TUGAS PEMROGRAMAN 03 - LEARNING

Pengantar Kecerdasan Buatan

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Deskripsi Tugas

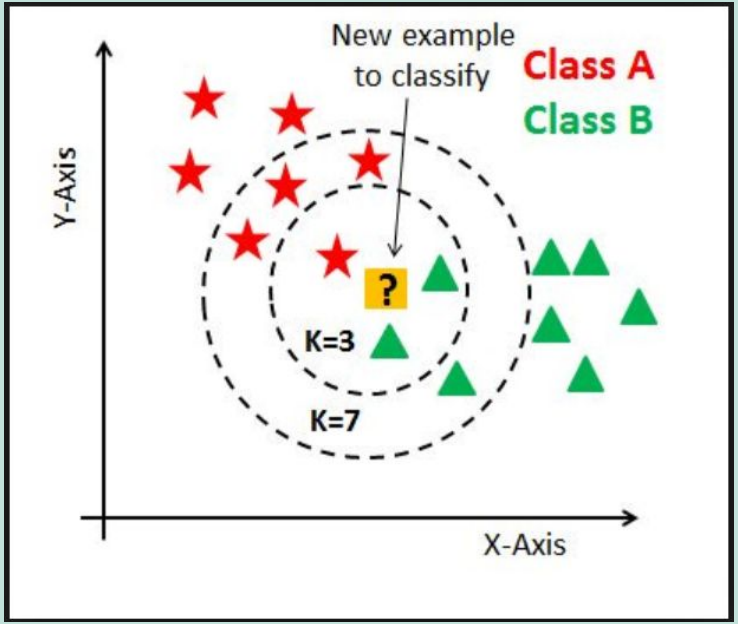
Diberikan file traintest.xlsx yang terdiri dari dua *sheet: train* dan *test,* yang berisi dataset untuk problem klasifikasi biner *(binary classification).*

Setiap *record* atau baris data dalam dataset tersebut secara umum terdiri dari nomor baris data (*id*), fitur input (x1 sampai x3), dan output kelas (y).

Fitur input terdiri dari nilai-nilai *integer* dalam *range* tertentu untuk setiap fitur. Sedangkan output kelas bernilai biner (0 atau 1).

id	x1	x2	x3	y
1	60	64	0	1
2	54	60	11	0
3	65	62	22	0
4	34	60	0	1
5	38	69	21	0

k-Nearest Neighbors



- *Instance-Based Learning* (IBL)
- *Lazy Learner* (pembelajar malas)
- Tidak melakukan proses belajar (dari data latih)
- Klasifikasi secara langsung berdasarkan tetangga terdekat
- Bekerja secara lokal
- Bisa digunakan untuk data apapun

Algoritma kNN

Secara sederhana, algoritma kNN bisa dituliskan hanya dengan dua langkah. Yang pertama adalah pelatihan, yaitu menyimpan setiap pola latih. Langkah kedua adalah klasifikasi. Setiap kali mengklasifikasikan sebuah pola, kNN harus memeriksa semua pola latih untuk menemukan sejumlah *k* pola terdekat.

Kelebihan

- Algoritma kNN kuat dalam mentraining data yang noisy
- Algoritma kNN efektif jika datanya besar
- Mudah diimplementasikan

Kekurangan

- Algoritma kNN perlu menentukan nilai parameter k
- Sensitif pada data pencilan
- Rentan pada variabel yang non-informatif

Normalisasi

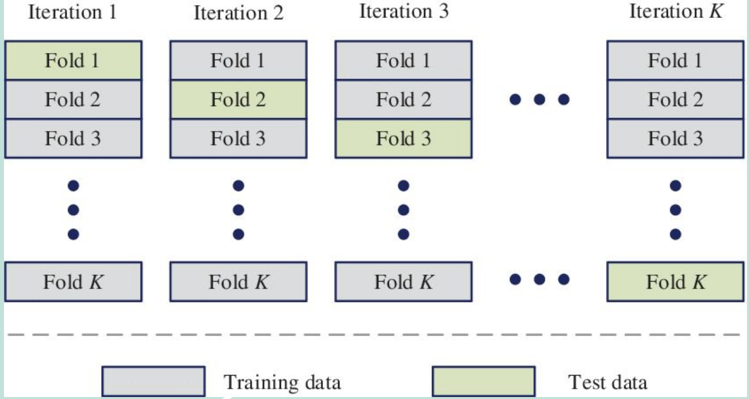
Proses membuat beberapa variabel memiliki rentang nilai yang sama, tidak ada yang terlalu besar maupun terlalu kecil sehingga dapat membuat analisis statistik menjadi lebih mudah

$$x_{new} = \frac{x_{old} - x_{min}}{x_{max} - x_{min}}$$

Min-Max Scaling

Validasi

Proses sangat penting dilakukan untuk memvalidasi kesesuaian antara model dan performansi agar tidak timbul kerugian dikarenakan model yang tidak valid



k-Fold Cross-Validation

Euclidean

Euclidean Distance didefinisikan sebagai jarak antara dua titik. Dengan kata lain, *Euclidean Distance* antara dua titik dalam ruang *Euclidean* didefinisikan sebagai panjang segmen garis antara dua titik.

$$d(i,j)=\sqrt{(x_{i1}-x_{j1})^2+(x_{i2}-x_{j2})^2+\ldots+(x_{ip}-x_{jp})^2}$$

Manhattan

Manhattan Distance adalah metrik jarak antara dua titik dalam ruang vektor berdimensi N. Ini adalah jumlah panjang proyeksi segmen garis antara titik-titik ke sumbu koordinat.

$$d(i,j)=|x_{i1}-x_{j1}|+|x_{i2}-x_{j2}|+\ldots+|x_{ip}-x_{jp}|$$

IMPLEMENTASI KODE PROGRAM

IMPORT DATASET

```
#import data train dari traintest.xlsx
dfTrain = pd.read_excel("https://github.com/berlianm/k-Nearest-Neighbors/blob/main/traintest.xlsx?raw=true", sheet_name='train')
dfTrain
```

	id	x1	x2	x3	y
0	1	60	64	0	1
1	2	54	60	11	0
2	3	65	62	22	0
3	4	34	60	0	1
4	5	38	69	21	0
...	...	...	...	...	...
291	292	59	64	1	1
292	293	65	67	0	1
293	294	53	65	12	0
294	295	57	64	1	0
295	296	54	59	7	1

296 rows × 5 columns

IMPORT **DATASET**

```
#import data test dari traintest.xlsx
dfTest = pd.read_excel("https://github.com/berlianm/k-Nearest-Neighbors/blob/main/traintest.xlsx?raw=true", sheet_name='test')
dfTest
```

	id	x1	x2	x3	y
0	297	43	59	2	?
1	298	67	66	0	?
2	299	58	60	3	?
3	300	49	63	3	?
4	301	45	60	0	?
5	302	54	58	1	?
6	303	56	66	3	?
7	304	42	69	1	?
8	305	50	59	2	?
9	306	59	60	0	?

MEMBACA DATA TRAIN & TEST

```
dfTrain.describe()
```

	id	x1	x2	x3	y
count	296.000000	296.000000	296.000000	296.000000	296.000000
mean	148.500000	52.462838	62.881757	4.111486	0.736486
std	85.592056	10.896367	3.233753	7.291816	0.441285
min	1.000000	30.000000	58.000000	0.000000	0.000000
25%	74.750000	44.000000	60.000000	0.000000	0.000000
50%	148.500000	52.000000	63.000000	1.000000	1.000000
75%	222.250000	61.000000	65.250000	5.000000	1.000000
max	296.000000	83.000000	69.000000	52.000000	1.000000

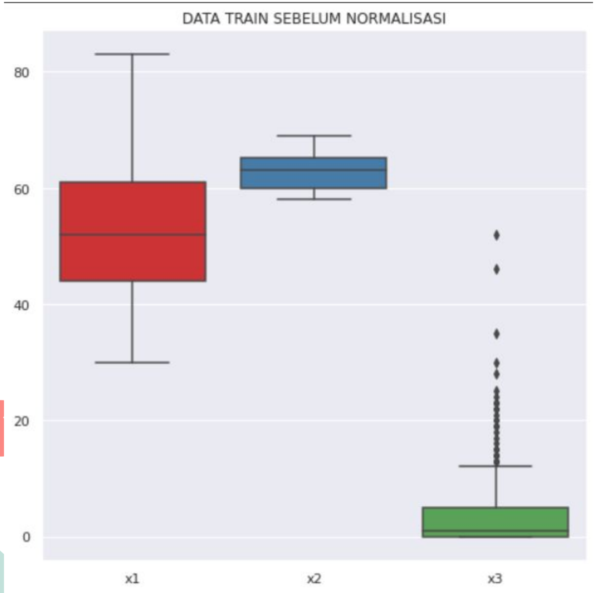
```
dfTest.describe()
```

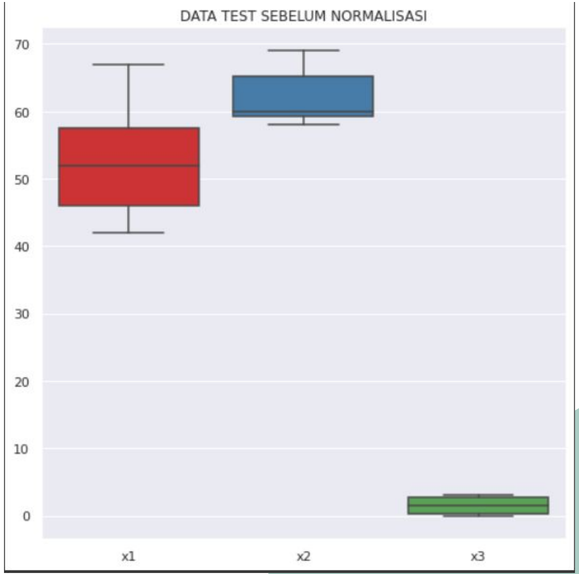
	id	x1	x2	x3
count	10.00000	10.000000	10.000000	10.000000
mean	301.50000	52.300000	62.000000	1.500000
std	3.02765	7.972871	3.771236	1.269296
min	297.00000	42.000000	58.000000	0.000000
25%	299.25000	46.000000	59.250000	0.250000
50%	301.50000	52.000000	60.000000	1.500000
75%	303.75000	57.500000	65.250000	2.750000
max	306.00000	67.000000	69.000000	3.000000

VISUALISASI DATA TRAIN & TEST

```
#menampilkan data train sebelum normalisasi (boxplot)
sns.set_theme(style="darkgrid")
ax = sns.boxplot(data=dfTrain[['x1', 'x2', 'x3']], orient="v", palette="Set1")
sns.set(rc={'figure.figsize':(8, 8)})
ax.set_xticklabels(['x1', 'x2', 'x3'])
plt.title('DATA TRAIN SEBELUM NORMALISASI')
```

```
#menampilkan data test sebelum normalisasi (boxplot)
sns.set_theme(style="darkgrid")
ax = sns.boxplot(data=dfTest[['x1', 'x2', 'x3']], orient="v", palette="Set1")
sns.set(rc={'figure.figsize':(8, 8)})
ax.set_xticklabels(['x1', 'x2', 'x3'])
plt.title('DATA TEST SEBELUM NORMALISASI')
```





NORMALISASI DATA TRAIN

```python
#normalisasi data train (min-maks scaling)
df_train_normalisasi = pd.DataFrame(index=dfTrain.index, columns=dfTrain.columns)

xMaks = dfTrain["x1"].max()
xMin  = dfTrain["x1"].min()

for i in range(len(dfTrain)):
    x = dfTrain["x1"][i]
    xBaru = (x - xMin) / (xMaks - xMin)
    df_train_normalisasi["x1"][i] = xBaru

xMaks = dfTrain["x2"].max()
xMin  = dfTrain["x2"].min()

for i in range(len(dfTrain)):
    x = dfTrain["x2"][i]
    xBaru = (x - xMin) / (xMaks - xMin)
    df_train_normalisasi["x2"][i] = xBaru

xMaks = dfTrain["x3"].max()
xMin  = dfTrain["x3"].min()

for i in range(len(dfTrain)):
    x = dfTrain["x3"][i]
    xBaru = (x - xMin) / (xMaks - xMin)
    df_train_normalisasi["x3"][i] = xBaru

df_train_normalisasi['x1'] = df_train_normalisasi['x1'].astype(float)
df_train_normalisasi['x2'] = df_train_normalisasi['x2'].astype(float)
df_train_normalisasi['x3'] = df_train_normalisasi['x3'].astype(float)
df_train_normalisasi['y']  = dfTrain['y']
df_train_normalisasi['id'] = dfTrain['id']
df_train_normalisasi
```

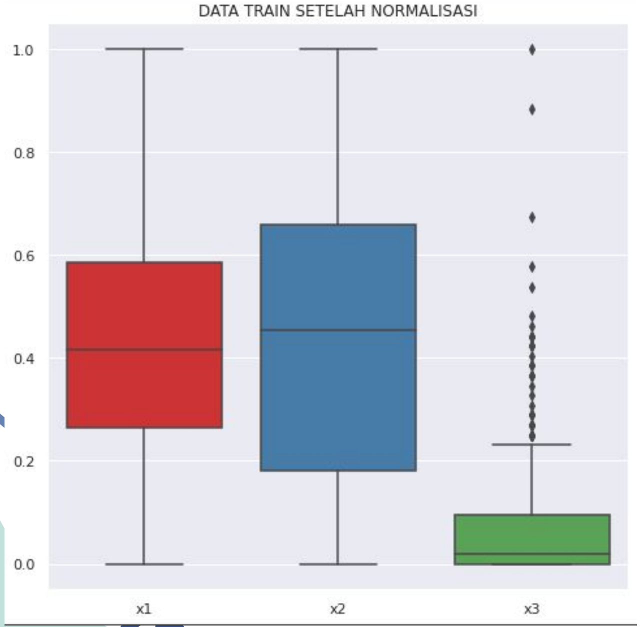
NORMALISASI DATA TEST

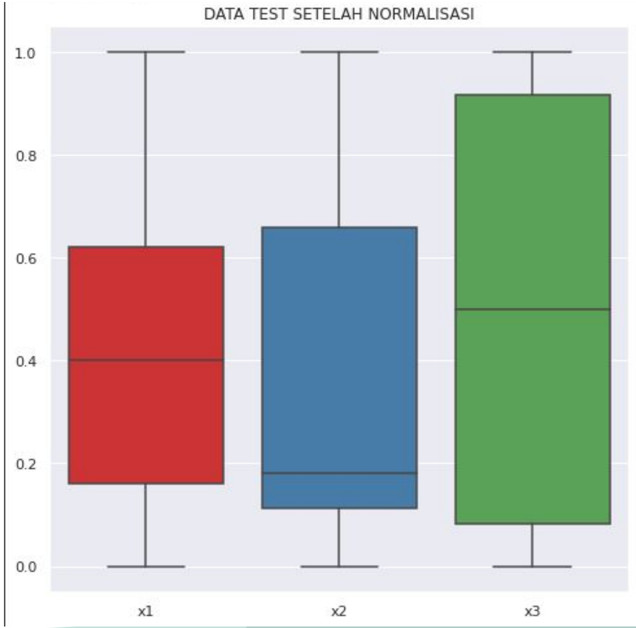
```
#normalisasi data test (min-maks scaling)
df_test_normalisasi = pd.DataFrame(index=dfTest.index, columns=dfTest.columns)

xMaks = dfTest["x1"].max()
xMin  = dfTest["x1"].min()

for i in range(len(dfTest)):
    x = dfTest["x1"][i]
    xBaru = (x - xMin) / (xMaks - xMin)
    df_test_normalisasi["x1"][i] = float(xBaru)

xMaks = dfTest["x2"].max()
xMin  = dfTest["x2"].min()

for i in range(len(dfTest)):
    x = dfTest["x2"][i]
    xBaru = (x - xMin) / (xMaks - xMin)
    df_test_normalisasi["x2"][i] = float(xBaru)

xMaks = dfTest["x3"].max()
xMin  = dfTest["x3"].min()

for i in range(len(dfTest)):
    x = dfTest["x3"][i]
    xBaru = (x - xMin) / (xMaks - xMin)
    df_test_normalisasi["x3"][i] = float(xBaru)

df_test_normalisasi['x1'] = df_test_normalisasi['x1'].astype(float)
df_test_normalisasi['x2'] = df_test_normalisasi['x2'].astype(float)
df_test_normalisasi['x3'] = df_test_normalisasi['x3'].astype(float)
df_test_normalisasi['id'] = dfTest['id'].astype(str)
df_test_normalisasi
```

VISUALISASI DATA TRAIN & TEST

```
#menampilkan data train sesudah normalisasi (boxplot)
sns.set_theme(style="darkgrid")
ax = sns.boxplot(data=df_train_normalisasi[['x1', 'x2', 'x3']], orient="v", palette="Set1")
sns.set(rc={'figure.figsize':(8, 8)})
ax.set_xticklabels(['x1', 'x2', 'x3'])
plt.title('DATA TRAIN SETELAH NORMALISASI')
```

```
#menampilkan data test sesudah normalisasi (boxplot)
sns.set_theme(style="darkgrid")
ax = sns.boxplot(data=df_test_normalisasi[['x1', 'x2', 'x3']], orient="v", palette="Set1")
sns.set(rc={'figure.figsize':(8, 8)})
ax.set_xticklabels(['x1', 'x2', 'x3'])
plt.title('DATA TEST SETELAH NORMALISASI')
```





EUCLIDEAN

```
#metode Eucledian
def Euclidean(df_train_normalisasi, test):
    result = []
    for i in range(len(df_train_normalisasi)):
        jarak_x = math.sqrt((((df_train_normalisasi['x1'][i] - test['x1']) ** 2) +
                             ((df_train_normalisasi['x2'][i] - test['x2']) ** 2) +
                             ((df_train_normalisasi['x3'][i] - test['x3']) ** 2)))
        result.append([jarak_x, df_train_normalisasi['y'][i]])

    return result
```

```
#metode Manhattan
def Manhattan(df_train_normalisasi, test):
    result = []
    for i in range(len(df_train_normalisasi)):
        jarak = (abs(df_train_normalisasi['x1'][i] - test['x1']) +
                 abs(df_train_normalisasi['x2'][i] - test['x2']) +
                 abs(df_train_normalisasi['x3'][i] - test['x3']))
        result.append([jarak , df_train_normalisasi['y'][i]])

    return result
```

MANHATTAN

PROSES kNN

```python
#memanggil fungsi Euclidean (sorting, k data teratas, melakukan label vote)
def kNN_Euclidean(df_train_normalisasi, df_test_normalisasi, k):
    hasil = []

    for i in range(len(df_test_normalisasi)):
        jarak = Euclidean(df_train_normalisasi, df_test_normalisasi.iloc[[i]])
        jarak = sorted(jarak, key=lambda x:x[0])
        jarak_K = jarak[:k]
        y_satu = 0
        y_nol = 0

        for j in range(k):
            if jarak_K[j][1] == 1:
                y_satu += 1
            else:
                y_nol += 1

        if y_satu > y_nol:
            hasil.append([df_test_normalisasi.loc[i, 'id'], 1])
        else:
            hasil.append([df_test_normalisasi.loc[i, 'id'], 0])

    df_Hasil = pd.DataFrame(hasil, columns = ['id', 'y'])

    return df_Hasil
```

```python
#memanggil fungsi Manhattan (sorting, k data teratas, melakukan label vote)
def kNN_Manhattan(df_train_normalisasi, df_test_normalisasi, k):
    hasil = []
    for i in range(len(df_test_normalisasi)):
        jarak = Manhattan(df_train_normalisasi, df_test_normalisasi.iloc[i])
        jarak = sorted(jarak, key=lambda x:x[0])
        jarak_K = jarak[:k]
        y_satu = 0
        y_nol = 0

        for j in range(k):
            if jarak_K[j][1] == 1:
                y_satu += 1
            else:
                y_nol += 1

        if y_satu > y_nol:
            hasil.append([df_test_normalisasi.loc[i, 'id'], 1])
        else:
            hasil.append([df_test_normalisasi.loc[i, 'id'], 0])

    df_Hasil = pd.DataFrame(hasil, columns = ['id', 'y'])

    return df_Hasil
```

```python
def kNN(df_train_normalisasi, df_test_normalisasi, k):
    return {
        'manhattan' : kNN_Manhattan(df_train_normalisasi, df_test_normalisasi, k),
        'euclidean' : kNN_Euclidean(df_train_normalisasi, df_test_normalisasi, k)
    }
```

VALIDASI

```
def validasi(df_train_normalisasi, k):
    #fold1
    test_fold1  = df_train_normalisasi.iloc[:59].drop('y', axis = 1)
    train_fold1 = df_train_normalisasi.iloc[59:].reset_index().drop('index', axis = 1)

    #fold2
    test_fold2  = df_train_normalisasi.iloc[59:118].drop('y', axis = 1).reset_index().drop('index', axis = 1)
    train_fold2 = pd.concat([df_train_normalisasi.iloc[:59], df_train_normalisasi.iloc[118:]]).reset_index().drop('index', axis = 1)

    #fold3
    test_fold3  = df_train_normalisasi.iloc[118:177].drop('y', axis = 1).reset_index().drop('index', axis = 1)
    train_fold3 = pd.concat([df_train_normalisasi.iloc[:118], df_train_normalisasi.iloc[177:]]).reset_index().drop('index', axis = 1)

    #fold4
    test_fold4  = df_train_normalisasi.iloc[177:236].drop('y', axis = 1).reset_index().drop('index', axis = 1)
    train_fold4 = pd.concat([df_train_normalisasi.iloc[:177], df_train_normalisasi.iloc[236:]]).reset_index().drop('index', axis = 1)

    #fold5
    test_fold5  = df_train_normalisasi.iloc[236:295].drop('y', axis = 1).reset_index().drop('index', axis = 1)
    train_fold5 = df_train_normalisasi.iloc[0:236].reset_index().drop('index', axis = 1)

    #hasil validasi
    hasil_fold1  = kNN(train_fold1, test_fold1, k)
    hasil_fold2  = kNN(train_fold2, test_fold2, k)
    hasil_fold3  = kNN(train_fold3, test_fold3, k)
    hasil_fold4  = kNN(train_fold4, test_fold4, k)
    hasil_fold5  = kNN(train_fold5, test_fold5, k)
    akurasi = []
```

VALIDASI

```
valid = 0
#fold 1
for i in range(len(hasil_fold1['euclidean'])):
    if hasil_fold1['euclidean']['y'][i] == df_train_normalisasi['y'][i]:
        valid += 1
akurasi_fold = valid / len(hasil_fold1['euclidean'])
akurasi.append(akurasi_fold)

valid = 0
#fold 2
for i in range(len(hasil_fold1['euclidean'])):
    if hasil_fold2['euclidean']['y'][i] == df_train_normalisasi.iloc[59:118]['y'][i+59]:
        valid += 1
akurasi_fold = valid / len(hasil_fold1['euclidean'])
akurasi.append(akurasi_fold)

valid = 0
#fold 3
for i in range(len(hasil_fold1['euclidean'])):
    if hasil_fold3['euclidean']['y'][i] == df_train_normalisasi.iloc[118:177]['y'][i+118]:
        valid += 1
akurasi_fold = valid / len(hasil_fold1['euclidean'])
akurasi.append(akurasi_fold)

valid = 0
#fold 4
for i in range(len(hasil_fold1['euclidean'])):
    if hasil_fold4['euclidean']['y'][i] == df_train_normalisasi.iloc[177:236]['y'][i+177]:
        valid += 1
akurasi_fold = valid / len(hasil_fold1['euclidean'])
akurasi.append(akurasi_fold)

valid = 0
#fold 5
for i in range(len(hasil_fold1['euclidean'])):
    if hasil_fold5['euclidean']['y'][i] == df_train_normalisasi.iloc[236:295]['y'][i+236]:
        valid += 1
akurasi_fold = valid / len(hasil_fold1['euclidean'])
akurasi.append(akurasi_fold)


return akurasi
```

OUTPUT

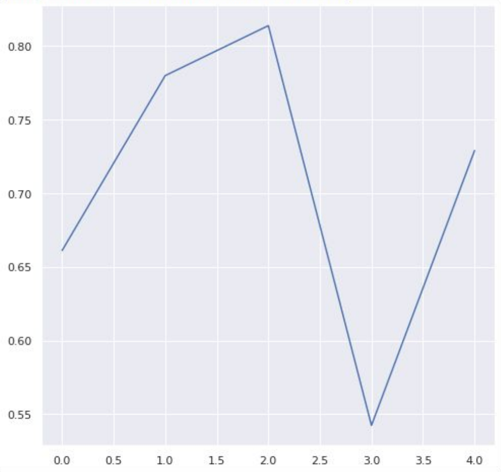
```
dataResult = pd.ExcelWriter('Result_Euclidean.xlsx')
kNN['euclidean'].to_excel(dataResult)
dataResult.save()
```

```
dataResult = pd.ExcelWriter('Result_Manhattan.xlsx')
kNN['manhattan'].to_excel(dataResult)
dataResult.save()
```

KESIMPULAN
HASIL & EVALUASI

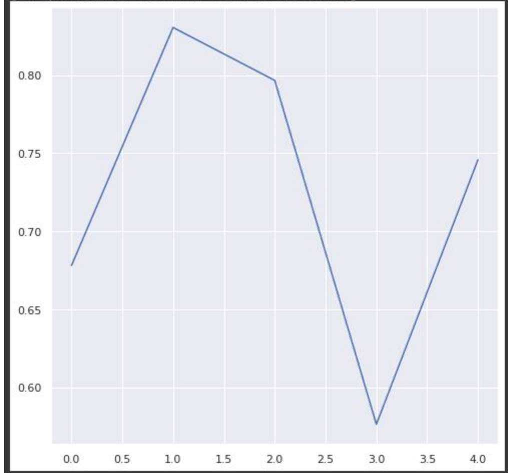
k = 5

```
[0.6610169491525424, 0.7796610169491526, 0.8135593220338984, 0.5423728813559322, 0.7288135593220338]
hasil validasi dengan k=5
[<matplotlib.lines.Line2D at 0x7fcf70f64550>]
```



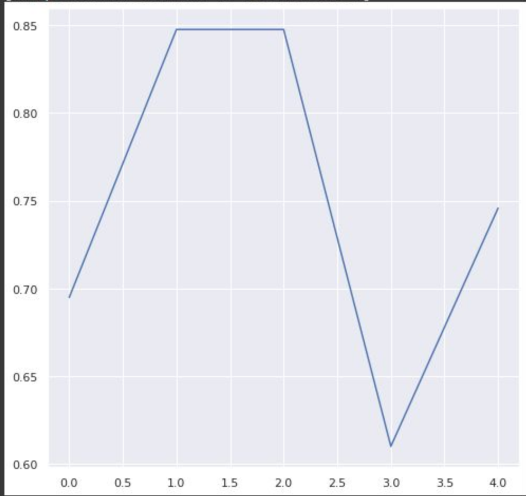
k = 9

```
[0.6779661016949152, 0.8305084745762712, 0.7966101694915254, 0.576271186440678, 0.7457627118644068]
hasil validasi dengan k=9
[<matplotlib.lines.Line2D at 0x7fcf70ee5190>]
```



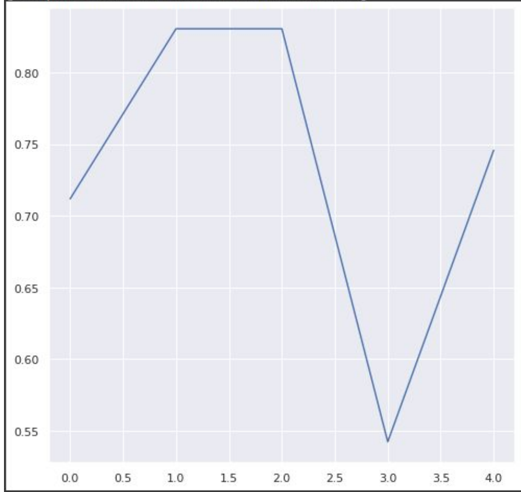
k = 15

```
[0.6949152542372882, 0.847457627118644, 0.847457627118644, 0.6101694915254238, 0.7457627118644068]
hasil validasi dengan k=15
[<matplotlib.lines.Line2D at 0x7fcf70ee9210>]
```



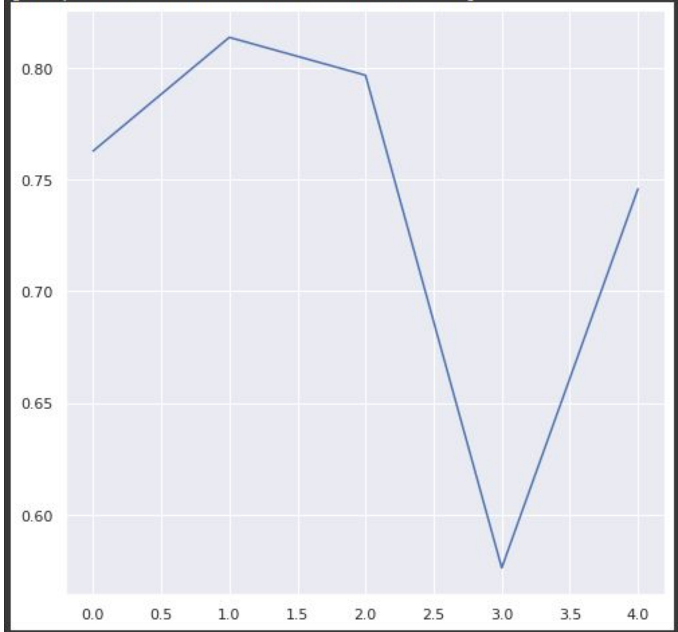
k = 19

```
[0.711864406779661, 0.8305084745762712, 0.8305084745762712, 0.5423728813559322, 0.7457627118644068]
hasil validasi dengan k=19
[<matplotlib.lines.Line2D at 0x7fcf70dd9750>]
```



k = 25

```
[0.7627118644067796, 0.8135593220338984, 0.7966101694915254, 0.576271186440678, 0.7457627118644068]
hasil validasi dengan k=25
[<matplotlib.lines.Line2D at 0x7fcf70d4a6d0>]
```



TABEL HASIL EVALUASI

k \ Fold	1	2	3	4	5
5	66%	77%	81%	54%	72%
9	67%	83%	79%	57%	74%
15	69%	**84%**	**84%**	61%	74%
19	71%	83%	83%	54%	74%
25	76%	81%	79%	57%	74%
Rata Rata	69,8%	81,6%	81,2%	56,6%	73,6%

OUTPUT

k = 15

	id	y
0	297	1
1	298	1
2	299	0
3	300	0
4	301	1
5	302	0
6	303	1
7	304	1
8	305	0
9	306	1

Euclidean

	id	y
0	297	0
1	298	1
2	299	0
3	300	0
4	301	1
5	302	0
6	303	0
7	304	1
8	305	0
9	306	1

Manhattan

Kami menggunakan rumus *Min-Max* untuk proses normalisasi (*pre-processing*), beberapa metode dalam pencarian jarak (jarak atribut numerik), yakni *Euclidean* dan *Manhattan*, serta menggunakan *k-fold cross-validation* untuk proses validasi.

Hasil akurasi tertinggi yang didapat adalah pada k = 15 dengan nilai sebesar 84%. Yang selanjutnya diproses pada *Euclidean* dan *Manhattan* agar memperoleh hasil akhir dari data testing (y).


TERIMA KASIH