Sameer_Nepal_DSC_630_Project

November 1, 2022

[119]:
```
# importing the libraries

import pandas as pd
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
```

[2]:
```
#reading the dataset
df = pd.read_csv('birth.csv')
```

[3]:
```
df.head(10)
```

[3]:
```
   fage  mage       mature  weeks     premie  visits  gained  weight  \
0  34.0    34  younger mom     37  full term    14.0    28.0    6.96
1  36.0    31  younger mom     41  full term    12.0    41.0    8.86
2  37.0    36   mature mom     37  full term    10.0    28.0    7.51
3   NaN    16  younger mom     38  full term     NaN    29.0    6.19
4  32.0    31  younger mom     36     premie    12.0    48.0    6.75
5  32.0    26  younger mom     39  full term    14.0    45.0    6.69
6  37.0    36   mature mom     36     premie    10.0    20.0    6.13
7  29.0    24  younger mom     40  full term    13.0    65.0    6.74
8  30.0    32  younger mom     39  full term    15.0    25.0    8.94
9  29.0    26  younger mom     39  full term    11.0    22.0    9.12

  lowbirthweight     sex      habit      marital   whitemom
0        not low    male  nonsmoker      married      white
1        not low  female  nonsmoker      married      white
2        not low  female  nonsmoker      married  not white
3        not low    male  nonsmoker  not married      white
4        not low  female  nonsmoker      married      white
5        not low  female  nonsmoker      married      white
6        not low  female  nonsmoker      married      white
7        not low    male  nonsmoker  not married      white
8        not low  female  nonsmoker      married      white
```

```
9        not low    male  nonsmoker  not married  not white
```

We will look into the dataset to see which are oject to convert to the numeric values

[4]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 13 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   fage            886 non-null    float64
 1   mage            1000 non-null   int64
 2   mature          1000 non-null   object
 3   weeks           1000 non-null   int64
 4   premie          1000 non-null   object
 5   visits          944 non-null    float64
 6   gained          958 non-null    float64
 7   weight          1000 non-null   float64
 8   lowbirthweight  1000 non-null   object
 9   sex             1000 non-null   object
 10  habit           981 non-null    object
 11  marital         1000 non-null   object
 12  whitemom        1000 non-null   object
dtypes: float64(4), int64(2), object(7)
memory usage: 101.7+ KB
```

[5]:
```python
from sklearn import preprocessing
from collections import defaultdict
dic = defaultdict(preprocessing.LabelEncoder)
# Encoding the categorical variable
fit = df.select_dtypes(include=['object']).apply(lambda x: dic[x.name].
 ↪fit_transform(x))

#Converting the categorical columns using the encoding
for x in list(dic.keys()):
    df[x] = dic[x].transform(df[x])
```

[6]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 13 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   fage            886 non-null    float64
 1   mage            1000 non-null   int64
 2   mature          1000 non-null   int64
 3   weeks           1000 non-null   int64
```

```
 4   premie          1000 non-null   int64
 5   visits          944 non-null    float64
 6   gained          958 non-null    float64
 7   weight          1000 non-null   float64
 8   lowbirthweight  1000 non-null   int64
 9   sex             1000 non-null   int64
 10  habit           1000 non-null   int64
 11  marital         1000 non-null   int64
 12  whitemom        1000 non-null   int64
dtypes: float64(4), int64(9)
memory usage: 101.7 KB
```

[7]:
```
#checking the data
df.head()
```

[7]:
```
   fage  mage  mature  weeks  premie  visits  gained  weight  lowbirthweight  \
0  34.0    34       1     37       0    14.0    28.0    6.96               1
1  36.0    31       1     41       0    12.0    41.0    8.86               1
2  37.0    36       0     37       0    10.0    28.0    7.51               1
3   NaN    16       1     38       0     NaN    29.0    6.19               1
4  32.0    31       1     36       1    12.0    48.0    6.75               1

   sex  habit  marital  whitemom
0    1      0        0         1
1    0      0        0         1
2    0      0        0         0
3    1      0        1         1
4    0      0        0         1
```

[8]:
```
# filling the missing data
df.fillna(df.median(), inplace = True)
```

[9]:
```
df.isnull().sum()
```

[9]:
```
fage              0
mage              0
mature            0
weeks             0
premie            0
visits            0
gained            0
weight            0
lowbirthweight    0
sex               0
habit             0
marital           0
whitemom          0
dtype: int64
```

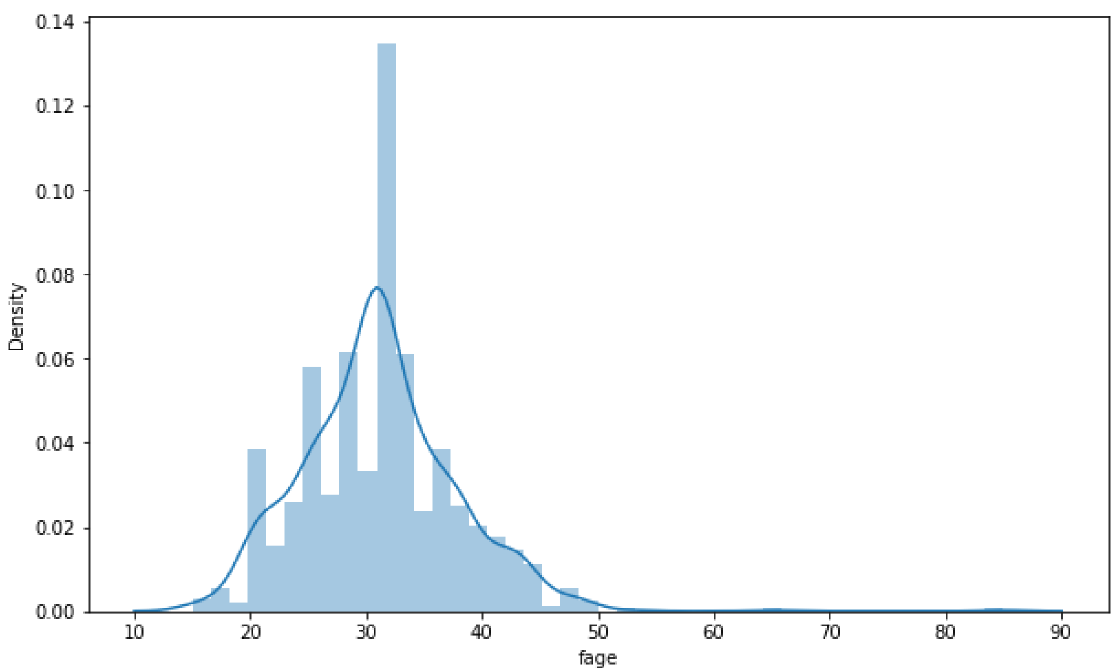
We are trying to predict if the baby will be low birth or not so lowbirthweight will be our varibale that we want to predict. We will create new data frame with all the variables except the dependent variable.

[10]:
```
target = df['lowbirthweight']
independent = df.drop(columns = ['lowbirthweight'])
```

Here, the target is the dataframe with just the target variable lowbirthweight and independent is the dataframe without the target variable.

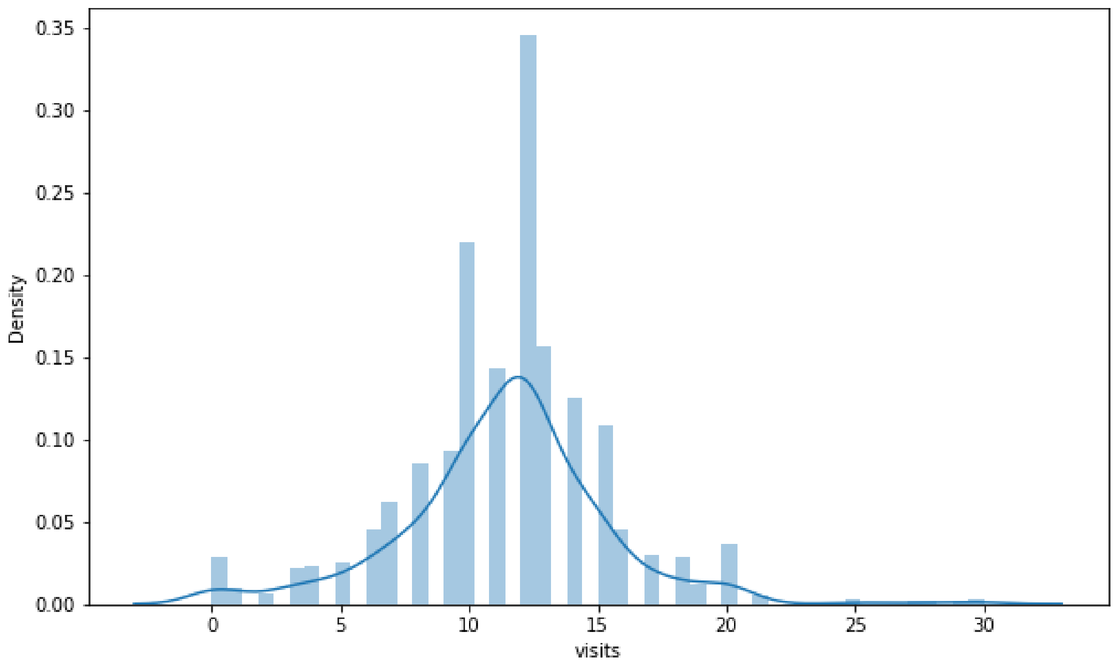
[61]:
```
# Distribution plot to see the skewness of the data
import matplotlib.pyplot as plt
fig, ax = plt.subplots(figsize =(10,6))
sns.distplot(df.fage)
```

[61]: <AxesSubplot:xlabel='fage', ylabel='Density'>



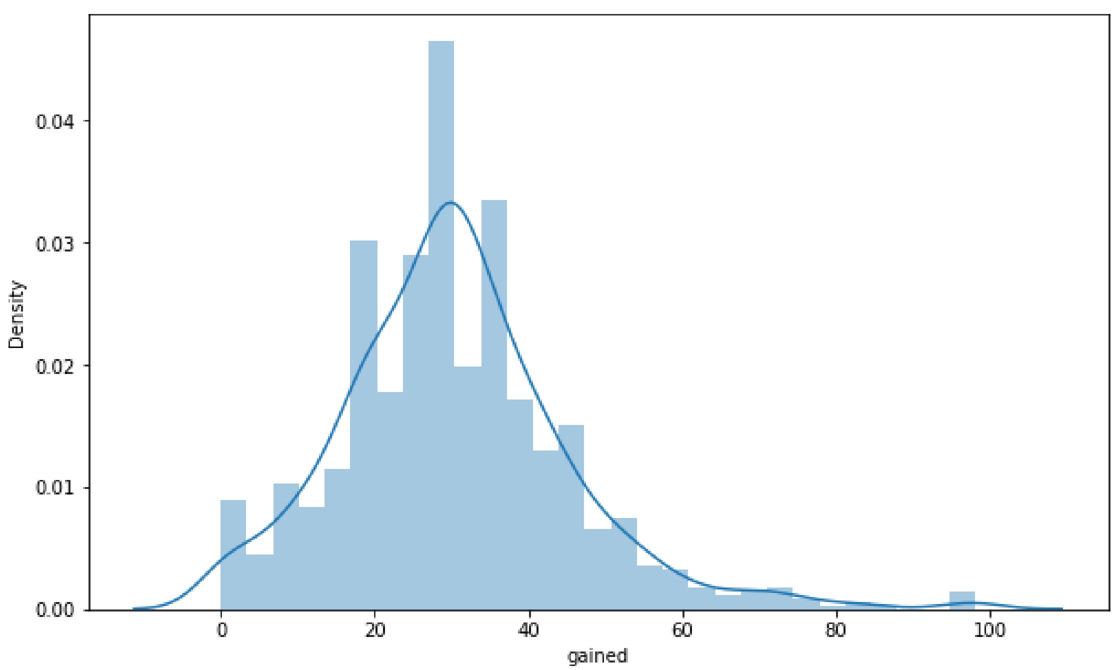
[62]:
```
fig, ax = plt.subplots(figsize =(10,6))
sns.distplot(df.visits)
```

[62]: <AxesSubplot:xlabel='visits', ylabel='Density'>




```
[63]: fig, ax = plt.subplots(figsize =(10,6))
      sns.distplot(df.gained)
```

```
[63]: <AxesSubplot:xlabel='gained', ylabel='Density'>
```



Fage, visits and gained data is little skewed so we will use median to fill the missing values.

[17]:
```
# Lets look at the dataframe for features i.e independent
independent.head()
```

[17]:
```
   fage  mage  mature  weeks  premie  visits  gained  weight  sex  habit  \
0  34.0    34       1     37       0    14.0    28.0    6.96    1      0
1  36.0    31       1     41       0    12.0    41.0    8.86    0      0
2  37.0    36       0     37       0    10.0    28.0    7.51    0      0
3  31.0    16       1     38       0    12.0    29.0    6.19    1      0
4  32.0    31       1     36       1    12.0    48.0    6.75    0      0

   marital  whitemom
0        0         1
1        0         1
2        0         0
3        1         1
4        0         1
```

We will use some techniques for feature selection

[19]:
```
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier()
rfc.fit(independent,target)
```

[19]:
```
RandomForestClassifier()
```

[48]:
```
feature_imp = pd.DataFrame(rfc.feature_importances_, columns = ['RF_Value'],␣
 ↪index = independent.columns)
feature_imp = feature_imp.reset_index()
```

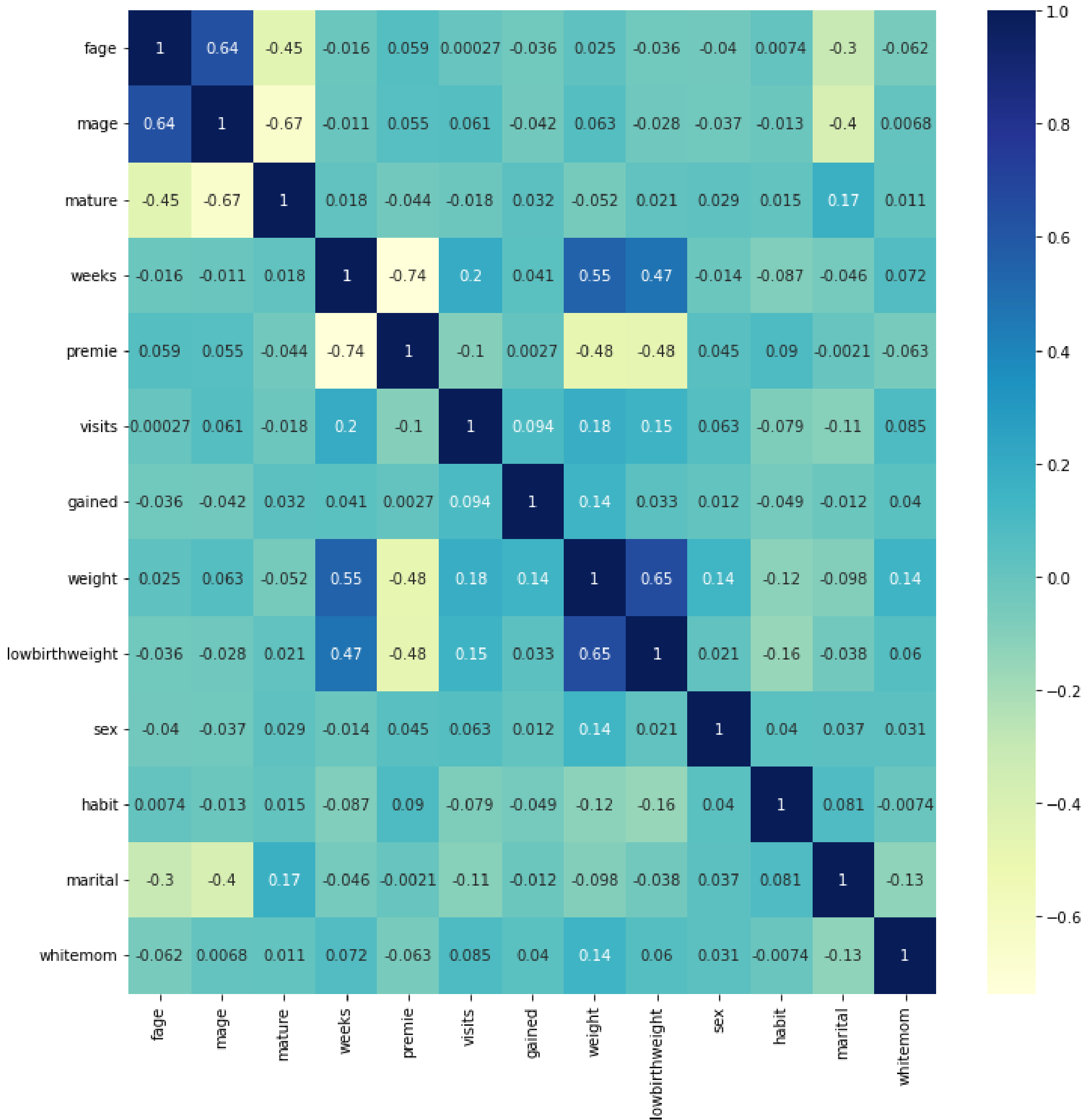
[49]:
```
feature_imp.sort_values(['RF_Value'], ascending = 0)
```

[49]:
```
       index  RF_Value
7     weight  0.675066
3      weeks  0.118978
4     premie  0.066919
5     visits  0.030589
6     gained  0.028004
1       mage  0.027362
0       fage  0.023058
9      habit  0.011839
10   marital  0.005578
8        sex  0.005341
11  whitemom  0.004059
2     mature  0.003209
```

Here we have different features with the importance value. Weight has the highest value because it is the weight of the baby at birth.It will be omitted from the dataset as it is showing same observation as lowbirthweight.

Looking at the correlation matrix

[29]:
```python
fig, ax = plt.subplots(figsize=(12,12))
dataplot = sns.heatmap(df.corr(), cmap="YlGnBu", annot=True)

# displaying heatmap
plt.show()
```



Weight has high correlation and will be removed from the data because it might cause the overfitting in the modelling.

Using the recursive feature elimination

[64]:
```
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression

lgr = LogisticRegression()
rfe = RFE(lgr, 8)
fit = rfe.fit(independent, target)
```

[51]:
```
selected_feature = pd.DataFrame(rfe.support_, columns = ['RFE_Selected'], index␣
↪= independent.columns)
selected_feature = selected_feature.reset_index()
selected_feature[selected_feature['RFE_Selected'] == True]
```

[51]:

	index	RFE_Selected
2	mature	True
3	weeks	True
4	premie	True
5	visits	True
7	weight	True
8	sex	True
9	habit	True
10	marital	True

Using ExtraTreesClassifier to fit a number of randomized decision trees to the data and is a from of ensemble learning

[52]:
```
from sklearn.ensemble import ExtraTreesClassifier

model1 = ExtraTreesClassifier()
model1.fit(independent, target)
ext = pd.DataFrame(model1.feature_importances_, columns = ["ExtraTree_Value"],␣
↪index=independent.columns)
ext =ext.reset_index()
ext.sort_values(['ExtraTree_Value'], ascending = 0)
```

[52]:

	index	ExtraTree_Value
7	weight	0.434552
4	premie	0.143632
3	weeks	0.105350
5	visits	0.059456
6	gained	0.055640
0	fage	0.055568
1	mage	0.052225
9	habit	0.030102
8	sex	0.019932
10	marital	0.018870

```
11  whitemom         0.012909
2     mature         0.011764
```

Using Lasso Regression for feature selection

[53]:
```
from sklearn.svm import LinearSVC
from sklearn.feature_selection import SelectFromModel
lsvc = LinearSVC(C=0.01, penalty="l1", dual=False).fit(independent, target)
model2 = SelectFromModel(lsvc,prefit=True)
l1 = pd.DataFrame(model2.get_support(), columns = ["L1"], index=independent.
 ↪columns)
l1 = l1.reset_index()
l1[l1['L1'] == True]
```

[53]:

	index	L1
0	fage	True
1	mage	True
3	weeks	True
6	gained	True
7	weight	True

Combining the results together

[55]:
```
from functools import reduce
all_df = [feature_imp, selected_feature, ext, l1]
result = reduce(lambda left,right: pd.merge(left,right,on='index'), all_df)
result
```

[55]:

	index	RF_Value	RFE_Selected	ExtraTree_Value	L1
0	fage	0.023058	False	0.055568	True
1	mage	0.027362	False	0.052225	True
2	mature	0.003209	True	0.011764	False
3	weeks	0.118978	True	0.105350	True
4	premie	0.066919	True	0.143632	False
5	visits	0.030589	True	0.059456	False
6	gained	0.028004	False	0.055640	True
7	weight	0.675066	True	0.434552	True
8	sex	0.005341	True	0.019932	False
9	habit	0.011839	True	0.030102	False
10	marital	0.005578	True	0.018870	False
11	whitemom	0.004059	False	0.012909	False

Contructing a table for total score

[65]:
```
columns = ['RF_Value', 'ExtraTree_Value']
table = pd.DataFrame({},[])
table['index'] = result['index']
for x in columns:
```

```
    table[x] = result['index'].isin(list(result.nlargest(6,x)['index'])).
↪astype(int)

table['RFE_Selected'] = result['RFE_Selected'].astype(int)
table['L1'] = result['L1'].astype(int)

table['Total'] = table.sum(axis=1)
table.sort_values('Total', ascending =0)
```

[65]:

	index	RF_Value	ExtraTree_Value	RFE_Selected	L1	Total
3	weeks	1	1	1	1	4
7	weight	1	1	1	1	4
4	premie	1	1	1	0	3
5	visits	1	1	1	0	3
6	gained	1	1	0	1	3
0	fage	0	1	0	1	2
1	mage	1	0	0	1	2
2	mature	0	0	1	0	1
8	sex	0	0	1	0	1
9	habit	0	0	1	0	1
10	marital	0	0	1	0	1
11	whitemom	0	0	0	0	0

The above table shows what the important feature are that are related to the lowbirthweight. My aim was to find if the smoking habit cause the low bith weight but after looking at the table construted above we can tell that habit have low contribution to the low birth weight and other facotors are involved in this process.

I will be now looking into creating the model that predicts if the baby will be low bith weight on the basis of different factors present in the data set but will be dropping whitemom and maritial column form the dataset.

[66]:

```
#Looking at our dataframe
df.head()
```

[66]:

	fage	mage	mature	weeks	premie	visits	gained	weight	lowbirthweight	\
0	34.0	34	1	37	0	14.0	28.0	6.96	1	
1	36.0	31	1	41	0	12.0	41.0	8.86	1	
2	37.0	36	0	37	0	10.0	28.0	7.51	1	
3	31.0	16	1	38	0	12.0	29.0	6.19	1	
4	32.0	31	1	36	1	12.0	48.0	6.75	1	

	sex	habit	marital	whitemom
0	1	0	0	1
1	0	0	0	1
2	0	0	0	0

```
3    1      0        1          1
4    0      0        0          1
```

[69]:
```
#dropping column marital and whitemom after performing feature selection
df.drop(["marital","whitemom"], axis =1, inplace = True)
```

[70]:
```
df
```

[70]:
```
     fage  mage  mature  weeks  premie  visits  gained  weight  \
0    34.0    34       1     37       0    14.0    28.0    6.96
1    36.0    31       1     41       0    12.0    41.0    8.86
2    37.0    36       0     37       0    10.0    28.0    7.51
3    31.0    16       1     38       0    12.0    29.0    6.19
4    32.0    31       1     36       1    12.0    48.0    6.75
..    …     …       …      …      …      …       …       …
995  28.0    24       1     39       0    12.0    20.0    6.49
996  37.0    31       1     38       0     8.0    33.0    5.80
997  27.0    27       1     34       1     7.0    25.0    6.75
998  31.0    33       1     42       0     0.0    13.0    7.44
999  21.0    17       1     41       0    12.0    41.0    7.13

     lowbirthweight  sex  habit
0                 1    1      0
1                 1    0      0
2                 1    0      0
3                 1    1      0
4                 1    0      0
..              …    …      …
995               1    1      2
996               1    0      0
997               1    0      0
998               1    1      0
999               1    0      0

[1000 rows x 11 columns]
```

- Now we will use the remaining features to develop our model

[81]:
```
# splitting the data in training and test
X = df.drop(columns = ['lowbirthweight'])
y = df['lowbirthweight']

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=60,␣
 ↪train_size = .8)
print( '---Shape of Splits---')
print('X train:{}'.format(X_train.shape))
print('X test:{}'.format(X_test.shape))
print('y train:{}'.format(y_train.shape))
```

```
print('y test:{}'.format(y_test.shape))
```

```
---Shape of Splits---
X train:(800, 10)
X test:(200, 10)
y train:(800,)
y test:(200,)
```

Scaling the data before feeding to the model. It helps to reduce the effect of the outlier in the model's prediction.

[127]:
```
from sklearn.preprocessing import StandardScaler

# scalling the input data
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.fit_transform(X_test)
```

Developing the model using the final dataset for test and train

1. Logistic Regression Model

[88]:
```
# Building the Logistic Regression Model
model_1 = LogisticRegression()
model_1.fit(X_train,y_train)
y_pred = model_1.predict(X_test)

# testing the model and displaying the score
score = model_1.score(X_test,y_test)
print(score)
```

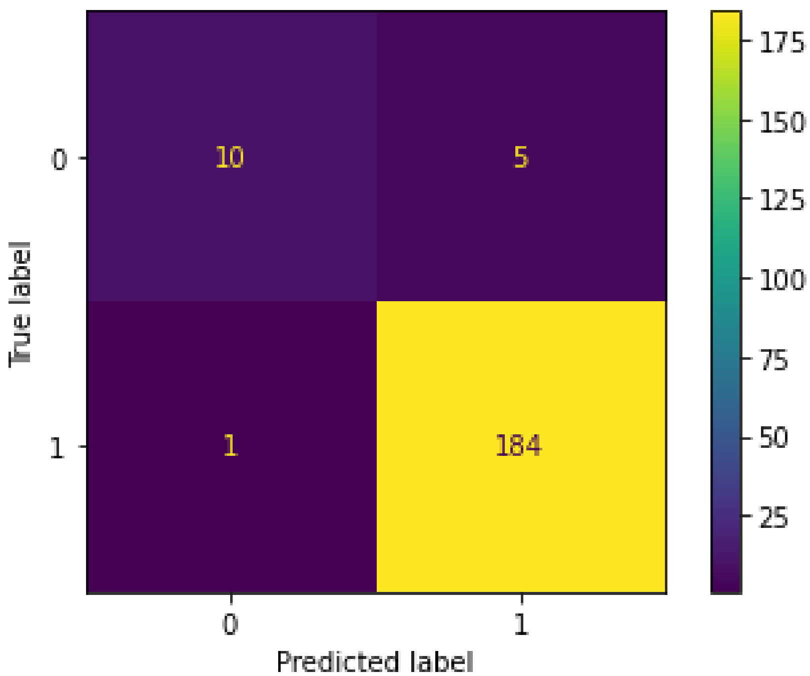
```
0.99
```

[90]:
```
# looking at the accuracy score of the model
accuracy = accuracy_score(y_test, y_pred)
print('Accuracy score: ', accuracy)
```

```
Accuracy score:  0.99
```

[139]:
```
# calculating the Confusion Matrix
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

# Plot the confusion matrix in graph
cm = confusion_matrix(y_test,y_pred)

# ploting with labels
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot()

# showing the matrix
```

```
plt.show()
```



Classification report is used to measure the quality of predictions from a classification algorithm. We will display the classification report for the model.

[107]:
```
# displaying the classification report
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      0.87      0.93        15
           1       0.99      1.00      0.99       185

    accuracy                           0.99       200
   macro avg       0.99      0.93      0.96       200
weighted avg       0.99      0.99      0.99       200
```

2. RandomForestClassifier Model

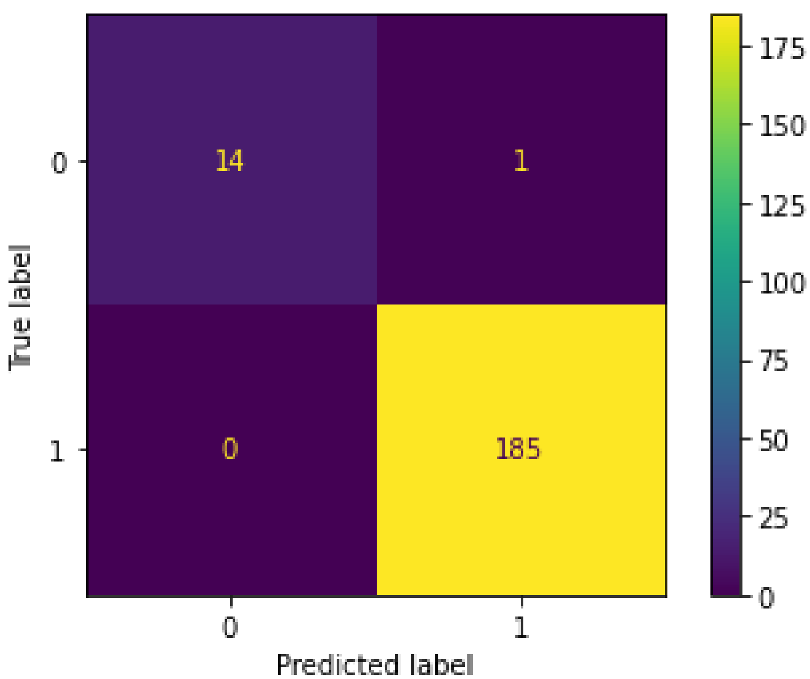
[116]:
```
# creating a RF classifier
clf = RandomForestClassifier(n_estimators = 100)

# fit function is used to train the model using the training sets as parameters
clf.fit(X_train, y_train)
```

```
# performing predictions on the test dataset
y_predic = clf.predict(X_test)

# metrics are used to find accuracy or error
from sklearn import metrics
print()

# using metrics module for accuracy calculation
print("ACCURACY OF THE MODEL: ", metrics.accuracy_score(y_test, y_predic))
```

```
ACCURACY OF THE MODEL:  0.995
```

[131]:

```
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

# Plot the confusion matrix in graph
cm = confusion_matrix(y_test,y_predic)

# ploting with labels
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot()

# showing the matrix
plt.show()
```



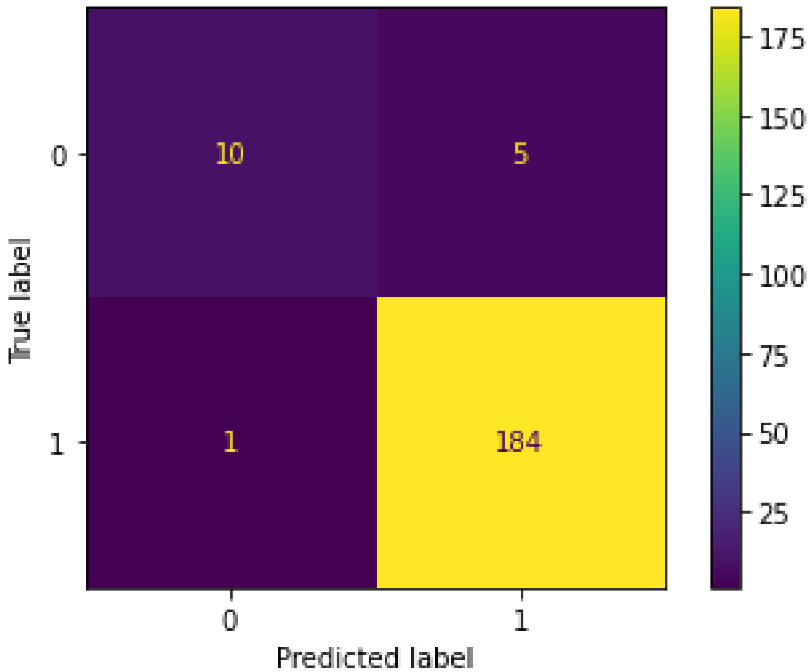
[132]:
```
# Looking at the model classification report
print(classification_report(y_test, y_predic))
```

```
              precision    recall  f1-score   support

           0       1.00      0.93      0.97        15
           1       0.99      1.00      1.00       185

    accuracy                           0.99       200
   macro avg       1.00      0.97      0.98       200
weighted avg       1.00      0.99      0.99       200
```

3. KNN Classification Model

[141]:
```
# creating the model
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=1)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
ac = metrics.accuracy_score(y_test,y_pred)
print('Accuracy score of model is', ac)

# ploting confusion matrix with labels
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot()

# showing the matrix
plt.show()

# Looking at the model classification report
print(classification_report(y_test, y_pred))
```

```
Accuracy score of model is 0.97
```




```
              precision    recall  f1-score   support

           0       0.91      0.67      0.77        15
           1       0.97      0.99      0.98       185

    accuracy                           0.97       200
   macro avg       0.94      0.83      0.88       200
weighted avg       0.97      0.97      0.97       200
```

[ ]: