

LightGBM Classifier in Python

```
In [6]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
In [7]: import os
for dirname, _, filenames in os.walk(r"C:\Users\Prachi\Documents\VS Code Files\Mach
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

C:\Users\Prachi\Documents\VS Code Files\Machine Learning\Classification\LightGBM C
lassifier\Breast Cancer Detection.ipynb
C:\Users\Prachi\Documents\VS Code Files\Machine Learning\Classification\LightGBM C
lassifier\Breast_cancer_data.csv

```
In [8]: # ignore warnings
import warnings
warnings.filterwarnings("ignore")
```

Read the dataset

```
In [9]: # Load and preview data
df = pd.read_csv('Breast_cancer_data.csv')
df.head()
```

```
Out[9]:
```

	mean_radius	mean_texture	mean_perimeter	mean_area	mean_smoothness	diagnosis
0	17.99	10.38	122.80	1001.0	0.11840	0
1	20.57	17.77	132.90	1326.0	0.08474	0
2	19.69	21.25	130.00	1203.0	0.10960	0
3	11.42	20.38	77.58	386.1	0.14250	0
4	20.29	14.34	135.10	1297.0	0.10030	0

```
In [10]: # view summary of dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 6 columns):
 #   Column                Non-Null Count  Dtype  
---  -
 0   mean_radius           569 non-null    float64
 1   mean_texture          569 non-null    float64
 2   mean_perimeter        569 non-null    float64
 3   mean_area             569 non-null    float64
 4   mean_smoothness       569 non-null    float64
 5   diagnosis             569 non-null    int64   
dtypes: float64(5), int64(1)
memory usage: 26.8 KB
```

Check the distribution of target variable

```
In [11]: # check the distribution of the target variable
df['diagnosis'].value_counts()
```

```
Out[11]: diagnosis
1      357
0      212
Name: count, dtype: int64
```

Declare feature vector and target variable

```
In [12]: X = df[['mean_radius', 'mean_texture', 'mean_perimeter', 'mean_area', 'mean_smoothness',
y = df['diagnosis']
```

Split dataset into training and test set

```
In [13]: #split the dataset into the training set and test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_s
```

LightGBM Model Development and Training

```
In [16]: # build the lightgbm model
import lightgbm as lgb
clf = lgb.LGBMClassifier()
clf.fit(X_train, y_train)
```

[illegible]

[illegible]

Out[16]:

- ▼ LGBMClassifier

Model Prediction

```
In [17]: # predict the results
y_pred=clf.predict(X_test)
```

View Accuracy

```
In [18]: # view accuracy
from sklearn.metrics import accuracy_score
accuracy=accuracy_score(y_pred, y_test)
print('LightGBM Model accuracy score: {0:0.4f}'.format(accuracy_score(y_test, y_pre

LightGBM Model accuracy score: 0.9298
```

Compare train and test accuracy

```
In [19]: y_pred_train = clf.predict(X_train)

In [20]: print('Training-set accuracy score: {0:0.4f}'.format(accuracy_score(y_train, y_pre

Training-set accuracy score: 1.0000
```

check for overfitting

```
In [21]: # print the scores on training and test set

print('Training set score: {:.4f}'.format(clf.score(X_train, y_train)))

print('Test set score: {:.4f}'.format(clf.score(X_test, y_test)))

Training set score: 1.0000
Test set score: 0.9298
```

Confusion Matrix

```
In [22]: # view confusion-matrix
# Print the Confusion Matrix and slice it into four pieces

from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
print('Confusion matrix\n\n', cm)
print('\nTrue Positives(TP) = ', cm[0,0])
print('\nTrue Negatives(TN) = ', cm[1,1])
print('\nFalse Positives(FP) = ', cm[0,1])
print('\nFalse Negatives(FN) = ', cm[1,0])
```

Confusion matrix

```
[[ 55   8]
 [  4 104]]
```

True Positives(TP) = 55

True Negatives(TN) = 104

False Positives(FP) = 8

False Negatives(FN) = 4

Classification Metrics

```
In [23]: from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

	precision	recall	f1-score	support
0	0.93	0.87	0.90	63
1	0.93	0.96	0.95	108
accuracy			0.93	171
macro avg	0.93	0.92	0.92	171
weighted avg	0.93	0.93	0.93	171