plot() plt.show()
```

```
For the amounts of training data is:  1689
Accuracy of LogisticRegression:  0.8723404255319149
```

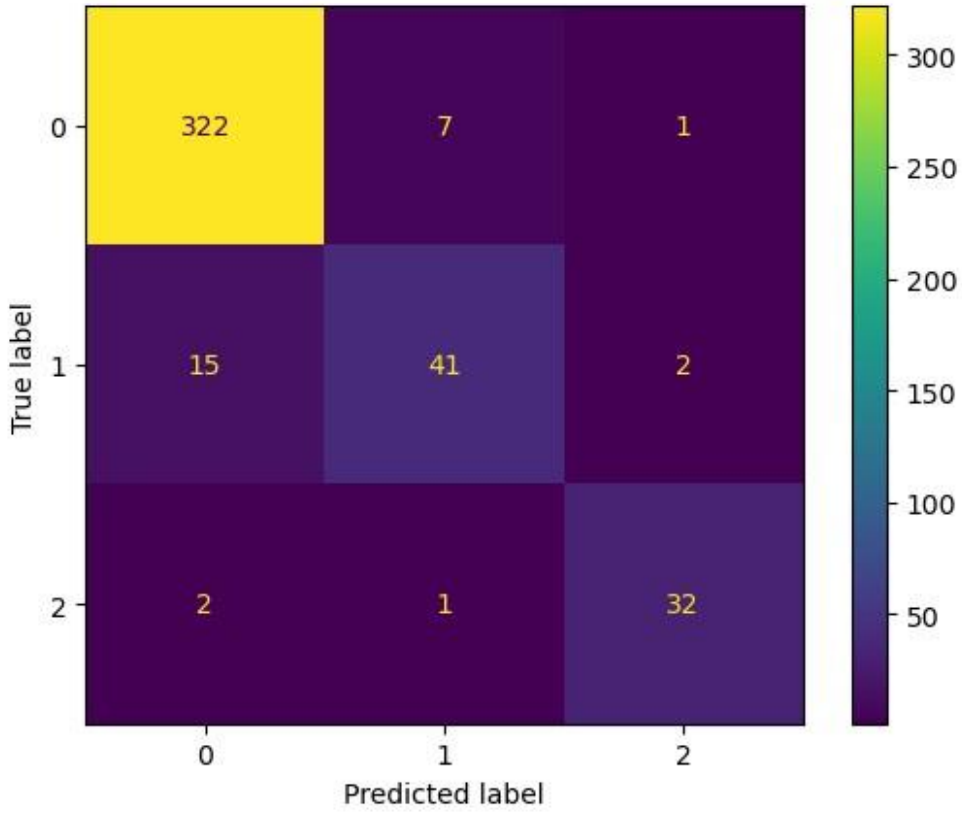


DECISION TREE CLASSIFIER

```
model = DecisionTreeClassifier() model.fit(X_train,
y_train)
print("For the amounts of training data is: ",size)
print("Accuracy of DecisionTree: ",model.score(X_test, y_test))
y_pred = model.predict(X_test) cm = confusion_matrix(y_test,
y_pred) cm_display = ConfusionMatrixDisplay(cm).plot()
plt.show()
```

```
For the amounts of training data is:  1689
```

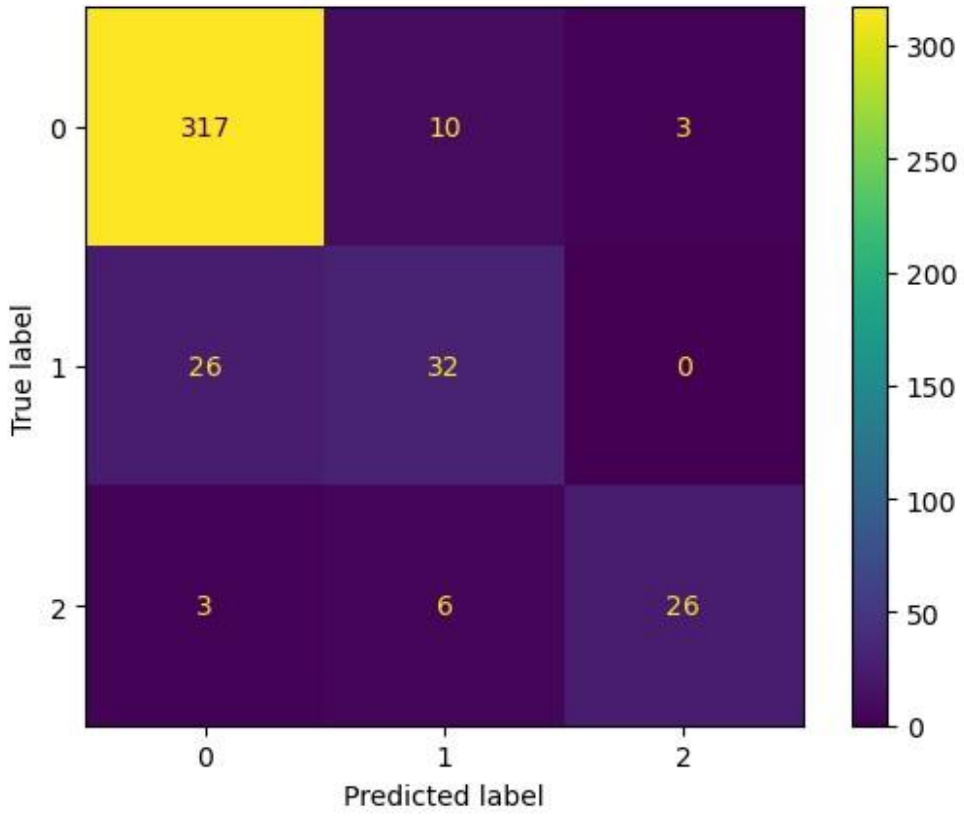
Accuracy of DecisionTree: 0.933806146572104



KNNEIGHBORS CLASSIFIER

```
from sklearn.neighbors import KNeighborsClassifier model
= KNeighborsClassifier(n_neighbors=5) model.fit(X_train,
y_train)
print("For the amounts of training data is: ",size)
print("Accuracy of K-NN:",model.score(X_test, y_test))
y_pred = model.predict(X_test) cm =
confusion_matrix(y_test, y_pred) cm_display =
ConfusionMatrixDisplay(cm).plot() plt.show()
```

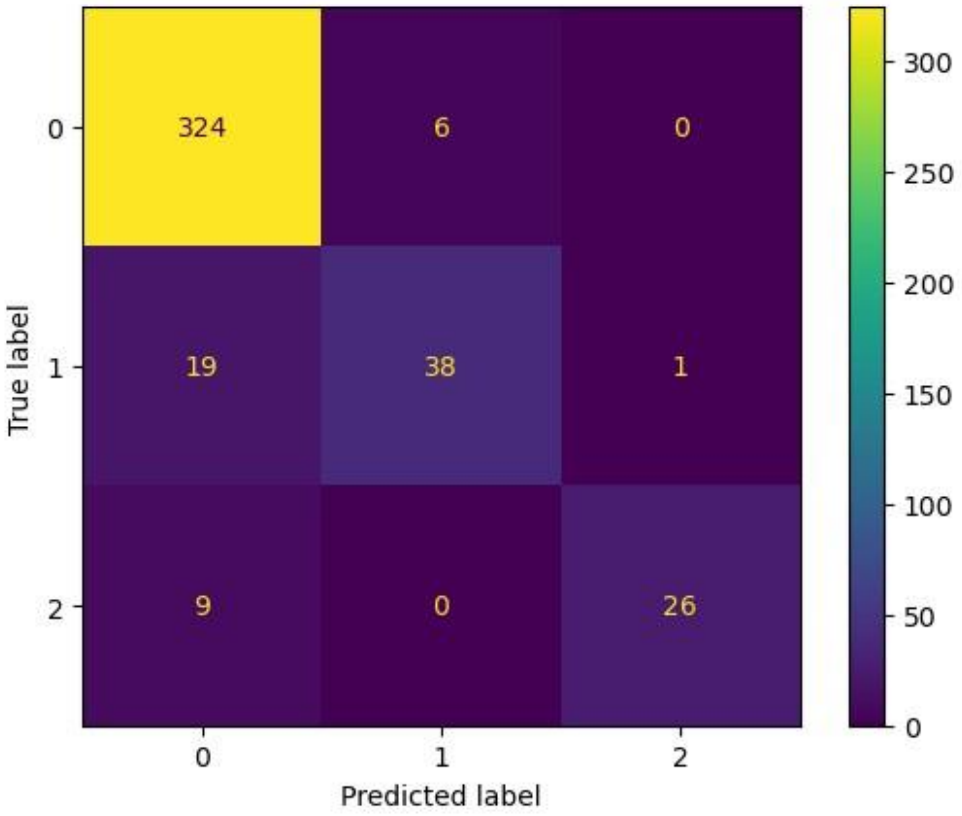
For the amounts of training data is: 1689 Accuracy
of K-NN: 0.8865248226950354



ADABOOST CLASSIFIER

```
from sklearn.ensemble import AdaBoostClassifier model =
AdaBoostClassifier(n_estimators=250, learning_rate=0.1)
model.fit(X_train, y_train)
print("For the amounts of training data is: ",size)
print("Accuracy of AdaBoost:",model.score(X_test, y_test))
y_pred = model.predict(X_test) cm =
confusion_matrix(y_test, y_pred) cm_display =
ConfusionMatrixDisplay(cm).plot() plt.show()
```

```
For the amounts of training data is:  1689
Accuracy of AdaBoost: 0.91725768321513
```




```
model = LogisticRegression(max_iter=1000, C=0.01, penalty="l2",
solver="newton-cg") model.fit(X_train, y_train) print("For the C is :
0.01 ,Accuracy : ",model.score(X_test,y_test))

model = LogisticRegression(max_iter=1000, C=0.001, penalty="l2",
solver="newton-cg") model.fit(X_train, y_train) print("For the C is :
0.001 ,Accuracy : ",model.score(X_test,y_test))

model = LogisticRegression(max_iter=1000, C=0.0001, penalty="l2",
solver="newton-cg") model.fit(X_train, y_train) print("For the C is :
0.0001 ,Accuracy : ",model.score(X_test,y_test))
```

```
For the C is : 0.01 ,Accuracy :  0.8747044917257684
For the C is : 0.001 ,Accuracy :  0.8723404255319149
For the C is : 0.0001 ,Accuracy :  0.851063829787234
```

```
model = KNeighborsClassifier(n_neighbors=3) model.fit(X_train, y_train)
print("For the n_neighbors is 3, Accuracy :",model.score(X_test, y_test))

model = KNeighborsClassifier(n_neighbors=5) model.fit(X_train,
y_train)
print("For the n_neighbors is 5, Accuracy :",model.score(X_test, y_test))

model = KNeighborsClassifier(n_neighbors=7) model.fit(X_train, y_train)
print("For the n_neighbors is 7, Accuracy :",model.score(X_test, y_test))
```

```
For the n_neighbors is 3, Accuracy : 0.8936170212765957
For the n_neighbors is 5, Accuracy : 0.8865248226950354
For the n_neighbors is 7, Accuracy : 0.8770685579196218
```

```
X_train1 = X_train.iloc[:1400,:] y_train1
= y_train.iloc[:1400]
size = X_train1.shape[0]

model = LogisticRegression(max_iter=1000, C=0.009, penalty="l2",
solver="newton-cg") model.fit(X_train1, y_train1)
print("For the amounts of training data is: ",size)
print("Accuracy of LogisticRegression: ",model.score(X_test,y_test)) print("
")

model = DecisionTreeClassifier() model.fit(X_train1,
y_train1)
print("For the amounts of training data is: ",size) print("Accuracy
of DecisionTree: ",model.score(X_test, y_test)) print(" ")

model = KNeighborsClassifier(n_neighbors=5) model.fit(X_train1,
y_train1)
print("For the amounts of training data is: ",size)
print("Accuracy of K-NN:",model.score(X_test, y_test)) print("
")

model = AdaBoostClassifier(n_estimators=250, learning_rate=0.1)
model.fit(X_train1, y_train1)
print("For the amounts of training data is: ",size)
print("Accuracy of AdaBoost:",model.score(X_test, y_test)) print("
")

rfc = RandomForestClassifier(n_estimators=100, random_state=42) rfc
= rfc.fit(X_train, y_train)
print("For the amounts of training data is: ",size)
print("Accuracy of RandomForestClassifier :",model.score(X_test, y_test))
print(" ")
```

```
For the amounts of training data is:  1400
Accuracy of LogisticRegression:  0.7807570977917981

For the amounts of training data is:  1400
Accuracy of DecisionTree:  0.9211356466876972

For the amounts of training data is:  1400
Accuracy of K-NN: 0.9132492113564669
```

```
For the amounts of training data is:  1400
Accuracy of AdaBoost: 0.9132492113564669

For the amounts of training data is:  1400
Accuracy of RandomForestClassifier : 0.9132492113564669



(2112, 20)
```

CHAPTER 6

CONCLUSION

Fetal health is a critical aspect of prenatal care, as it directly impacts the health outcomes of both the mother and the developing fetus. Monitoring fetal health through regular medical check-ups and tests is essential for identifying potential risks and managing them appropriately. Early

detection of fetal distress or other complications can improve the chances of a healthy pregnancy and delivery, while promoting overall fetal development and health can help ensure the longterm health of the newborn.

Various medical procedures and tests are available to monitor fetal health, including ultrasound examinations, fetal heart rate monitoring, and amniotic fluid volume assessments. In addition, machine learning algorithms and models can be used to predict fetal health and identify potential risks. These tools can assist healthcare professionals in providing personalized care to expectant mothers and can help improve the accuracy of fetal health assessments.

Overall, prioritizing fetal health is an essential component of prenatal care. With proper monitoring and management, potential risks can be identified and addressed, leading to a higher likelihood of a successful pregnancy and delivery. By promoting fetal development and health, healthcare professionals can help ensure that newborns have the best possible chance for a healthy start to life.