Klasifikasi Kanker Payudara menggunakan Decision Tree Classifier

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Identitas

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Link Dataset http://archive.ics.uci.edu/ml/machine-learning-databases/breast-cancer-wisconsin/wdbc.data

Informasi mengenai dataset Breast Cancer

- https://archive.ics.uci.edu/dataset/17/breast+cancer+wisconsin+diagnostic
- https://rpubs.com/Kevin_Nguyen_Tran/662211
- https://www.kaggle.com/datasets/uciml/breast-cancer-wisconsin-data

1. Mengumpulkan Data

1. Mengambil dataset dari UCI Dataset
2. Mengunduh file dataset tersebut

Tentang Dataset diberikan sebuah dataset bernama Breast Cancer dataset dimana pada dataset tersebut terdapat:

- Total 30 atribut variabel independen dan 1 variabel dependen yaitu diagnosis, sedangkan 1 atribut lainnya tidak digunakan yaitu atribut ID
- Variabel Dependen adalah diagnosis dimana terbagi menjadi 2 kategori, yaitu:
  - M (malignant) = Kanker Ganas
  - B (benign) = Kanker Jinak
- Data pasien penderita kanker yang digunakan sebanyak 569 data

2. Menelaah Data

tahapannya terdiri dari:

- Load library yang diperlukan
- Load dataset
- Memberi nama header atribut
- Menganalisa tipe dan relasi data (melihat tipe dataset, ukuran dataset, distribusi class, dan deskripsi dataset).
- Memberikan laporan atau kesimpulan dari kegiatan menelaah data.

```
# load library yang diperlukan

import numpy as np
```

```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import pydotplus
import matplotlib.image as mpimg
import graphviz

from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import confusion_matrix
from sklearn.pipeline import Pipeline
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn import tree
from IPython.display import Image

# load dataset

dataset = pd.read_csv("breastcancer.csv", header=None)
dataset.head()
```

```
         0  1      2      3       4       5        6        7       8  
\
0    842302  M  17.99  10.38  122.80  1001.0  0.11840  0.27760  0.3001

1    842517  M  20.57  17.77  132.90  1326.0  0.08474  0.07864  0.0869

2  84300903  M  19.69  21.25  130.00  1203.0  0.10960  0.15990  0.1974

3  84348301  M  11.42  20.38   77.58   386.1  0.14250  0.28390  0.2414

4  84358402  M  20.29  14.34  135.10  1297.0  0.10030  0.13280  0.1980


        9   ...     22     23      24      25      26      27      28  
29  \
0  0.14710  ...  25.38  17.33  184.60  2019.0  0.1622  0.6656  0.7119  
0.2654
1  0.07017  ...  24.99  23.41  158.80  1956.0  0.1238  0.1866  0.2416  
0.1860
2  0.12790  ...  23.57  25.53  152.50  1709.0  0.1444  0.4245  0.4504  
0.2430
3  0.10520  ...  14.91  26.50   98.87   567.7  0.2098  0.8663  0.6869  
0.2575
4  0.10430  ...  22.54  16.67  152.20  1575.0  0.1374  0.2050  0.4000  
0.1625
```

```
       30      31
0  0.4601  0.11890
1  0.2750  0.08902
2  0.3613  0.08758
3  0.6638  0.17300
4  0.2364  0.07678

[5 rows x 32 columns]
```

```
dataset.shape
```

```
(569, 32)
```

```
# Memberikan penamaan kolom-kolom pada dataset

dataset.columns = ['id', 'diagnosis', 'radius_mean',
                   'texture_mean', 'perimeter_mean',
                   'area_mean', 'smoothness_mean', 'compactness_mean',

                   'concavity_mean', 'concave points_mean',
'symmetry_mean',
                   'fractal_dimension_mean', 'radius_se',
'texture_se',
                   'perimeter_se', 'area_se', 'smoothness_se',
'compactness_se',
                   'concavity_se', 'concave points_se', 'symmetry_se',
'fractal_dimension_se',
                   'radius_worst', 'texture_worst', 'perimeter_worst',
'area_worst', 'smoothness_worst', 'compactness_worst',
                   'concavity_worst', 'concave points_worst',
'symmetry_worst', 'fractal_dimension_worst']
```

```
dataset.to_csv('breastcancer_with_header.csv', index=False)
```

```
dataset = pd.read_csv("breastcancer_with_header.csv")
dataset.head()
```

```
         id diagnosis  radius_mean  texture_mean  perimeter_mean
area_mean  \
0    842302         M        17.99         10.38          122.80
1001.0
1    842517         M        20.57         17.77          132.90
1326.0
2  84300903         M        19.69         21.25          130.00
1203.0
3  84348301         M        11.42         20.38           77.58
386.1
4  84358402         M        20.29         14.34          135.10
1297.0
```

```
   smoothness_mean  compactness_mean  concavity_mean  concave
points_mean  \
0          0.11840           0.27760          0.3001
0.14710
1          0.08474           0.07864          0.0869
0.07017
2          0.10960           0.15990          0.1974
0.12790
3          0.14250           0.28390          0.2414
0.10520
4          0.10030           0.13280          0.1980
0.10430

   ...  radius_worst  texture_worst  perimeter_worst  area_worst  \
0  ...         25.38          17.33           184.60      2019.0
1  ...         24.99          23.41           158.80      1956.0
2  ...         23.57          25.53           152.50      1709.0
3  ...         14.91          26.50            98.87       567.7
4  ...         22.54          16.67           152.20      1575.0

   smoothness_worst  compactness_worst  concavity_worst  concave
points_worst  \
0            0.1622             0.6656           0.7119
0.2654
1            0.1238             0.1866           0.2416
0.1860
2            0.1444             0.4245           0.4504
0.2430
3            0.2098             0.8663           0.6869
0.2575
4            0.1374             0.2050           0.4000
0.1625

   symmetry_worst  fractal_dimension_worst
0          0.4601                  0.11890
1          0.2750                  0.08902
2          0.3613                  0.08758
3          0.6638                  0.17300
4          0.2364                  0.07678

[5 rows x 32 columns]
```

```python
# Menganalisa tipe dan relasi data

# Melihat tipe dataset
type(dataset)
```

```
pandas.core.frame.DataFrame
```

```python
# Melihat ukuran dataset
print(dataset.shape)
```

```
(569, 32)
```

```python
# Melihat informasi tipe data semua kolom
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 32 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   id                       569 non-null    int64  
 1   diagnosis                569 non-null    object 
 2   radius_mean              569 non-null    float64
 3   texture_mean             569 non-null    float64
 4   perimeter_mean           569 non-null    float64
 5   area_mean                569 non-null    float64
 6   smoothness_mean          569 non-null    float64
 7   compactness_mean         569 non-null    float64
 8   concavity_mean           569 non-null    float64
 9   concave points_mean      569 non-null    float64
 10  symmetry_mean            569 non-null    float64
 11  fractal_dimension_mean   569 non-null    float64
 12  radius_se                569 non-null    float64
 13  texture_se               569 non-null    float64
 14  perimeter_se             569 non-null    float64
 15  area_se                  569 non-null    float64
 16  smoothness_se            569 non-null    float64
 17  compactness_se           569 non-null    float64
 18  concavity_se             569 non-null    float64
 19  concave points_se        569 non-null    float64
 20  symmetry_se              569 non-null    float64
 21  fractal_dimension_se     569 non-null    float64
 22  radius_worst             569 non-null    float64
 23  texture_worst            569 non-null    float64
 24  perimeter_worst          569 non-null    float64
 25  area_worst               569 non-null    float64
 26  smoothness_worst         569 non-null    float64
 27  compactness_worst        569 non-null    float64
 28  concavity_worst          569 non-null    float64
 29  concave points_worst     569 non-null    float64
 30  symmetry_worst           569 non-null    float64
 31  fractal_dimension_worst  569 non-null    float64
dtypes: float64(30), int64(1), object(1)
memory usage: 142.4+ KB
```

```python
# Melihat distribusi Class (apa saja jenisnya)
dataset['diagnosis'].unique()
```

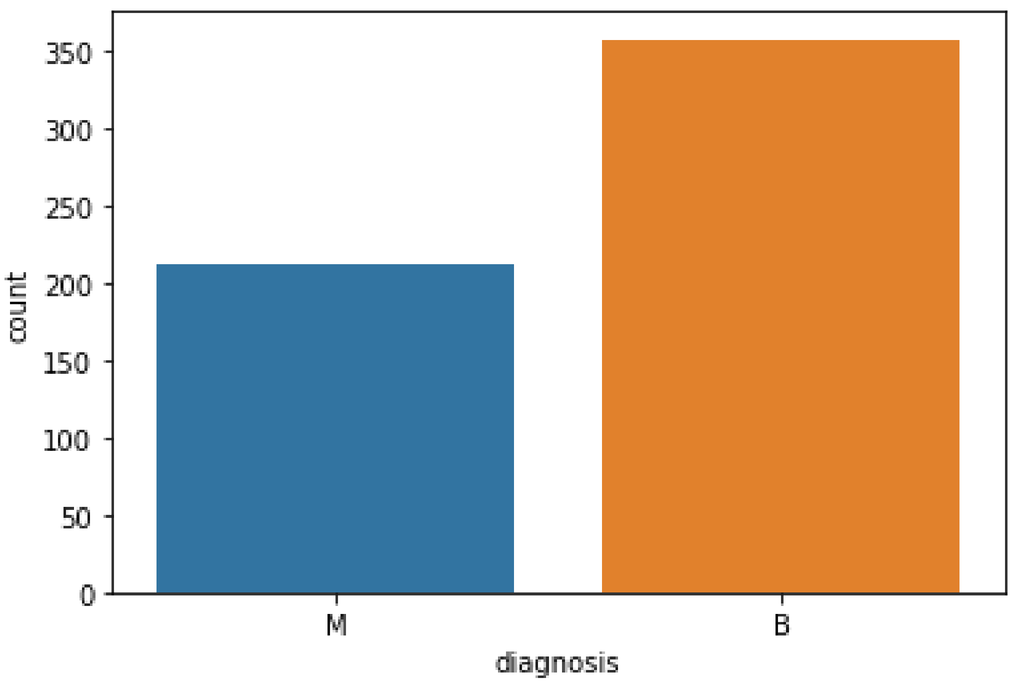
```
array(['M', 'B'], dtype=object)
```

```python
dataset['diagnosis'].value_counts()
```

```
B    357
M    212
Name: diagnosis, dtype: int64
```

```python
# Melihat distribusi Class (jumlahnya tiap Class)
sns.countplot(data=dataset, x='diagnosis')
```

```
<AxesSubplot:xlabel='diagnosis', ylabel='count'>
```




```python
# hapus kolom "Id"

dataset = dataset.drop(labels="id", axis=1)
```

```python
# Melihat deskripsi dataset
dataset.describe()
```

```
       radius_mean  texture_mean  perimeter_mean    area_mean  \
count   569.000000    569.000000      569.000000   569.000000
mean     14.127292     19.289649       91.969033   654.889104
std       3.524049      4.301036       24.298981   351.914129
min       6.981000      9.710000       43.790000   143.500000
25%      11.700000     16.170000       75.170000   420.300000
50%      13.370000     18.840000       86.240000   551.100000
75%      15.780000     21.800000      104.100000   782.700000
max      28.110000     39.280000      188.500000  2501.000000
```

```
       smoothness_mean  compactness_mean  concavity_mean  concave
points_mean  \
count       569.000000        569.000000      569.000000
569.000000
mean          0.096360          0.104341        0.088799
0.048919
std           0.014064          0.052813        0.079720
0.038803
min           0.052630          0.019380        0.000000
0.000000
25%           0.086370          0.064920        0.029560
0.020310
50%           0.095870          0.092630        0.061540
0.033500
75%           0.105300          0.130400        0.130700
0.074000
max           0.163400          0.345400        0.426800
0.201200

       symmetry_mean  fractal_dimension_mean  ...  radius_worst  \
count     569.000000              569.000000  ...    569.000000
mean        0.181162                0.062798  ...     16.269190
std         0.027414                0.007060  ...      4.833242
min         0.106000                0.049960  ...      7.930000
25%         0.161900                0.057700  ...     13.010000
50%         0.179200                0.061540  ...     14.970000
75%         0.195700                0.066120  ...     18.790000
max         0.304000                0.097440  ...     36.040000

       texture_worst  perimeter_worst   area_worst
smoothness_worst  \
count     569.000000       569.000000   569.000000        569.000000

mean       25.677223       107.261213   880.583128          0.132369

std         6.146258        33.602542   569.356993          0.022832

min        12.020000        50.410000   185.200000          0.071170

25%        21.080000        84.110000   515.300000          0.116600

50%        25.410000        97.660000   686.500000          0.131300

75%        29.720000       125.400000  1084.000000          0.146000

max        49.540000       251.200000  4254.000000          0.222600


       compactness_worst  concavity_worst  concave points_worst  \
```

```
count          569.000000       569.000000             569.000000
mean             0.254265         0.272188               0.114606
std              0.157336         0.208624               0.065732
min              0.027290         0.000000               0.000000
25%              0.147200         0.114500               0.064930
50%              0.211900         0.226700               0.099930
75%              0.339100         0.382900               0.161400
max              1.058000         1.252000               0.291000

       symmetry_worst  fractal_dimension_worst
count      569.000000               569.000000
mean         0.290076                 0.083946
std          0.061867                 0.018061
min          0.156500                 0.055040
25%          0.250400                 0.071460
50%          0.282200                 0.080040
75%          0.317900                 0.092080
max          0.663800                 0.207500

[8 rows x 30 columns]
```

Kesimpulan

- Tipe datanya adalah float64, untuk kolom diagnosis bertipe Object
- Jumlah fitur (30) lebih sedikit dibandingkan dengan jumlah record data pasien (569) maka termasuk **Low Dimensional Dataset**
- Jumlah distribusi diagnosis:
  - class M sebanyak 212 pasien
  - class B sebanyak 357 pasien

3. Memvalidasi Data

```
# mengecek apakah ada data yang bernilai null atau tidak
dataset.isnull().sum()
```

```
diagnosis                  0
radius_mean                0
texture_mean               0
perimeter_mean             0
area_mean                  0
smoothness_mean            0
compactness_mean           0
concavity_mean             0
concave points_mean        0
symmetry_mean              0
fractal_dimension_mean     0
radius_se                  0
texture_se                 0
perimeter_se               0
area_se                    0
smoothness_se              0
```

```
compactness_se             0
concavity_se               0
concave points_se          0
symmetry_se                0
fractal_dimension_se       0
radius_worst               0
texture_worst              0
perimeter_worst            0
area_worst                 0
smoothness_worst           0
compactness_worst          0
concavity_worst            0
concave points_worst       0
symmetry_worst             0
fractal_dimension_worst    0
dtype: int64
```

4. Menentukan Objek Data

Objek data pada dataset Breast Cancer Wisconsin adalah diagnosis, fitur-gitur berbasis pengukuran, serta variasi rata-rata, standar deviasi, dan nilai maksimum/terburuk dari fitur-fitur tersebut. Adapun rinciannya sebagai berikut:

1. Target: kolom diagnosis terdiri dari 2:
   - "M" untuk tumor ganas
   - "B" untuk tumor jinak
2. Fitur-fitur berbasis pengukuran dari sel-sel tumor yang telah diamati melalui mikroskop seperti:
   - `radius_mean` : Rata-rata jarak dari pusat ke titik-titik pada tepi tumor
   - `texture_mean` : Standar deviasi tingkat kecerahan pada gambar sel tumor
   - `perimeter_mean` : Panjang total garis tengah pada tepi tumor
   - `area_mean` : Area di dalam kontur tumor
   - `smoothness_mean` : variasi lokal dalam panjang garis pada kontur tumor.
   - `compactness_mean` : Perbandingan keliling kuadrat dengan luas - 1.0 atau penulisan rumusnya: (perimeter^2 / area) - 1.0.
   - `concavity_mean` : Tingkat keparahan bagian cekung dari kontur tumor
   - `concave points_mean` : Jumlah titik konveks pada kontur tumor
   - `symmetry_mean` : Simetri sel tumor
   - `fractial_dimension_mean` : perkiraan kurva sejajar dari kontur tumor
3. Selain, fitur-fitur berbasis pengukuran, juga terdapat fitur yang diukur dengan standar deviasi dan standard error (se) untuk masing-masing fitur tersebut.

5. Membersihkan Data

- Hapus data duplikat

```
dataset.duplicated()
```

```
0      False
1      False
2      False
3      False
4      False
       ...
564    False
565    False
566    False
567    False
568    False
Length: 569, dtype: bool
```

Dapat dilihat bahwa tidak ada data duplikat

```python
# replace column diagnosis from string to numeric values

dataset['diagnosis'].replace({'M': 1, 'B': 0}, inplace=True)
```

6. Mengkonstruksi Data

Terdiri dari:

- Representasi fitur dan merubah tipenya
- Membagi data menjadi training dan testing
- Membandingkan Data Original, Data Normalisasi, Data Original PCA, dan Data Normalisasi PCA

```python
# Mengecek Representasi Fitur
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 31 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   diagnosis                569 non-null    int64
 1   radius_mean              569 non-null    float64
 2   texture_mean             569 non-null    float64
 3   perimeter_mean           569 non-null    float64
 4   area_mean                569 non-null    float64
 5   smoothness_mean          569 non-null    float64
 6   compactness_mean         569 non-null    float64
 7   concavity_mean           569 non-null    float64
 8   concave points_mean      569 non-null    float64
 9   symmetry_mean            569 non-null    float64
 10  fractal_dimension_mean   569 non-null    float64
 11  radius_se                569 non-null    float64
 12  texture_se               569 non-null    float64
 13  perimeter_se             569 non-null    float64
 14  area_se                  569 non-null    float64
```

```
 15  smoothness_se            569 non-null    float64
 16  compactness_se           569 non-null    float64
 17  concavity_se             569 non-null    float64
 18  concave points_se        569 non-null    float64
 19  symmetry_se              569 non-null    float64
 20  fractal_dimension_se     569 non-null    float64
 21  radius_worst             569 non-null    float64
 22  texture_worst            569 non-null    float64
 23  perimeter_worst          569 non-null    float64
 24  area_worst               569 non-null    float64
 25  smoothness_worst         569 non-null    float64
 26  compactness_worst        569 non-null    float64
 27  concavity_worst          569 non-null    float64
 28  concave points_worst     569 non-null    float64
 29  symmetry_worst           569 non-null    float64
 30  fractal_dimension_worst  569 non-null    float64
dtypes: float64(30), int64(1)
memory usage: 137.9 KB
```

Membagi data Training dan Testing

```
X = dataset.drop(['diagnosis'], axis=1)
y = dataset['diagnosis']

# menampilkan X
X.head()
```

```
   radius_mean  texture_mean  perimeter_mean  area_mean
smoothness_mean  \
0        17.99         10.38          122.80     1001.0
0.11840
1        20.57         17.77          132.90     1326.0
0.08474
2        19.69         21.25          130.00     1203.0
0.10960
3        11.42         20.38           77.58      386.1
0.14250
4        20.29         14.34          135.10     1297.0
0.10030

   compactness_mean  concavity_mean  concave points_mean
symmetry_mean  \
0           0.27760          0.3001              0.14710
0.2419
1           0.07864          0.0869              0.07017
0.1812
2           0.15990          0.1974              0.12790
0.2069
3           0.28390          0.2414              0.10520
0.2597
4           0.13280          0.1980              0.10430
```

```
0.1809

   fractal_dimension_mean  ...  radius_worst  texture_worst  
perimeter_worst  \
0                 0.07871  ...         25.38          17.33           
184.60   
1                 0.05667  ...         24.99          23.41           
158.80   
2                 0.05999  ...         23.57          25.53           
152.50   
3                 0.09744  ...         14.91          26.50            
98.87   
4                 0.05883  ...         22.54          16.67           
152.20   

   area_worst  smoothness_worst  compactness_worst  concavity_worst  \
0      2019.0            0.1622             0.6656           0.7119   
1      1956.0            0.1238             0.1866           0.2416   
2      1709.0            0.1444             0.4245           0.4504   
3       567.7            0.2098             0.8663           0.6869   
4      1575.0            0.1374             0.2050           0.4000   

   concave points_worst  symmetry_worst  fractal_dimension_worst  
0                0.2654          0.4601                  0.11890  
1                0.1860          0.2750                  0.08902  
2                0.2430          0.3613                  0.08758  
3                0.2575          0.6638                  0.17300  
4                0.1625          0.2364                  0.07678  

[5 rows x 30 columns]
```

```
# menampilkan y

y.head()
```

```
0    1
1    1
2    1
3    1
4    1
Name: diagnosis, dtype: int64
```

6.1 Data Original

```
# Membagi data menjadi training = 70% dan testing = 30%
X_train, X_test, y_train, y_test = train_test_split(X,y, 
test_size=0.3, random_state=42)

X_train.shape, X_test.shape
```

```
((398, 30), (171, 30))
```

6.2 Data Normalisasi

```
# Normalisasi menggunakan StandardScaler
X_norm = StandardScaler().fit_transform(X)

# Melihat hasil normalisasi dengan StandardScaler
X_norm
```

```
array([[ 1.09706398, -2.07333501,  1.26993369, ...,  2.29607613,
         2.75062224,  1.93701461],
       [ 1.82982061, -0.35363241,  1.68595471, ...,  1.0870843 ,
        -0.24388967,  0.28118999],
       [ 1.57988811,  0.45618695,  1.56650313, ...,  1.95500035,
         1.152255  ,  0.20139121],
       ...,
       [ 0.70228425,  2.0455738 ,  0.67267578, ...,  0.41406869,
        -1.10454895, -0.31840916],
       [ 1.83834103,  2.33645719,  1.98252415, ...,  2.28998549,
         1.91908301,  2.21963528],
       [-1.80840125,  1.22179204, -1.81438851, ..., -1.74506282,
        -0.04813821, -0.75120669]])
```

```
X_train_norm, X_test_norm, y_train_norm, y_test_norm =
train_test_split(X_norm,y, test_size=0.3, random_state=42)
```

6.3 Data Original PCA

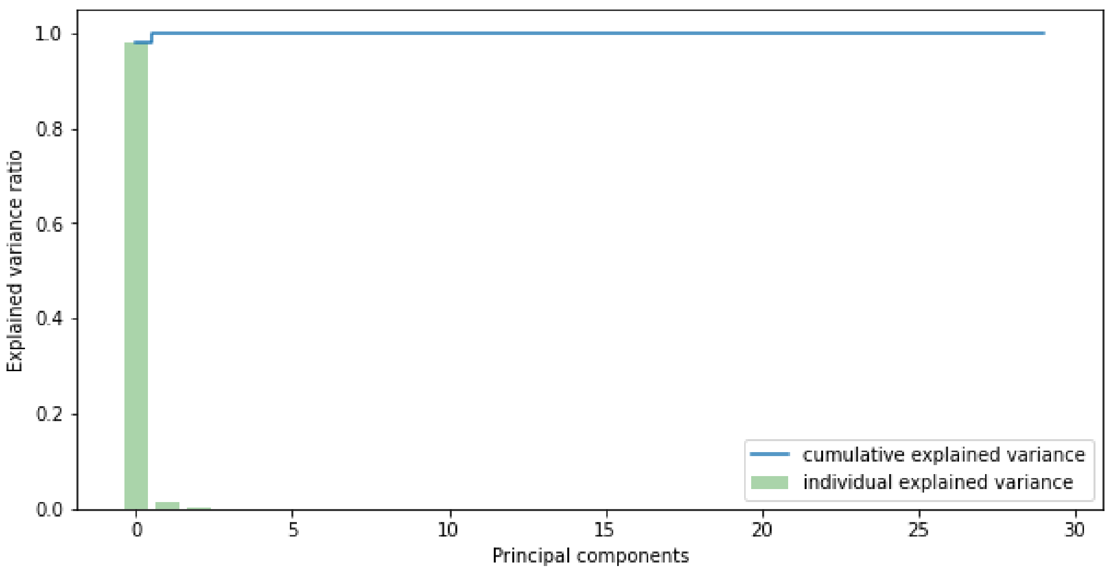
```
pca = PCA(random_state=42)
pca.fit(X)
ori_pca_array = pca.transform(X)
ori_pca = pd.DataFrame(ori_pca_array)
print("Heads of Original_PCA:",ori_pca.head())
var_ratio = pca.explained_variance_ratio_
print("\n Explained Variance Ratio:",var_ratio)
sv = pca.singular_values_
print("\n Singular Value:",sv)
```

```
Heads of Original_PCA:             0           1          2          3
4          5  \
0  1160.142574 -293.917544  48.578398  -8.711975  32.000486  1.265415

1  1269.122443   15.630182 -35.394534  17.861283  -4.334874 -0.225872

2   995.793889   39.156743  -1.709753   4.199340  -0.466529 -2.652811

3  -407.180803  -67.380320   8.672848 -11.759867   7.115461  1.299436

4   930.341180  189.340742   1.374801   8.499183   7.613289  1.021160


         6          7          8          9   ...         20         21
22  \
```

```
0  0.931337  0.148167  0.745463  0.589359  ...  0.021189  0.000241
0.002528
1 -0.046037  0.200804 -0.485828 -0.084035  ...  0.005237  0.021069
0.001565
2 -0.779745 -0.274026 -0.173874 -0.186994  ... -0.009865 -0.002394 -
0.004125
3 -1.267304 -0.060555 -0.330639 -0.144155  ...  0.011169  0.007063
0.001537
4 -0.335522  0.289109  0.036087 -0.138502  ... -0.009916  0.010269
0.002204

         23        24        25        26        27        28
29
0  0.011560  0.005773  0.001377 -0.001982  0.001293  0.001989
0.000704
1  0.006968 -0.006978  0.001411 -0.000083 -0.001347  0.000686 -
0.001061
2 -0.004007  0.000709 -0.003781  0.000178  0.000018 -0.000775
0.000405
3  0.007003 -0.010261 -0.002899  0.000016  0.001369 -0.002139 -
0.001657
4  0.002764  0.002455  0.001665  0.003290  0.000273  0.001783
0.000327

[5 rows x 30 columns]

 Explained Variance Ratio: [9.82044672e-01 1.61764899e-02 1.55751075e-
03 1.20931964e-04
 8.82724536e-05 6.64883951e-06 4.01713682e-06 8.22017197e-07
 3.44135279e-07 1.86018721e-07 6.99473205e-08 1.65908880e-08
 6.99641650e-09 4.78318306e-09 2.93549214e-09 1.41684927e-09
 8.29577731e-10 5.20405883e-10 4.08463983e-10 3.63313378e-10
 1.72849737e-10 1.27487508e-10 7.72682973e-11 6.28357718e-11
 3.57302295e-11 2.76396041e-11 8.14452259e-12 6.30211541e-12
 4.43666945e-12 1.55344680e-12]

 Singular Value: [1.58766659e+04 2.03767928e+03 6.32279658e+02
1.76183095e+02
 1.50524184e+02 4.13110857e+01 3.21108643e+01 1.45256018e+01
 9.39849429e+00 6.90990396e+00 4.23720255e+00 2.06361416e+00
 1.34008242e+00 1.10803170e+00 8.68028820e-01 6.03053036e-01
 4.61447425e-01 3.65480981e-01 3.23795320e-01 3.05375632e-01
 2.10633792e-01 1.80895390e-01 1.40829733e-01 1.26998082e-01
 9.57660526e-02 8.42286020e-02 4.57221348e-02 4.02195178e-02
 3.37459936e-02 1.99683360e-02]
```

```python
# Visualisasi Data Original PCA
cum_var_ratio = np.cumsum(var_ratio)

plt.figure(figsize=(10, 5))
```

```
plt.bar(range(len(var_ratio)),
        var_ratio,
        alpha=0.3333,
        align='center',
        label='individual explained variance',
        color = 'g')
plt.step(range(len(cum_var_ratio)),
         cum_var_ratio,
         where='mid',
         label='cumulative explained variance')
plt.ylabel('Explained variance ratio')
plt.xlabel('Principal components')
plt.legend(loc='best')
plt.show()

print("Cumulative explained ratio:",cum_var_ratio)
```




```
Cumulative explained ratio: [0.98204467 0.99822116 0.99977867
0.9998996  0.99998788 0.99999453
 0.99999854 0.99999936 0.99999971 0.99999989 0.99999996 0.99999998
 0.99999999 0.99999999 1.         1.         1.         1.
 1.         1.         1.         1.         1.         1.
 1.         1.         1.         1.         1.         1.        ]

# Dipilih 15 PC
pca = PCA(n_components=15, random_state=42)
pca.fit(X)
ori_pca_array = pca.transform(X)
ori_pca = pd.DataFrame(data=ori_pca_array, columns = ['PC1',
'PC2','PC3','PC4','PC5','PC6','PC7','PC8','PC9','PC10','PC11','PC12','
PC13','PC14','PC15'])
```

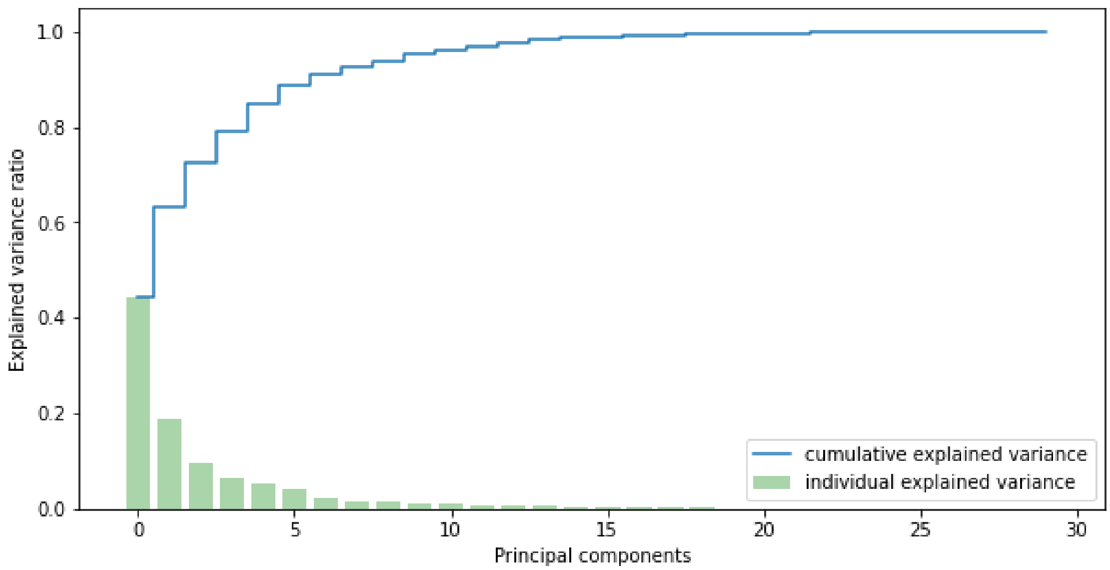
```
X_train_pca, X_test_pca, y_train_pca, y_test_pca =
train_test_split(ori_pca,y, test_size=0.3, random_state=42)
```

6.4 Data Normalisasi PCA

```
pca = PCA(random_state=42)
pca.fit(X_norm)
norm_pca_array = pca.transform(X_norm)
norm_pca = pd.DataFrame(norm_pca_array)
print("Heads of iris_pca:",norm_pca.head())
var_ratio = pca.explained_variance_ratio_
print("\n Explained variance ratio:",var_ratio)
sv = pca.singular_values_
print("\n Singular Value:",sv)
```

```
Heads of iris_pca:          0          1         2         3         4
5         6   \
0  9.192837   1.948583 -1.123166  3.633731 -1.195110  1.411424
2.159370
1  2.387802  -3.768172 -0.529293  1.118264  0.621775  0.028656
0.013358
2  5.733896  -1.075174 -0.551748  0.912083 -0.177086  0.541452 -
0.668166
3  7.122953  10.275589 -3.232790  0.152547 -2.960878  3.053422
1.429911
4  3.935302  -1.948072  1.389767  2.940639  0.546747 -1.226495 -
0.936213

         7         8         9   ...        20        21        22
23  \
0 -0.398407 -0.157118 -0.877402  ...  0.096515  0.068850  0.084519 -
0.175256
1  0.240988 -0.711905  1.106995  ... -0.077327 -0.094578 -0.217718
0.011290
2  0.097374  0.024066  0.454275  ...  0.311067 -0.060309 -0.074291
0.102762
3  1.059565 -1.405440 -1.116975  ...  0.434193 -0.203266 -0.124105
0.153430
4  0.636376 -0.263805  0.377704  ... -0.116545 -0.017650  0.139454 -
0.005332

         24        25        26        27        28        29
0 -0.151020 -0.201503 -0.252585 -0.033914  0.045648 -0.047169
1 -0.170510 -0.041129  0.181270  0.032624 -0.005687 -0.001868
2  0.171158  0.004735  0.049569  0.047026  0.003146  0.000751
3  0.077496 -0.275225  0.183462  0.042484 -0.069295 -0.019937
4  0.003062  0.039254  0.032168 -0.034786  0.005038  0.021214

[5 rows x 30 columns]

 Explained variance ratio: [4.42720256e-01 1.89711820e-01 9.39316326e-
```

```
02 6.60213492e-02
 5.49576849e-02 4.02452204e-02 2.25073371e-02 1.58872380e-02
 1.38964937e-02 1.16897819e-02 9.79718988e-03 8.70537901e-03
 8.04524987e-03 5.23365745e-03 3.13783217e-03 2.66209337e-03
 1.97996793e-03 1.75395945e-03 1.64925306e-03 1.03864675e-03
 9.99096464e-04 9.14646751e-04 8.11361259e-04 6.01833567e-04
 5.16042379e-04 2.72587995e-04 2.30015463e-04 5.29779290e-05
 2.49601032e-05 4.43482743e-06]

 Singular Value: [86.93235745 56.90677266 40.04263937 33.57058877
30.62887007 26.2104161
 19.60102663 16.46800391 15.4017255  14.12602481 12.93205441
12.19019359
 11.71889139  9.4519063   7.31866075  6.74106325  5.81360925
5.47175363
  5.30591648  4.21066503  4.12971871  3.95133143  3.72155031
3.20519874
  2.96796958  2.15709923  1.98150547  0.95096438  0.65273958
0.27514088]

# Visualisasi Data Normalisasi PCA
cum_var_ratio = np.cumsum(var_ratio)

plt.figure(figsize=(10, 5))
plt.bar(range(len(var_ratio)),
        var_ratio,
        alpha=0.3333,
        align='center',
        label='individual explained variance',
        color = 'g')
plt.step(range(len(cum_var_ratio)),
         cum_var_ratio,
         where='mid',
         label='cumulative explained variance')
plt.ylabel('Explained variance ratio')
plt.xlabel('Principal components')
plt.legend(loc='best')
plt.show()

print("Cumulative explained ratio:",cum_var_ratio)
```




```
Cumulative explained ratio: [0.44272026 0.63243208 0.72636371
0.79238506 0.84734274 0.88758796
 0.9100953  0.92598254 0.93987903 0.95156881 0.961366   0.97007138
 0.97811663 0.98335029 0.98648812 0.98915022 0.99113018 0.99288414
 0.9945334  0.99557204 0.99657114 0.99748579 0.99829715 0.99889898
 0.99941502 0.99968761 0.99991763 0.99997061 0.99999557 1.        ]
```

```
# Dipilih 15 PC
pca = PCA(n_components=15, random_state=42)
pca.fit(X_norm)
norm_pca_array = pca.transform(X_norm)
norm_pca = pd.DataFrame(data=norm_pca_array, columns = ['PC1',
'PC2','PC3','PC4','PC5','PC6','PC7','PC8','PC9','PC10','PC11','PC12','
PC13','PC14','PC15'])

X_train_norm_pca, X_test_norm_pca, y_train_norm_pca, y_test_norm_pca =
train_test_split(norm_pca,y, test_size=0.3, random_state=42)
```

7. Menentukan Label Data

Label Data pada konteks dataset ini terletak pada kolom diagnosis, yaitu:

- class "M" untuk mengidentifikasikan tumor ganas
- class "B" untuk mengidentifikasikan tumor jinak

8. Membangun Model

- Teknik Pemodelan yang dipakai:
  - Menggunakan Decision Tree
  - Parameter yang dipakai:
    - [criterion: gini, entropy]
    - [max_depth]

- [min sample split]
- [min sample leaf]

- Skenario Pengujian
  - Menggunakan akurasi, presisi dan recall.
  - Pengujian menggunakan Data Original.
  - Pengujian menggunakan Data yang sudah dinormalisasi.
  - Pengujian menggunakan Data Original yang diberikan PCA.
  - Pengujian menggunakan Data yang sudah dinormalisasi dan diberikan PCA.

Decision Tree

```
# Pemodelan Decision Tree
classifier_dt_pipeline = Pipeline([
                          ('model',DecisionTreeClassifier()),

                          ])

parameters_dt = {
                "model__max_depth": np.arange(1,21),
                "model__min_samples_leaf": np.arange(1,101,2),
                "model__min_samples_split": np.arange(2,11),
                "model__criterion": ['gini','entropy'],
                "model__random_state": [42]
}
```

8.1 Pemodelan dengan Data Original

```
ori_classifier_dt = GridSearchCV(classifier_dt_pipeline,
parameters_dt, cv=3, n_jobs=-1)

ori_classifier_dt.fit(X_train,y_train.ravel())

GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('model',
DecisionTreeClassifier())]),
             n_jobs=-1,
             param_grid={'model__criterion': ['gini', 'entropy'],
                         'model__max_depth': array([ 1,  2,  3,  4,
5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
       18, 19, 20]),
                         'model__min_samples_leaf': array([ 1,  3,  5,
7,  9, 11, 13, 15, 17, 19, 21, 23, 25, 27, 29, 31, 33,
       35, 37, 39, 41, 43, 45, 47, 49, 51, 53, 55, 57, 59, 61, 63, 65,
67,
       69, 71, 73, 75, 77, 79, 81, 83, 85, 87, 89, 91, 93, 95, 97,
99]),
                         'model__min_samples_split': array([ 2,  3,
4,  5,  6,  7,  8,  9, 10]),
                         'model__random_state': [42]})

ori_classifier_dt.best_estimator_
```

```
Pipeline(steps=[('model',
                 DecisionTreeClassifier(criterion='entropy',
max_depth=3,
                                        min_samples_leaf=11,
                                        random_state=42))])
```

```
for param_name in sorted(parameters_dt.keys()):
    print('%s: %r' %
(param_name,ori_classifier_dt.best_params_[param_name]))
```

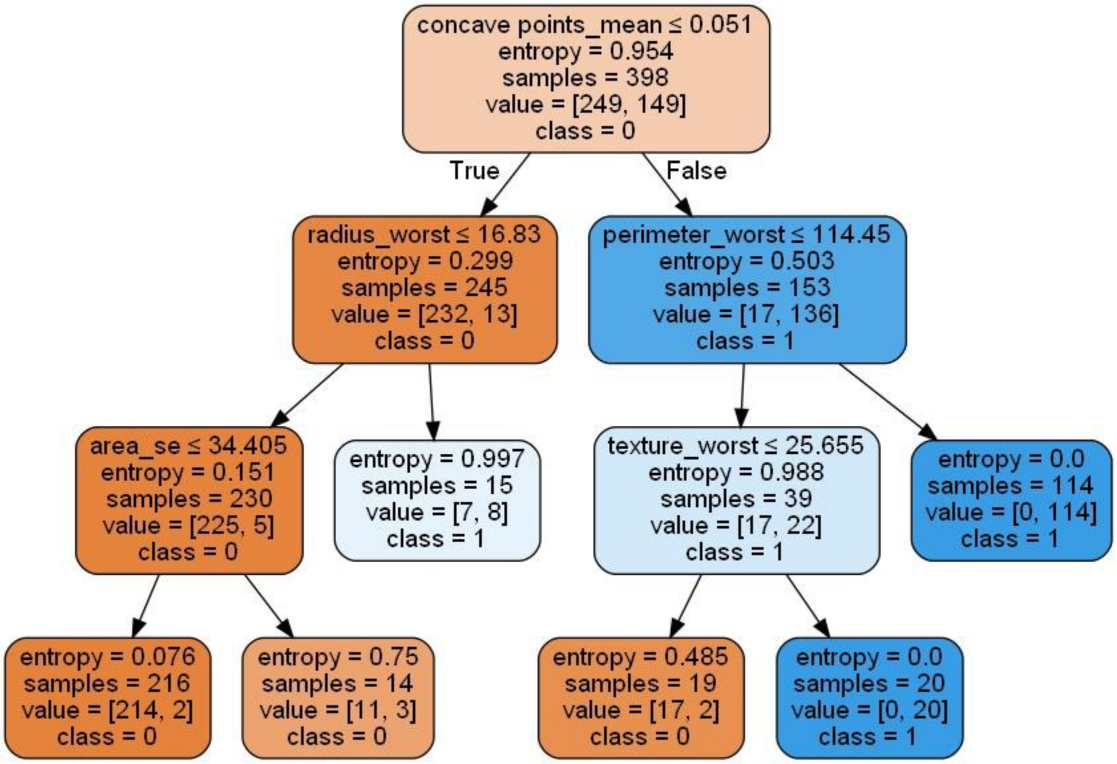
```
model__criterion: 'entropy'
model__max_depth: 3
model__min_samples_leaf: 11
model__min_samples_split: 2
model__random_state: 42
```

Visualisasi Decision Tree data Original

```
# Mencari nama langkah untuk Decision Tree Classifier dalam pipeline
best_estimator = ori_classifier_dt.best_estimator_
steps = best_estimator.named_steps
classifier_dt_name = next(key for key, value in steps.items() if
isinstance(value, tree.DecisionTreeClassifier))

# Membuat objek Decision Tree Classifier terbaik setelah tuning
best_classifier_dt = steps[classifier_dt_name]

# Membuat visualisasi decision tree menggunakan pydotplus
dot_data = tree.export_graphviz(best_classifier_dt, out_file=None,
                                feature_names=X_train.columns,

class_names=ori_classifier_dt.best_estimator_.classes_.astype(str),
                                filled=True, rounded=True,
                                special_characters=True)
graph = pydotplus.graph_from_dot_data(dot_data)

# Menyimpan visualisasi decision tree dalam format JPG
graph.write_jpg("dt_ori.jpg")
```

```
True
```

```
# Menampilkan visualisasi decision tree di Jupyter Notebook
Image(filename="dt_ori.jpg")
```



8.2 Pemodelan dengan Data Normalisasi

```
norm_classifier_dt = GridSearchCV(classifier_dt_pipeline, 
parameters_dt, cv=3, n_jobs=-1)

norm_classifier_dt.fit(X_train_norm,y_train_norm.ravel())

GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('model', 
DecisionTreeClassifier())]),
             n_jobs=-1,
             param_grid={'model__criterion': ['gini', 'entropy'],
                         'model__max_depth': array([ 1,  2,  3,  4, 
5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
       18, 19, 20]),
                         'model__min_samples_leaf': array([ 1,  3,  5, 
7,  9, 11, 13, 15, 17, 19, 21, 23, 25, 27, 29, 31, 33,
       35, 37, 39, 41, 43, 45, 47, 49, 51, 53, 55, 57, 59, 61, 63, 65, 
67,
       69, 71, 73, 75, 77, 79, 81, 83, 85, 87, 89, 91, 93, 95, 97, 
99]),
                         'model__min_samples_split': array([ 2,  3, 
4,  5,  6,  7,  8,  9, 10]),
                         'model__random_state': [42]})

norm_classifier_dt.best_estimator_
```

```
Pipeline(steps=[('model',
                 DecisionTreeClassifier(criterion='entropy',
max_depth=3,
                                        min_samples_leaf=11,
                                        random_state=42))])
```

```
for param_name in sorted(parameters_dt.keys()):
    print('%s: %r' %
(param_name,norm_classifier_dt.best_params_[param_name]))
```

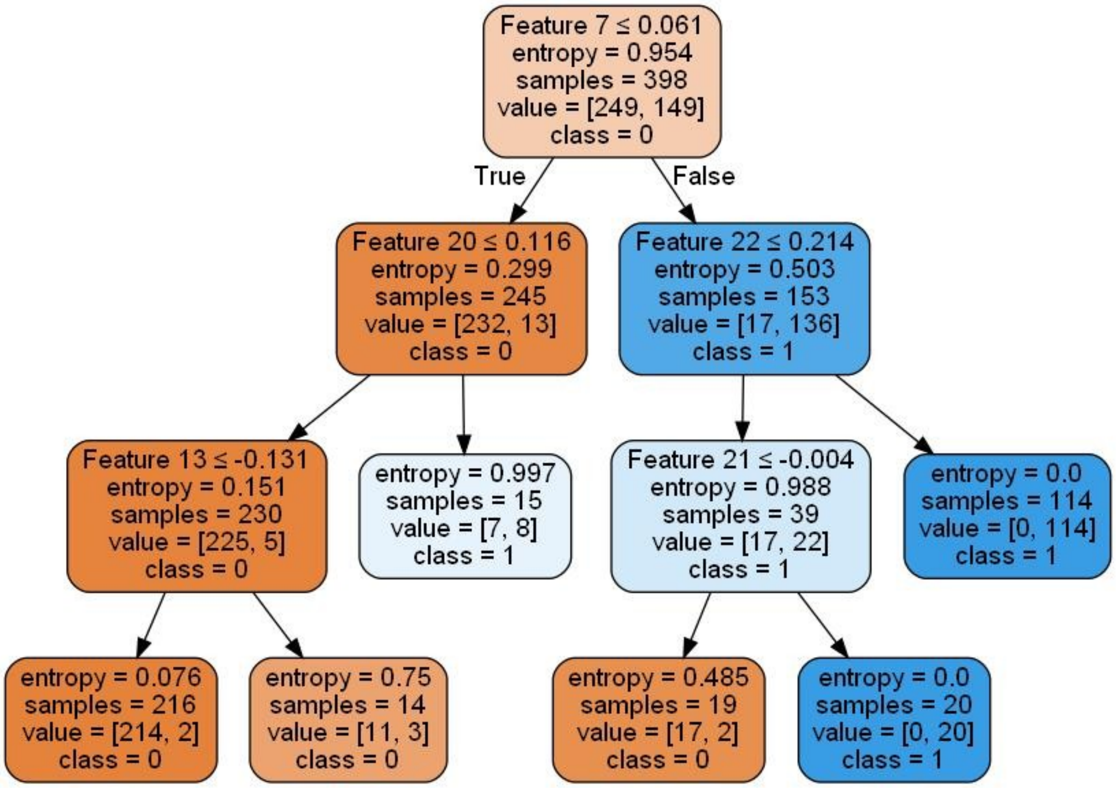
```
model__criterion: 'entropy'
model__max_depth: 3
model__min_samples_leaf: 11
model__min_samples_split: 2
model__random_state: 42
```

Visualisasi Decision Tree data Normalisasi

```
# Mencari nama langkah untuk Decision Tree Classifier dalam pipeline
best_estimator = norm_classifier_dt.best_estimator_
steps = best_estimator.named_steps
classifier_dt_name = next(key for key, value in steps.items() if
isinstance(value, tree.DecisionTreeClassifier))

# Membuat objek Decision Tree Classifier terbaik setelah tuning
best_classifier_dt = steps[classifier_dt_name]

# Membuat visualisasi decision tree menggunakan pydotplus
dot_data = tree.export_graphviz(best_classifier_dt, out_file=None,
                               feature_names=[f'Feature {i}' for i in
range(X_train_norm.shape[1])],

class_names=ori_classifier_dt.best_estimator_.classes_.astype(str),
                               filled=True, rounded=True,
                               special_characters=True)
graph = pydotplus.graph_from_dot_data(dot_data)

# Menyimpan visualisasi decision tree dalam format JPG
graph.write_jpg("dt_norm.jpg")
```

```
True
```

```
# Menampilkan visualisasi decision tree di Jupyter Notebook
Image(filename="dt_norm.jpg")
```



8.3 Pemodelan dengan Data Original + PCA

```
ori_pca_classifier_dt = GridSearchCV(classifier_dt_pipeline,
parameters_dt, cv=3, n_jobs=-1)

ori_pca_classifier_dt.fit(X_train_pca,y_train_pca.ravel())

GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('model',
DecisionTreeClassifier())]),
             n_jobs=-1,
             param_grid={'model__criterion': ['gini', 'entropy'],
                         'model__max_depth': array([ 1,  2,  3,  4,
5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
       18, 19, 20]),
                         'model__min_samples_leaf': array([ 1,  3,  5,
7,  9, 11, 13, 15, 17, 19, 21, 23, 25, 27, 29, 31, 33,
       35, 37, 39, 41, 43, 45, 47, 49, 51, 53, 55, 57, 59, 61, 63, 65,
67,
       69, 71, 73, 75, 77, 79, 81, 83, 85, 87, 89, 91, 93, 95, 97,
99]),
                         'model__min_samples_split': array([ 2,  3,
4,  5,  6,  7,  8,  9, 10]),
                         'model__random_state': [42]})

ori_pca_classifier_dt.best_estimator_
```

```
Pipeline(steps=[('model',
                 DecisionTreeClassifier(max_depth=6,
min_samples_leaf=3,
                                        random_state=42))])
```

```
for param_name in sorted(parameters_dt.keys()):
    print('%s: %r' %
(param_name,ori_pca_classifier_dt.best_params_[param_name]))
```

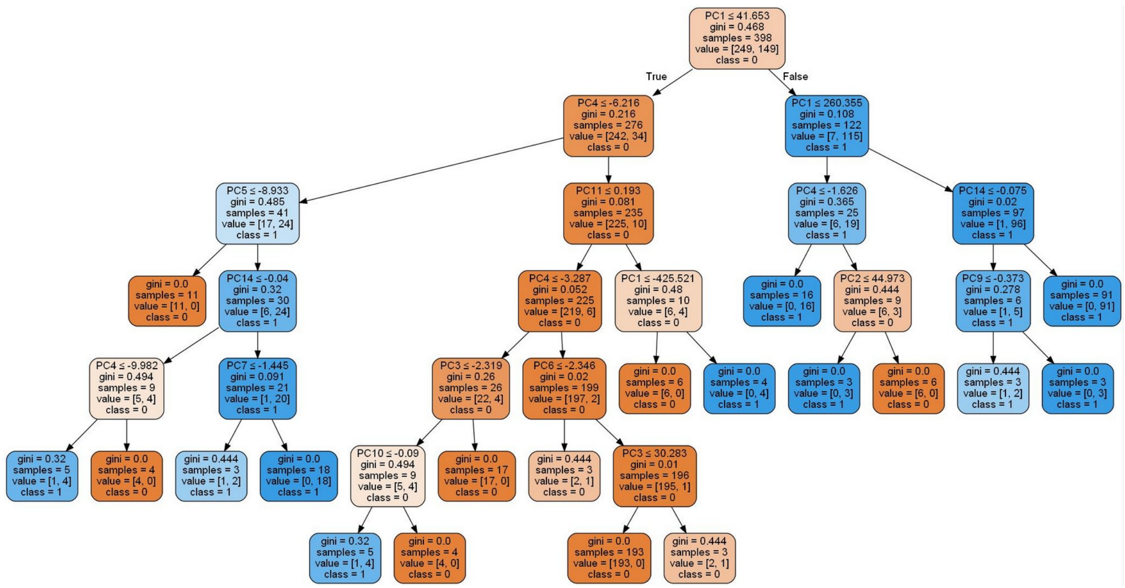
```
model__criterion: 'gini'
model__max_depth: 6
model__min_samples_leaf: 3
model__min_samples_split: 2
model__random_state: 42
```

Visualisasi Decision Tree data Original + PCA

```
# Mencari nama langkah untuk Decision Tree Classifier dalam pipeline
best_estimator = ori_pca_classifier_dt.best_estimator_
steps = best_estimator.named_steps
classifier_dt_name = next(key for key, value in steps.items() if
isinstance(value, tree.DecisionTreeClassifier))

# Membuat objek Decision Tree Classifier terbaik setelah tuning
best_classifier_dt = steps[classifier_dt_name]

# Membuat visualisasi decision tree
dot_data = tree.export_graphviz(best_classifier_dt, out_file=None,
                                feature_names=[f'PC{i}' for i in
range(1, X_train_pca.shape[1]+1)],
                                class_names=list(map(str,
ori_pca_classifier_dt.best_estimator_.classes_)),
                                filled=True, rounded=True,
                                special_characters=True)
graph = pydotplus.graph_from_dot_data(dot_data)

# Menyimpan visualisasi decision tree dalam format JPG
graph.write_jpg("dt_ori_pca.jpg")
```

```
True
```

```
# Menampilkan visualisasi decision tree di Jupyter Notebook
Image(filename="dt_ori_pca.jpg")
```



8.4 Pemodelan dengan Data Normalisasi + PCA

```
norm_pca_classifier_dt = GridSearchCV(classifier_dt_pipeline,
parameters_dt, cv=3, n_jobs=-1)

norm_pca_classifier_dt.fit(X_train_norm_pca,y_train_norm_pca.ravel())

GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('model',
DecisionTreeClassifier())]),
             n_jobs=-1,
             param_grid={'model__criterion': ['gini', 'entropy'],
                         'model__max_depth': array([ 1,  2,  3,  4,
5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
       18, 19, 20]),
                         'model__min_samples_leaf': array([ 1,  3,  5,
7,  9, 11, 13, 15, 17, 19, 21, 23, 25, 27, 29, 31, 33,
       35, 37, 39, 41, 43, 45, 47, 49, 51, 53, 55, 57, 59, 61, 63, 65,
67,
       69, 71, 73, 75, 77, 79, 81, 83, 85, 87, 89, 91, 93, 95, 97,
99]),
                         'model__min_samples_split': array([ 2,  3,
4,  5,  6,  7,  8,  9, 10]),
                         'model__random_state': [42]})

norm_pca_classifier_dt.best_estimator_

Pipeline(steps=[('model',
                 DecisionTreeClassifier(criterion='entropy',
max_depth=5,
                                        min_samples_leaf=5,
random_state=42))])
```

```
for param_name in sorted(parameters_dt.keys()):
    print('%s: %r' % 
(param_name,norm_pca_classifier_dt.best_params_[param_name]))
```

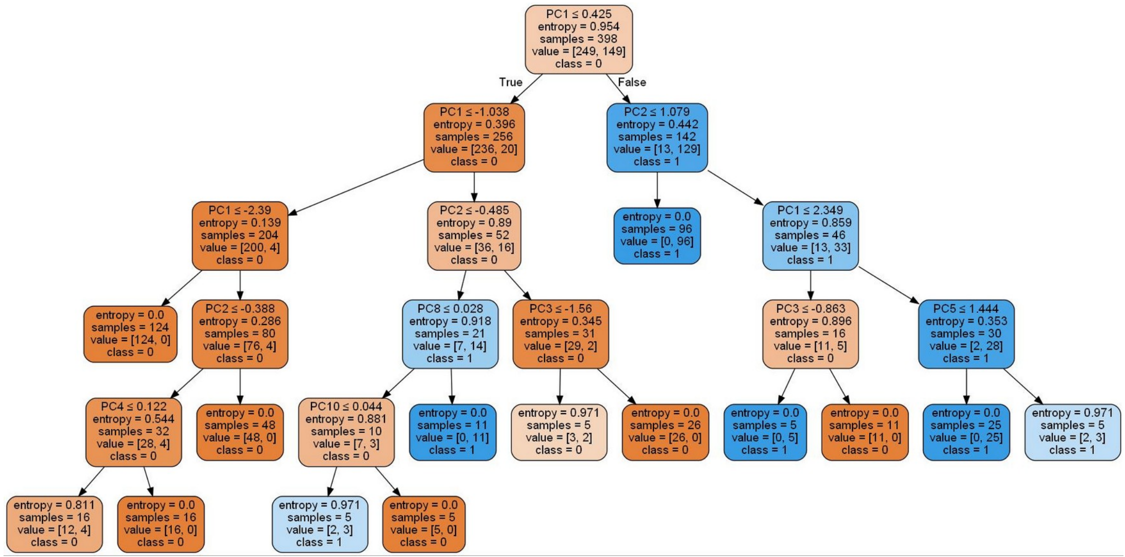
```
model__criterion: 'entropy'
model__max_depth: 5
model__min_samples_leaf: 5
model__min_samples_split: 2
model__random_state: 42
```

Visualisasi Decision Tree data Normalisasi + PCA

```
# Mencari nama langkah untuk Decision Tree Classifier dalam pipeline
best_estimator = norm_pca_classifier_dt.best_estimator_
steps = best_estimator.named_steps
classifier_dt_name = next(key for key, value in steps.items() if 
isinstance(value, tree.DecisionTreeClassifier))

# Membuat objek Decision Tree Classifier terbaik setelah tuning
best_classifier_dt = steps[classifier_dt_name]

# Membuat visualisasi decision tree
dot_data = tree.export_graphviz(best_classifier_dt, out_file=None, 
                                feature_names=[f'PC{i}' for i in 
range(1, X_train_norm_pca.shape[1]+1)],
                                class_names=list(map(str, 
norm_pca_classifier_dt.best_estimator_.classes_)),
                                filled=True, rounded=True,
                                special_characters=True)
graph = pydotplus.graph_from_dot_data(dot_data)

# Menyimpan visualisasi decision tree dalam format JPG
graph.write_jpg("dt_norm_pca.jpg")
```

```
True
```

```
# Menampilkan visualisasi decision tree di Jupyter Notebook
Image(filename="dt_norm_pca.jpg")
```



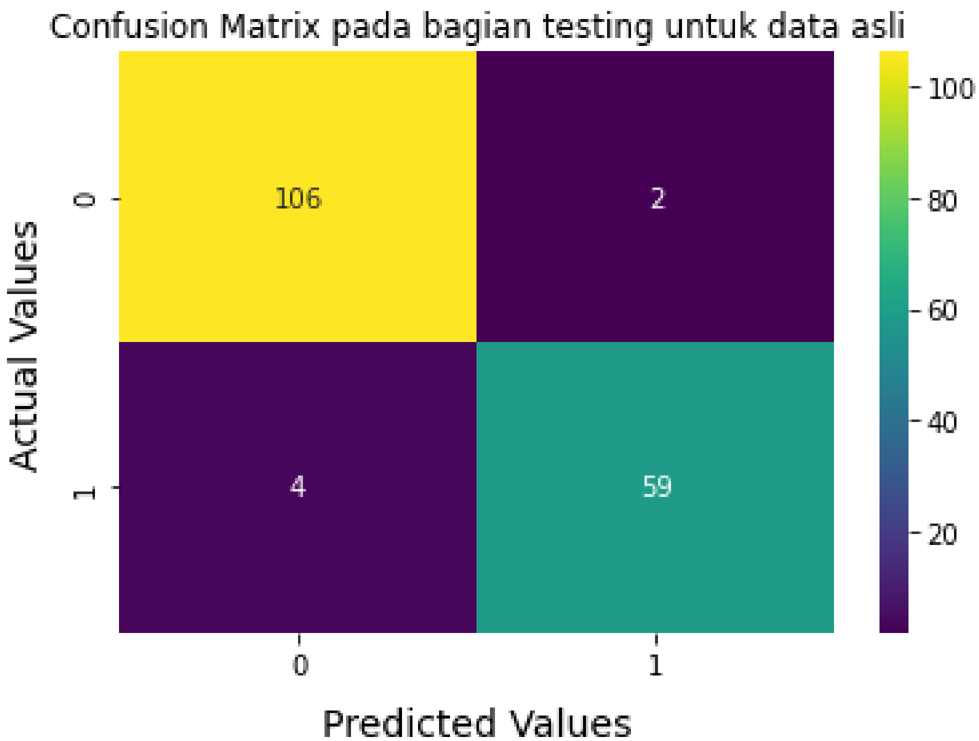
9. Evaluasi Hasil Pemodelan

9.1 Evaluasi dengan Data Original

```
ori_y_pred_dt_train = ori_classifier_dt.predict(X_train)

ori_accuracy_dt_train = accuracy_score(y_train,ori_y_pred_dt_train)
print('Akurasi pada training set: ', ori_accuracy_dt_train)

ori_precision_dt_train = precision_score(y_train,ori_y_pred_dt_train)
print('Precision pada training set: ', ori_precision_dt_train)

ori_recall_dt_train = recall_score(y_train,ori_y_pred_dt_train)
print('Recall pada training set: ', ori_recall_dt_train)

ori_y_pred_dt_test = ori_classifier_dt.predict(X_test)

ori_accuracy_dt_test = accuracy_score(y_test,ori_y_pred_dt_test)
print('Akurasi pada test set: ', ori_accuracy_dt_test)

ori_precision_dt_test = precision_score(y_test,ori_y_pred_dt_test)
print('Precision pada test set: ', ori_precision_dt_test)

ori_recall_dt_test = recall_score(y_test,ori_y_pred_dt_test)
print('Recall pada test set: ', ori_recall_dt_test)
```

```
Akurasi pada training set:  0.964824120603015
Precision pada training set:  0.9530201342281879
Recall pada training set:  0.9530201342281879
Akurasi pada test set:  0.9649122807017544
Precision pada test set:  0.9672131147540983
Recall pada test set:  0.9365079365079365
```

```
# Visualisasi Confusion Matrix dengan Seaborn
sns.heatmap(confusion_matrix(y_test,ori_y_pred_dt_test),annot=True,cma
p='viridis', fmt='.0f')
plt.xlabel('Predicted Values', fontdict={'size':14}, labelpad=10)
plt.ylabel('Actual Values', fontdict={'size':14}, labelpad=10)
plt.title('Confusion Matrix pada bagian testing untuk data asli')
plt.show()
```



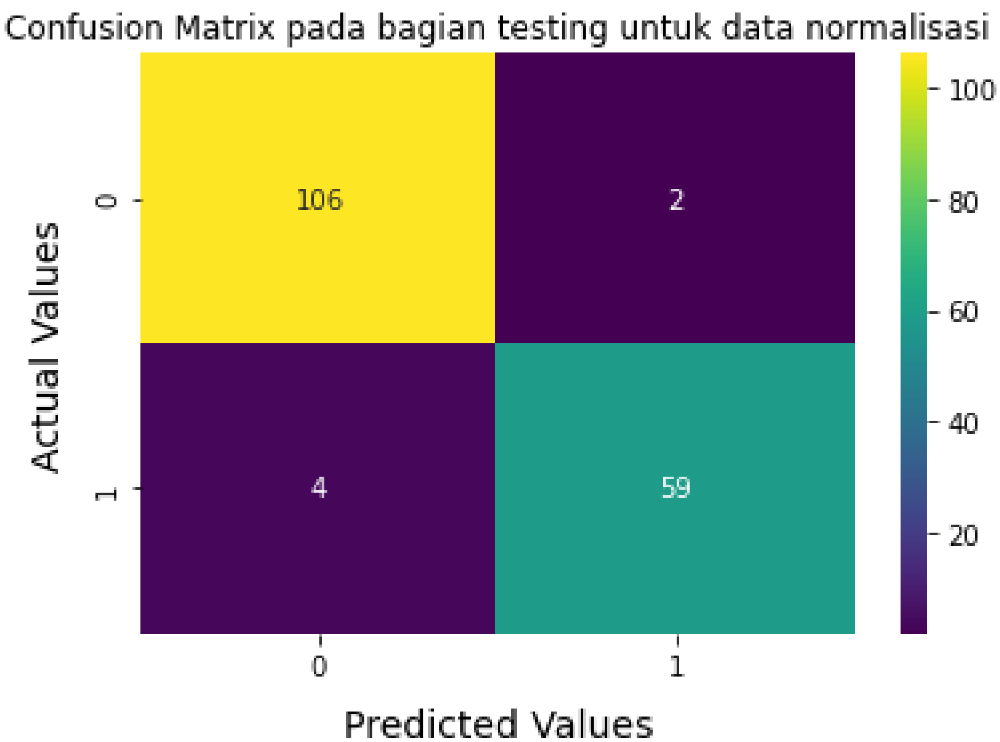
9.2 Evaluasi dengan Data Normalisasi

```
norm_y_pred_dt_train = norm_classifier_dt.predict(X_train_norm)

norm_accuracy_dt_train =
accuracy_score(y_train_norm,norm_y_pred_dt_train)
print('Akurasi pada training set: ', norm_accuracy_dt_train)

norm_precision_dt_train =
precision_score(y_train_norm,norm_y_pred_dt_train)
print('Precision pada training set: ', norm_precision_dt_train)

norm_recall_dt_train = recall_score(y_train_norm,norm_y_pred_dt_train)
print('Recall pada training set: ', norm_recall_dt_train)

norm_y_pred_dt_test = norm_classifier_dt.predict(X_test_norm)

norm_accuracy_dt_test =
accuracy_score(y_test_norm,norm_y_pred_dt_test)
```

```
print('Akurasi pada test set: ', norm_accuracy_dt_test)

norm_precision_dt_test =
precision_score(y_test_norm,norm_y_pred_dt_test)
print('Precision pada test set: ', norm_precision_dt_test)

norm_recall_dt_test = recall_score(y_test_norm,norm_y_pred_dt_test)
print('Recall pada test set: ', norm_recall_dt_test)
```

```
Akurasi pada training set:  0.964824120603015
Precision pada training set:  0.9530201342281879
Recall pada training set:  0.9530201342281879
Akurasi pada test set:  0.9649122807017544
Precision pada test set:  0.9672131147540983
Recall pada test set:  0.9365079365079365
```

```
# Visualisasi Confusion Matrix dengan Seaborn
sns.heatmap(confusion_matrix(y_test_norm,norm_y_pred_dt_test),annot=True,cmap='viridis', fmt='.0f')
plt.xlabel('Predicted Values', fontdict={'size':14}, labelpad=10)
plt.ylabel('Actual Values', fontdict={'size':14}, labelpad=10)
plt.title('Confusion Matrix pada bagian testing untuk data
normalisasi')
plt.show()
```

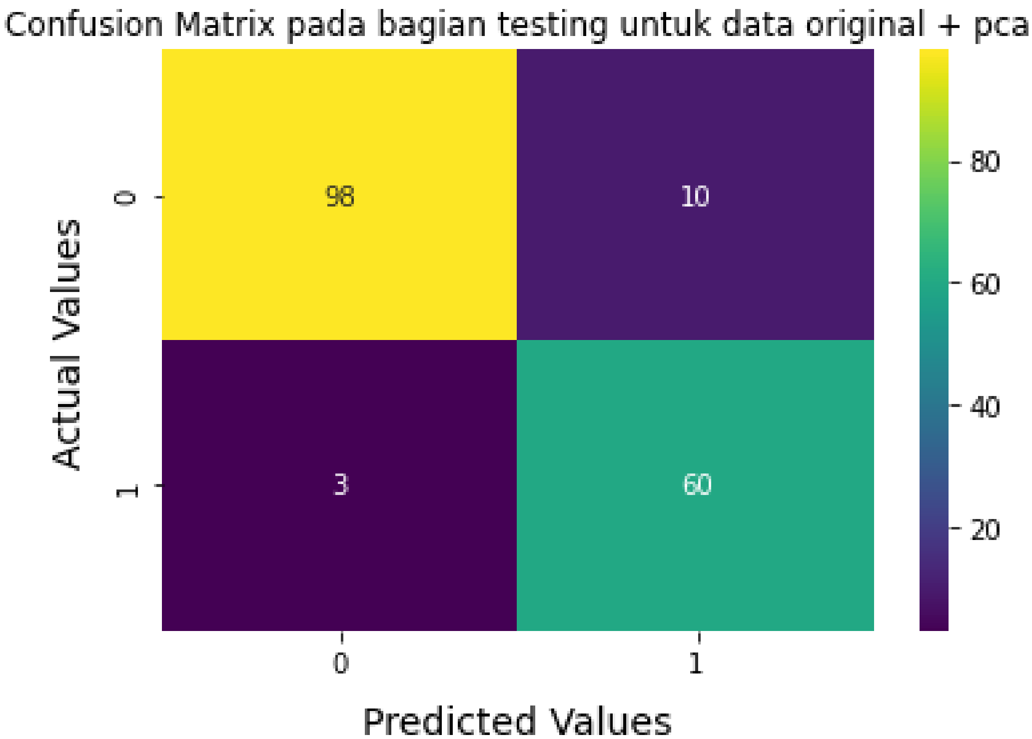


9.3 Evaluasi PCA dengan Data Original

```
ori_pca_y_pred_dt_train = ori_pca_classifier_dt.predict(X_train_pca)

ori_pca_accuracy_dt_train =
accuracy_score(y_train_pca,ori_pca_y_pred_dt_train)
print('Akurasi pada training set: ', ori_pca_accuracy_dt_train)

ori_pca_precision_dt_train =
precision_score(y_train_pca,ori_pca_y_pred_dt_train)
print('Precision pada training set: ', ori_pca_precision_dt_train)

ori_pca_recall_dt_train =
recall_score(y_train_pca,ori_pca_y_pred_dt_train)
print('Recall pada training set: ', ori_pca_recall_dt_train)

ori_pca_y_pred_dt_test = ori_pca_classifier_dt.predict(X_test_pca)

ori_pca_accuracy_dt_test =
accuracy_score(y_test_pca,ori_pca_y_pred_dt_test)
print('Akurasi pada test set: ', ori_pca_accuracy_dt_test)

ori_pca_precision_dt_test =
precision_score(y_test_pca,ori_pca_y_pred_dt_test)
print('Precision pada test set: ', ori_pca_precision_dt_test)

ori_pca_recall_dt_test =
recall_score(y_test_pca,ori_pca_y_pred_dt_test)
print('Recall pada test set: ', ori_pca_recall_dt_test)
```

```
Akurasi pada training set:  0.9849246231155779
Precision pada training set:  0.9735099337748344
Recall pada training set:  0.9865771812080537
Akurasi pada test set:  0.9239766081871345
Precision pada test set:  0.8571428571428571
Recall pada test set:  0.9523809523809523
```

```
# Visualisasi Confusion Matrix dengan Seaborn
sns.heatmap(confusion_matrix(y_test_pca,ori_pca_y_pred_dt_test),annot=
True,cmap='viridis', fmt='.0f')
plt.xlabel('Predicted Values', fontdict={'size':14}, labelpad=10)
plt.ylabel('Actual Values', fontdict={'size':14}, labelpad=10)
plt.title('Confusion Matrix pada bagian testing untuk data original +
pca')
plt.show()
```



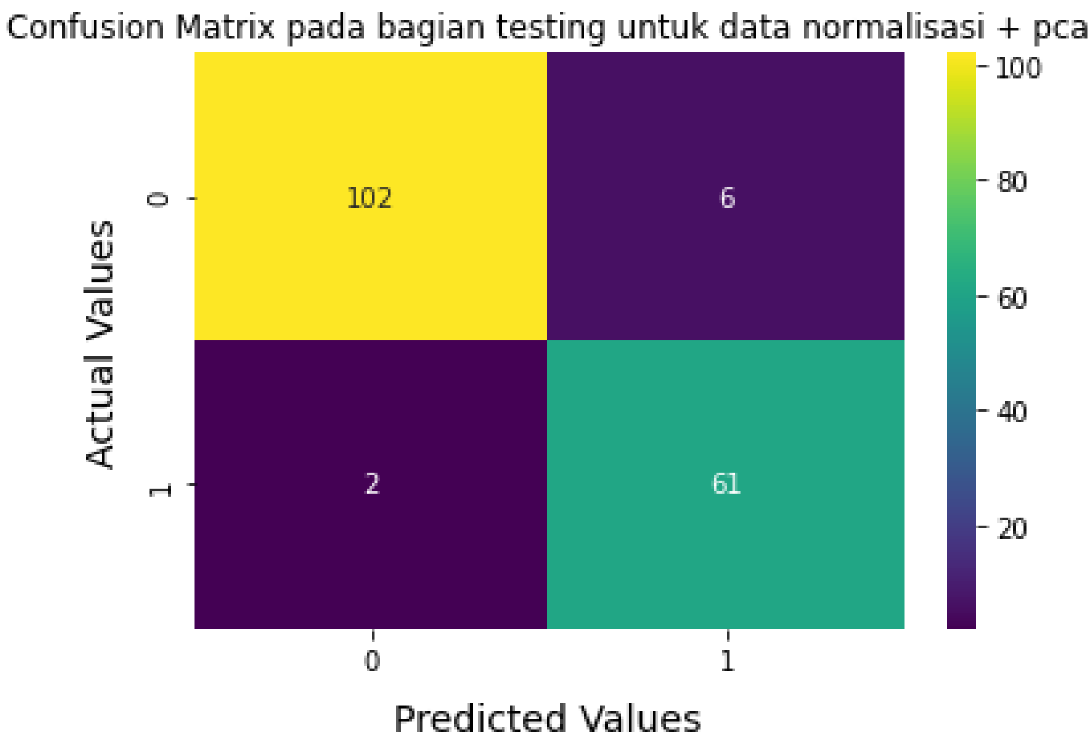
9.4 Evaluasi PCA dengan Data Normalisasi

```
norm_pca_y_pred_dt_train =
norm_pca_classifier_dt.predict(X_train_norm_pca)

norm_pca_accuracy_dt_train =
accuracy_score(y_train_norm_pca,norm_pca_y_pred_dt_train)
print('Akurasi pada training set: ', norm_pca_accuracy_dt_train)

norm_pca_precision_dt_train =
precision_score(y_train_norm_pca,norm_pca_y_pred_dt_train)
print('Precision pada training set: ', norm_pca_precision_dt_train)

norm_pca_recall_dt_train =
recall_score(y_train_norm_pca,norm_pca_y_pred_dt_train)
print('Recall pada training set: ', norm_pca_recall_dt_train)

norm_pca_y_pred_dt_test =
norm_pca_classifier_dt.predict(X_test_norm_pca)

norm_pca_accuracy_dt_test =
accuracy_score(y_test_norm_pca,norm_pca_y_pred_dt_test)
print('Akurasi pada test set: ', norm_pca_accuracy_dt_test)

norm_pca_precision_dt_test =
precision_score(y_test_norm_pca,norm_pca_y_pred_dt_test)
print('Precision pada test set: ', norm_pca_precision_dt_test)
```

```
norm_pca_recall_dt_test =
recall_score(y_test_norm_pca,norm_pca_y_pred_dt_test)
print('Recall pada test set: ', norm_pca_recall_dt_test)
```

```
Akurasi pada training set:  0.9748743718592965
Precision pada training set:  0.9727891156462585
Recall pada training set:  0.959731543624161
Akurasi pada test set:  0.9532163742690059
Precision pada test set:  0.9104477611940298
Recall pada test set:  0.9682539682539683
```

```
# Visualisasi Confusion Matrix dengan Seaborn
sns.heatmap(confusion_matrix(y_test_norm_pca,norm_pca_y_pred_dt_test),
annot=True,cmap='viridis', fmt='.0f')
plt.xlabel('Predicted Values', fontdict={'size':14}, labelpad=10)
plt.ylabel('Actual Values', fontdict={'size':14}, labelpad=10)
plt.title('Confusion Matrix pada bagian testing untuk data normalisasi
+ pca')
plt.show()
```

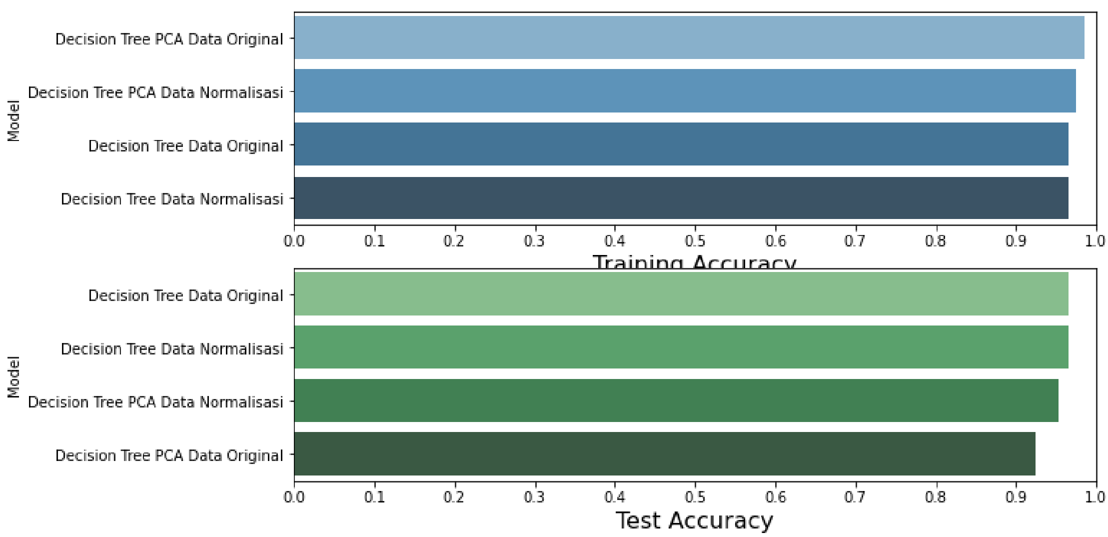


Review Pemodelan

```
models = [
          ('Decision Tree Data Original', ori_accuracy_dt_train,
ori_accuracy_dt_test),
          ('Decision Tree Data Normalisasi', norm_accuracy_dt_train,
norm_accuracy_dt_test),
```

```
          ('Decision Tree PCA Data Original',
ori_pca_accuracy_dt_train, ori_pca_accuracy_dt_test),
          ('Decision Tree PCA Data Normalisasi',
norm_pca_accuracy_dt_train, norm_pca_accuracy_dt_test),
         ]

# Melakukan perbandingan hasil training akurasi dan test akurasi
dengan 4 model
predict = pd.DataFrame(data = models, columns=['Model', 'Training
Accuracy', 'Test Accuracy'])
predict

                                Model  Training Accuracy  Test
Accuracy
0         Decision Tree Data Original           0.964824
0.964912
1      Decision Tree Data Normalisasi           0.964824
0.964912
2     Decision Tree PCA Data Original           0.984925
0.923977
3  Decision Tree PCA Data Normalisasi           0.974874
0.953216

models_comparison = [
                        ('Decision Tree Data Original',
ori_accuracy_dt_test, ori_recall_dt_test, ori_precision_dt_test),
                        ('Decision Tree Data Normalisasi',
norm_accuracy_dt_test, norm_recall_dt_test, norm_precision_dt_test),
                        ('Decision Tree PCA Data Original',
ori_pca_accuracy_dt_test, ori_pca_recall_dt_test,
ori_pca_precision_dt_test),
                        ('Decision Tree PCA Data Normalisasi',
norm_pca_accuracy_dt_test, norm_pca_recall_dt_test,
norm_pca_precision_dt_test),
                    ]

# Melakukan perbandingan hasil Akurasi, Presisi dan Recall pada data
Testing dengan 4 model
comparison = pd.DataFrame(data = models_comparison, columns=['Model',
'Accuracy', 'Recall', 'Precision'])
comparison

                                Model  Accuracy    Recall  Precision
0         Decision Tree Data Original  0.964912  0.936508   0.967213
1      Decision Tree Data Normalisasi  0.964912  0.936508   0.967213
2     Decision Tree PCA Data Original  0.923977  0.952381   0.857143
3  Decision Tree PCA Data Normalisasi  0.953216  0.968254   0.910448

# Visualisasi Perbandingan 4 model dengan Seaborn

f, axes = plt.subplots(2,1, figsize=(10,6))
```

```
predict.sort_values(by=['Training Accuracy'], ascending=False,
inplace=True)

sns.barplot(x='Training Accuracy', y='Model', data = predict,
palette='Blues_d', ax = axes[0])
#axes[0].set(xlabel='Region', ylabel='Charges')
axes[0].set_xlabel('Training Accuracy', size=16)
axes[0].set_ylabel('Model')
axes[0].set_xlim(0,1.0)
axes[0].set_xticks(np.arange(0, 1.1, 0.1))

predict.sort_values(by=['Test Accuracy'], ascending=False,
inplace=True)

sns.barplot(x='Test Accuracy', y='Model', data = predict,
palette='Greens_d', ax = axes[1])
#axes[0].set(xlabel='Region', ylabel='Charges')
axes[1].set_xlabel('Test Accuracy', size=16)
axes[1].set_ylabel('Model')
axes[1].set_xlim(0,1.0)
axes[1].set_xticks(np.arange(0, 1.1, 0.1))

plt.show()
```



Kesimpulan

1. Data yang diberikan dapat dikatakan cukup besar yaitu 569 data
2. Data yang diberikan sudah bersih (terbukti tidak ada data bernilai null ataupun duplikat)
3. Varibel independen sebanyak 30 variabel
4. Variabel dependen terbagi menjadi 2 kategori yaitu:

- M = Malignant (Ganas)
- B = Benign (Jinak)

5. Pembagian data training dan data testing yang saya lakukan adalah 70 / 30, dimana 70% adalah data training dan 30% adalah data testing
6. Model Decision Tree dengan data normalisasi dan dengan data original menghasilkan hasil yang sama yaitu pada **data training sebesar 96%** dan juga pada **data testing sebesar 96%**
7. Menurut pendapat penulis, implementasi model dengan data normalisasi akan lebih baik karena data lebih terdistribusi secara merata dalam rentang yang sama.

Sekian & Terimakasih