Studio Rallia

ALP Data Mining

Billy Agustian D

```
In [2]:
1 df = pd.read_csv('https://raw.githubusercontent.com/kimikato123/Billy-Agustian-Dharmawan_ALP_0706022010030/main/Dataset_Tera
2 df
```

Out[2]:

	gender	age	Time	Number_of_Warts	Type	Area	induration_diameter	Result_of_Treatment
0	1	15	11.00	6.0	1.0	30	25.0	0
1	1	27	11.75	NaN	1.0	208	6.0	0
2	1	32	12.00	9.0	1.0	43	50.0	0
3	1	33	1.75	7.0	2.0	379	7.0	0
4	1	34	5.00	7.0	3.0	64	7.0	0
...	...	...	...	...	...	...	...	...
85	2	51	4.00	1.0	1.0	65	7.0	1
86	2	51	6.00	6.0	NaN	80	2.0	1
87	2	52	2.25	5.0	1.0	63	7.0	1
88	2	53	10.00	1.0	2.0	30	25.0	1
89	2	53	7.25	6.0	NaN	81	7.0	1

90 rows × 8 columns

Saya memasukan data dari elearn menuju github lalu saya memasukan data raw ke dalam jupyter notebook

In [3]:

```
df.describe()
```

Out[3]:

	gender	age	Time	Number_of_Warts	Type	Area	induration_diameter	Result_of_Treatment
count	90.000000	90.000000	87.000000	89.000000	85.000000	90.000000	88.000000	90.000000
mean	1.544444	31.044444	7.221264	6.123596	1.752941	95.700000	14.500000	0.788889
std	0.500811	12.235435	3.151325	4.231431	0.829599	136.614643	17.378147	0.410383
min	1.000000	15.000000	1.000000	1.000000	1.000000	6.000000	2.000000	0.000000
25%	1.000000	20.250000	5.000000	2.000000	1.000000	35.500000	5.000000	1.000000
50%	2.000000	28.500000	7.750000	6.000000	2.000000	53.000000	7.000000	1.000000
75%	2.000000	41.750000	10.000000	9.000000	2.000000	80.750000	9.000000	1.000000
max	2.000000	56.000000	12.000000	19.000000	3.000000	900.000000	70.000000	1.000000

Dengan menggunakan describe saya dapat melihat statistik deskriptif data termasuk jumlah, rata-rata, standar deviasi, nilai minimum dan maksimum, dan nilai kuartil

In [4]:
```python
df.isnull().sum()
```

Out[4]:
```
gender                  0
age                     0
Time                    3
Number_of_Warts         1
Type                    5
Area                    0
induration_diameter     2
Result_of_Treatment     0
dtype: int64
```

In [5]:
```python
df.duplicated().any()
```

Out[5]:
```
False
```

Saya melakukan pengecekan apakah terdapat data yang kosong dan apakah terdapat data yang kembar

Data Preprocessing

```python
import pandas as pd
from sklearn.impute import KNNImputer
imputer = KNNImputer(n_neighbors=2)
df_KNN = pd.DataFrame(imputer.fit_transform(df),columns = df.columns)
df_KNN.isnull().sum()
```

```
gender                  0
age                     0
Time                    0
Number_of_Warts         0
Type                    0
Area                    0
induration_diameter     0
Result_of_Treatment     0
dtype: int64
```

KNNImputer adalah metode untuk memasukkan (atau mengisi) nilai yang hilang dalam kumpulan data menggunakan nilai pengamatan terdekat lainnya. Ini bisa menjadi teknik yang berguna untuk menangani data yang hilang karena mudah diimplementasikan dan dapat memberikan hasil yang masuk akal dalam banyak kasus.

In [8]:

```
df1 = df_KNN.copy()
df1['Result_of_Treatment'] = df1['Result_of_Treatment'].replace(0, 'Tidak Ada Kemajuan')
df1['Result_of_Treatment'] = df1['Result_of_Treatment'].replace(1, 'Ada Kemajuan')
df1['gender'] = df1['gender'].replace(2, 'Female')
df1['gender'] = df1['gender'].replace(1, 'Male')
df1
```

Out[8]:

	gender	age	Time	Number_of_Warts	Type	Area	induration_diameter	Result_of_Treatment
0	Male	15.0	11.00	6.0	1.0	30.0	25.0	Tidak Ada Kemajuan
1	Male	27.0	11.75	1.5	1.0	208.0	6.0	Tidak Ada Kemajuan
2	Male	32.0	12.00	9.0	1.0	43.0	50.0	Tidak Ada Kemajuan
3	Male	33.0	1.75	7.0	2.0	379.0	7.0	Tidak Ada Kemajuan
4	Male	34.0	5.00	7.0	3.0	64.0	7.0	Tidak Ada Kemajuan
...	...	...	...	...	...	...	...	...
85	Female	51.0	4.00	1.0	1.0	65.0	7.0	Ada Kemajuan
86	Female	51.0	6.00	6.0	1.5	80.0	2.0	Ada Kemajuan
87	Female	52.0	2.25	5.0	1.0	63.0	7.0	Ada Kemajuan
88	Female	53.0	10.00	1.0	2.0	30.0	25.0	Ada Kemajuan
89	Female	53.0	7.25	6.0	1.5	81.0	7.0	Ada Kemajuan

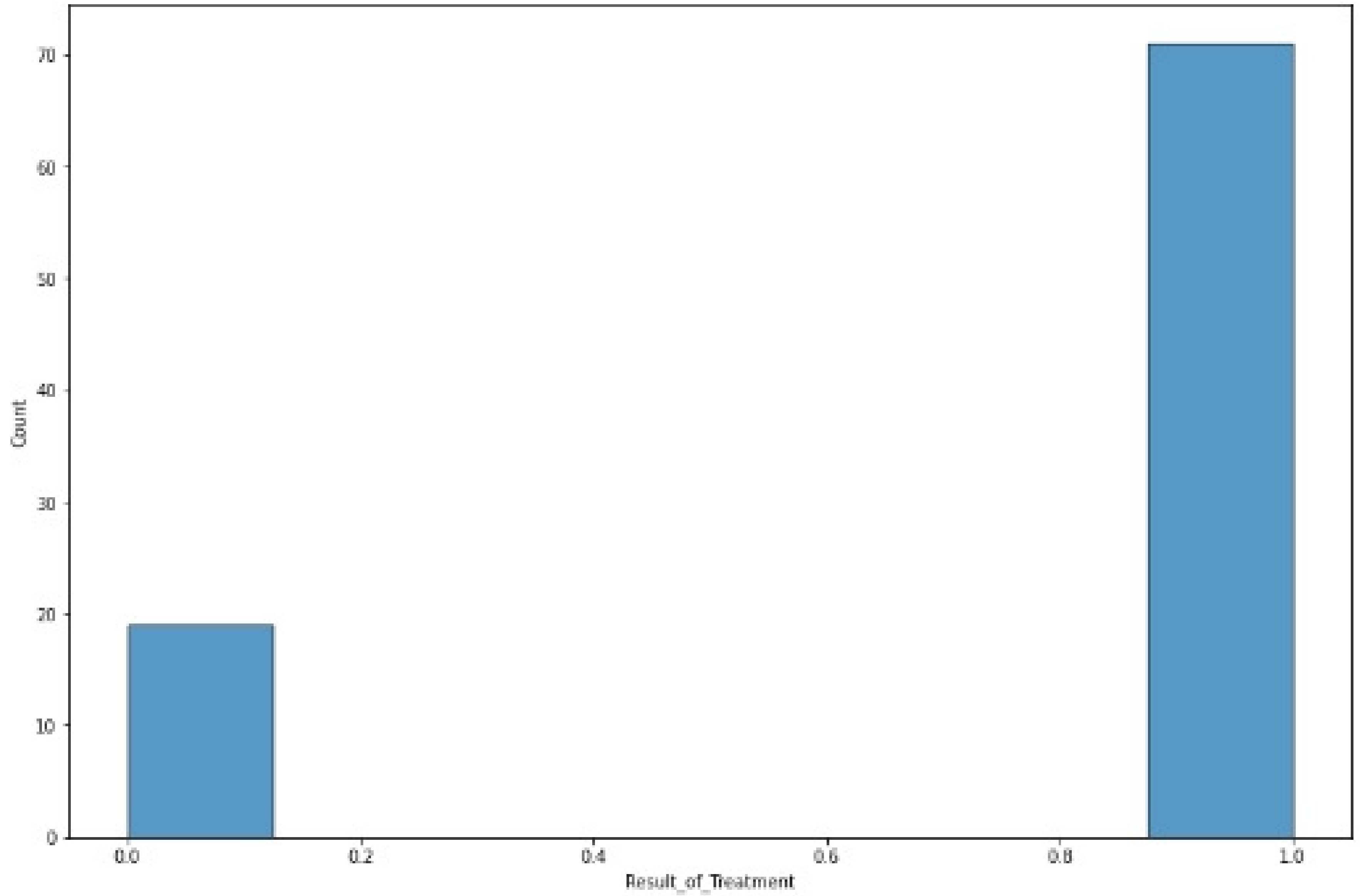
Mengganti gender dan result of treatmen menjadi sebuah penkelasan yang bersifat string (akan tetapi ini tidak akan dipakai dalam processing selanjutnya karena data diwajibkan menggunakan int atau float)

In [12]:

```
fig,axes = plt.subplots(2,2,figsize=(30,20))
sns.histplot(data=df,x='Result_of_Treatment',ax=axes[0,0])
```

Out[12]:

```
<AxesSubplot:xlabel='Result_of_Treatment', ylabel='Count'>
```



Data yang masih berupa imbalance dimana salah satu hasil mendominasi

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

```
sm = SMOTE(random_state=1)
x_sampling , y_sampling = sm.fit_resample(x,y)
```

```
fig = plt.subplots(figsize=(30,20))
sns.histplot(data=y_sampling)
plt.show()
```

SMOTE, atau Teknik Over-sampling Minoritas Sintetis, adalah metode yang dapat digunakan untuk melakukan oversample kelas minoritas dalam dataset dengan proporsi kelas yang tidak seimbang. Ini bekerja dengan mensintesis instance kelas minoritas baru yang mirip dengan yang sudah ada, bukan hanya menduplikasi instance yang ada, yang dapat membantu mengurangi overfitting.

Data Classification

```
X = df_KNN.iloc[:,:-1];
y = df_KNN.iloc[:,7];
```

```
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.1, shuffle=True)
```

```
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.fit_transform(X_test)
```

Persiapan data sebelum menjalani classification

Logistic Regresion

```
X_train1, X_test, y_train1, y_test = train_test_split(X, y, test_size = 0.1, random_state = 0)
```

```
classifier = LogisticRegression()
classifier.fit(X_train1, y_train1)
y_pred = classifier.predict(X_test)
print(y_pred)
```

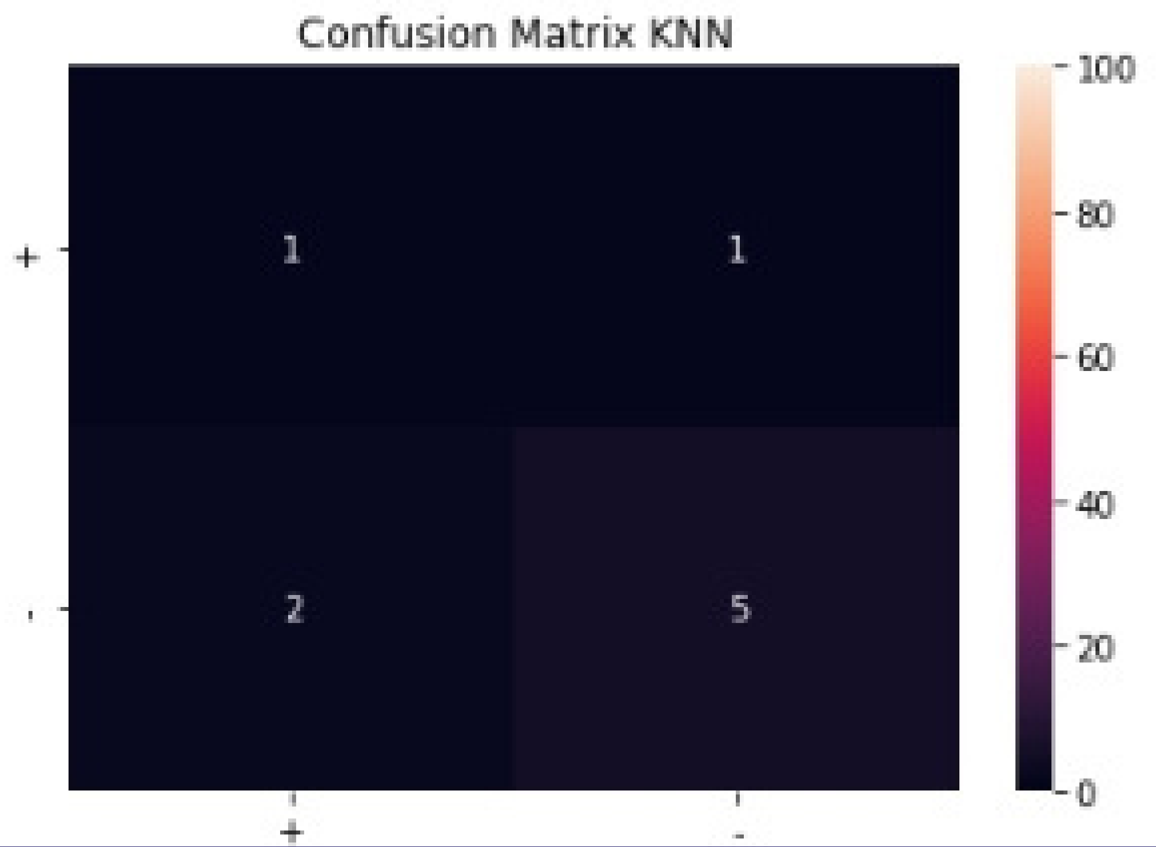
```
[1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

```
cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix\n", cm)
print("Accuracy Score: ", accuracy_score(y_test, y_pred))
```

```
Confusion Matrix
 [[1 1]
 [2 5]]
Accuracy Score:  0.6666666666666666
```

Berikut menggunakan cara Logistic regression yang menghasilkan nilai keakurasiaan yang cukup rendah

```
sns.heatmap(cm, annot=True, fmt='d', xticklabels=['+', '-'], yticklabels=['+', '-'], vmax=100, vmin=0)
plt.title('Confusion Matrix KNN')
plt.show()
```



Berikut merupakan Heatmap dari Logistic Regression

Classification using Naive Bayes

```
model = GaussianNB()
model.fit(X,y)
```

```
▾ GaussianNB
GaussianNB()
```

```
y_pred = model.predict(X_test)
print(y_pred)
```

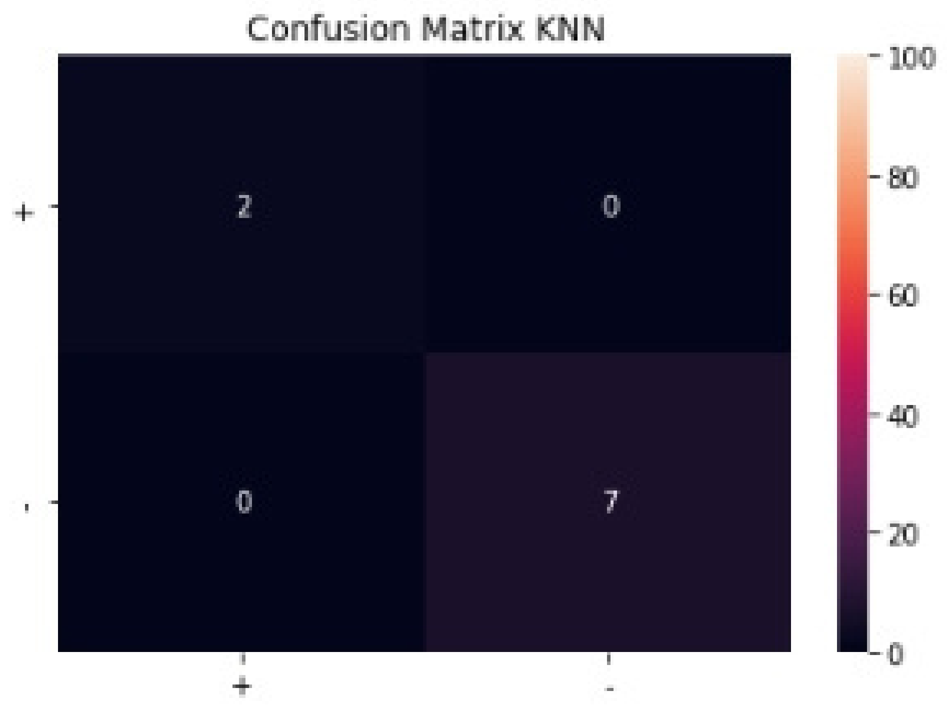
```
[0. 0. 1. 1. 1. 1. 1. 1. 1.]
```

```
cm2 = confusion_matrix(y_test, y_pred)
print("Confusion Matrix\n", cm2)
print("Accuracy Score: ", accuracy_score(y_test, y_pred))
```

```
Confusion Matrix
 [[2 0]
 [0 7]]
Accuracy Score:  1.0
```

Berikut menggunakan cara Naive Bayes yang menghasilkan nilai keakurasiaan sempurna yaitu 1

```
sns.heatmap(cm2, annot=True, fmt='d', xticklabels=['+', '-'], yticklabels=['+', '-'], vmax=100, vmin=0)
plt.title('Confusion Matrix KNN')
plt.show()
```



Berikut merupakan Heatmap dari Naive Bayes

Classification using KNN

```
]: classifier = KNeighborsClassifier(n_neighbors = 10, metric = "euclidean", p = 2)
   classifier.fit(X_train, y_train)
```

```
]: KNeighborsClassifier
   KNeighborsClassifier(metric='euclidean', n_neighbors=10)
```

```
]: y_pred = classifier.predict(X_test)
   print(y_pred)
```

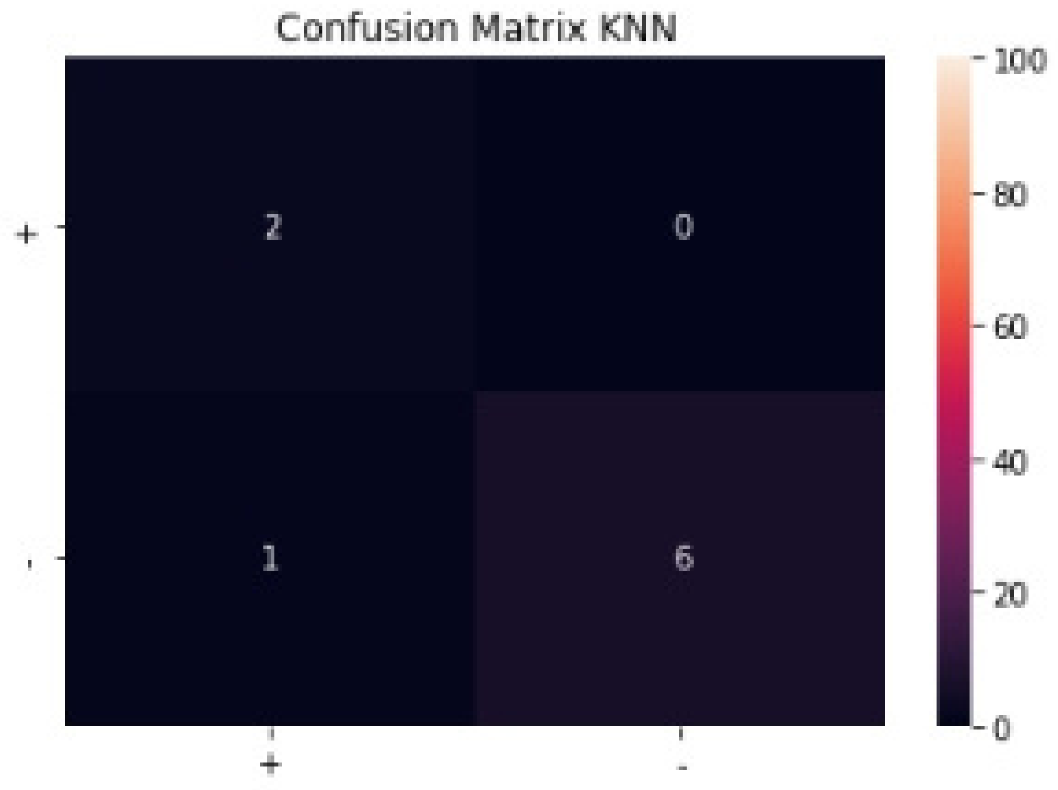
```
[1. 0. 1. 1. 1. 1. 1. 1. 1.]
```

```
]: cm3 = confusion_matrix(y_test, y_pred)
   print("Confusion Matrix\n", cm)
   print("Accuracy Score: ", accuracy_score(y_test, y_pred))
```

```
Confusion Matrix
 [[0 2]
 [0 7]]
Accuracy Score:  0.8888888888888888
```

Berikut menggunakan cara KNN Classifier yang menghasilkan nilai keakurasiaan menengah yaitu 0.8

```
In [26]:
sns.heatmap(cm3, annot=True, fmt='d', xticklabels=['+', '-'], yticklabels=['+', '-'], vmax=100, vmin=0)
plt.title('Confusion Matrix KNN')
plt.show()
```



Berikut merupakan Heatmap dari KNN Classifier

In [27]:

```
X = df_KNN.drop(['Result_of_Treatment'], axis = 1)
y = df_KNN['Result_of_Treatment']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1)
```

In [28]:

```
regressor = LinearRegression()
regressor.fit(X_train, y_train)
print(regressor.predict(X_test))
```

```
[0.82604462 0.70276638 0.72339332 0.95637629 0.89505696 0.7045288
 0.77059437 0.91191016 0.78146012]
```

In [29]:

```
reg = linear_model.LinearRegression()
reg.fit(df_KNN.drop(['Result_of_Treatment'], axis = 1),df_KNN['Result_of_Treatment'])
```

Out[29]:

```
▾ LinearRegression
LinearRegression()
```

In [30]:

```
reg.coef_
```

Out[30]:

```
array([ 0.02042666, -0.00416132, -0.04726091,  0.000682  ,  0.00088226,
        0.00010195, -0.00236522])
```

In [31]:

```
reg.intercept_
```

Out[31]:

```
1.2470704955540142
```

In [32]:

```
rms = sqrt(mean_squared_error(y_test, regressor.predict(X_test)))
print(rms)
```

```
0.21173497533896965
```

Regresi linier adalah metode statistik untuk memodelkan hubungan linier antara variabel dependen dan satu atau lebih variabel independen

Data clustering

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
dfscaler = sc.fit_transform(df_KNN.to_numpy())
dfscaler = pd.DataFrame(dfscaler, columns=['gender', 'age', 'Time', 'Number_of_Warts', 'Type', 'Area', 'induration_diameter'
dfscaler
```

	gender	age	Time	Number_of_Warts	Type	Area	induration_diameter	Result_of_Treatment
0	-1.093216	-1.318656	1.226795	-0.017146	-0.898251	-0.483609	0.602219	-1.933091
1	-1.093216	-0.332404	1.470261	-1.085490	-0.898251	0.826625	-0.505683	-1.933091
2	-1.093216	0.078535	1.551416	0.695083	-0.898251	-0.387918	2.059985	-1.933091
3	-1.093216	0.160723	-1.775945	0.220264	0.335987	2.085334	-0.447372	-1.933091
4	-1.093216	0.242910	-0.720928	0.220264	1.570225	-0.233339	-0.447372	-1.933091
...	...	...	...	...	...	...	...	...
85	0.914732	1.640101	-1.045549	-1.204195	-0.898251	-0.225979	-0.447372	0.517306
86	0.914732	1.640101	-0.396308	-0.017146	-0.281132	-0.115566	-0.738925	0.517306
87	0.914732	1.722289	-1.613635	-0.254556	-0.898251	-0.240700	-0.447372	0.517306
88	0.914732	1.804477	0.902175	-1.204195	0.335987	-0.483609	0.602219	0.517306
89	0.914732	1.804477	0.009468	-0.017146	-0.281132	-0.108205	-0.447372	0.517306

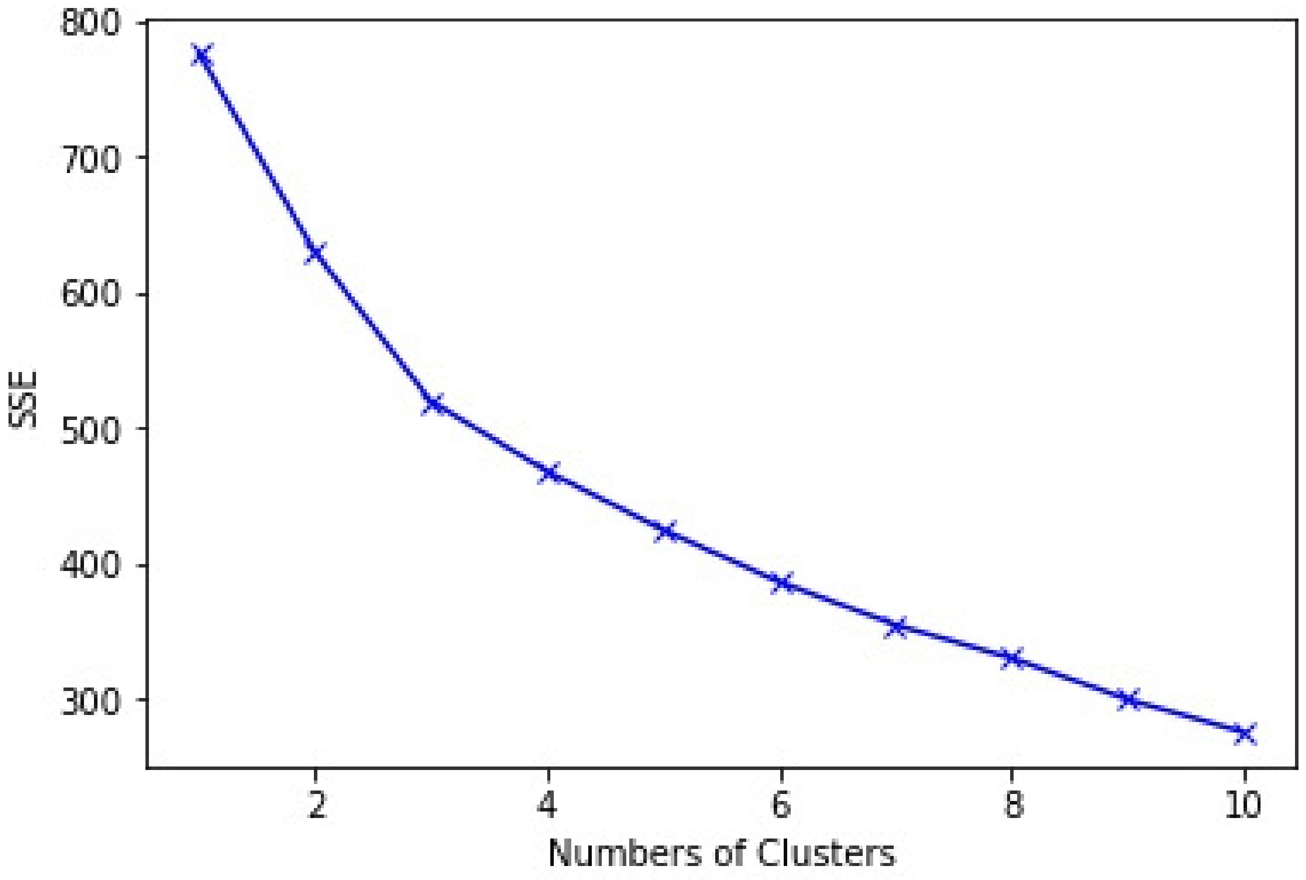
90 rows × 8 columns

Melakukan standar scaler pada data

```
SSE = []
K = range(1,11)
for num_clusters in K :
 kmeans = KMeans(n_clusters=num_clusters)
 kmeans.fit(dfscaler)
 SSE.append(kmeans.inertia_)
```

Menuentukan nilai K yang akan digunakan untuk Kmeans

```
plt.plot(K, SSE,'bx-')
plt.xlabel('Numbers of Clusters')
plt.ylabel('SSE')
plt.show()
```




```
k = KneeLocator(range(1,11), sse, curve='convex', direction='decreasing')
print('Elbow/Knee: ', k.elbow)
```

```
Elbow/Knee:  4
```

Menemukan jumlah Cluster

```python
kmeans = KMeans(init="random",n_clusters=4,max_iter=300,random_state=0)
pred = kmeans.fit_predict(dfscaler)
pred
dfscaler['K Means'] = pred
```

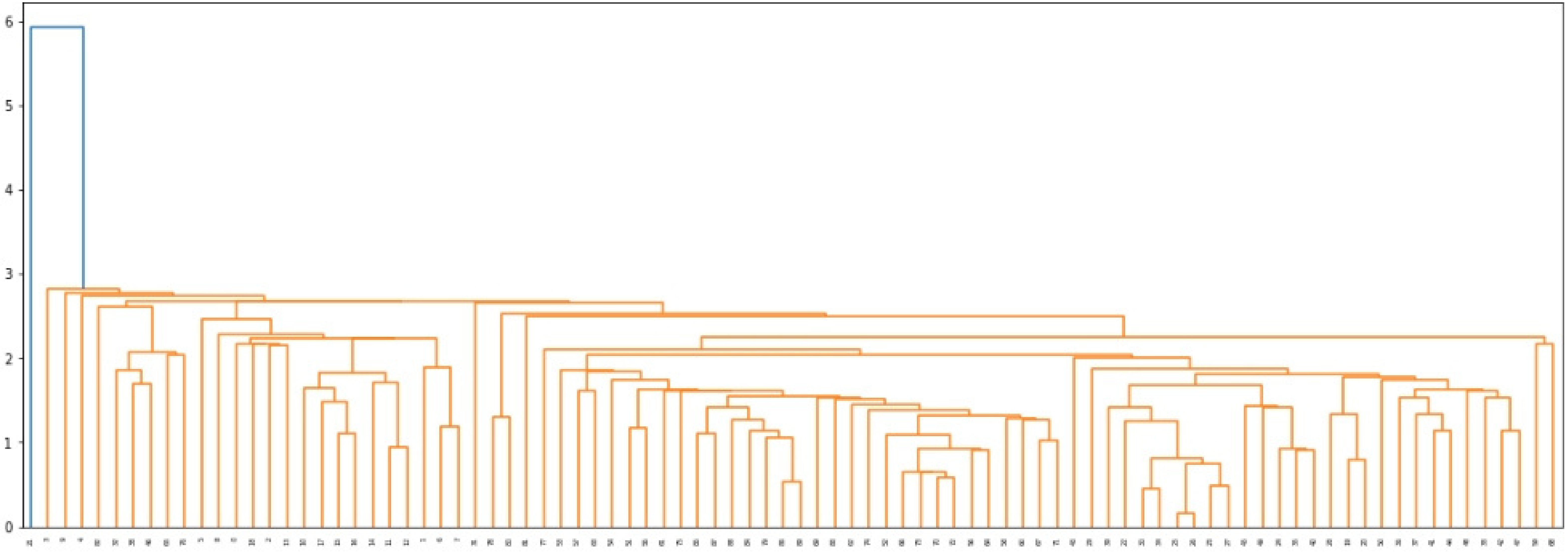
```
D:\Anaconda\lib\site-packages\sklearn\cluster\_kmeans.py:1334: UserWarning: KMeans is known to have a memory
th MKL, when there are less chunks than available threads. You can avoid it by setting the environment variab
=1.
  warnings.warn(
```

```python
dfscaler.groupby('K Means').agg(
gender = ('gender', pd.Series.mean),
age = ('age', pd.Series.mean),
Time = ('Time', pd.Series.mean),
Number_of_Warts = ('Number_of_Warts', pd.Series.mean),
Type = ('Type', pd.Series.mean),
Area = ('Area', pd.Series.mean),
induration_diameter = ('induration_diameter', pd.Series.mean),
Result_of_Treatment = ('Result_of_Treatment', pd.Series.mean), Count = ('K Means', 'count')
)
```

K Means	gender	age	Time	Number_of_Warts	Type	Area	induration_diameter	Result_of_Treatment	Count
0	-0.232667	-0.038876	0.160185	-0.118893	-0.369292	2.904493	0.019113	0.517306	7
1	-0.089242	0.457512	0.839054	0.094964	-0.178279	-0.069356	0.067705	-1.933091	18
2	0.167588	-0.072461	0.039665	-0.387064	-0.439000	-0.274937	-0.382281	0.460320	43
3	-0.180513	-0.220329	-0.814994	0.716666	1.121411	-0.330035	0.685709	0.517306	22

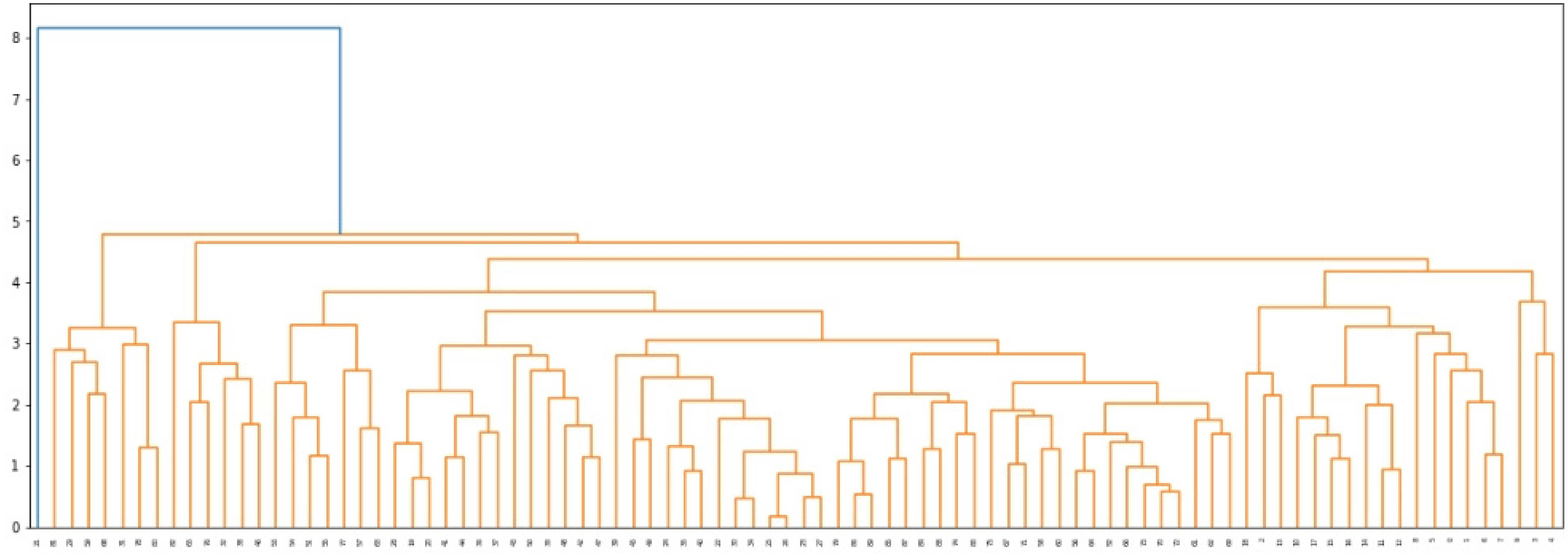
Menemukan berapa jumlah data yang ada dalam 4 Cluster

```
plt.figure(figsize=(20,7))
linkage_data = linkage(dfscaler, method='single', metric='euclidean',)
dendrogram(linkage_data)
plt.show()
```



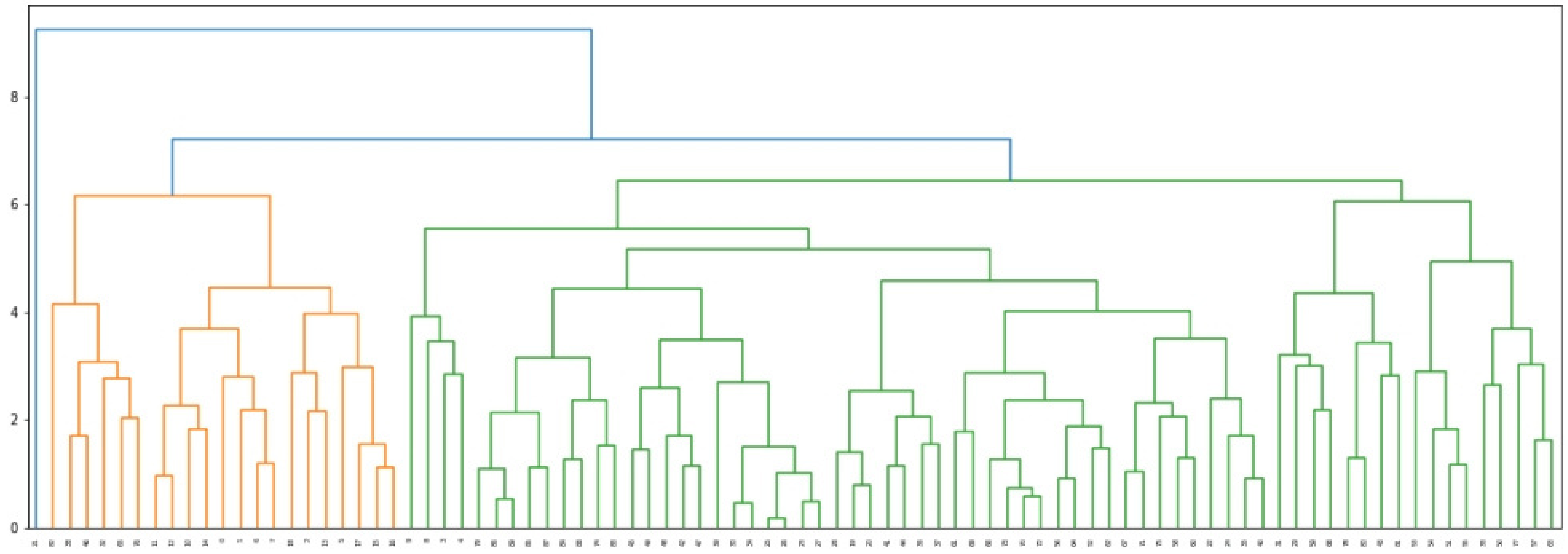
Dendrogram Single

```python
plt.figure(figsize=(20,7))
linkage_data = linkage(dfscaler, method='average', metric='euclidean',)
dendrogram(linkage_data)
plt.show()
```



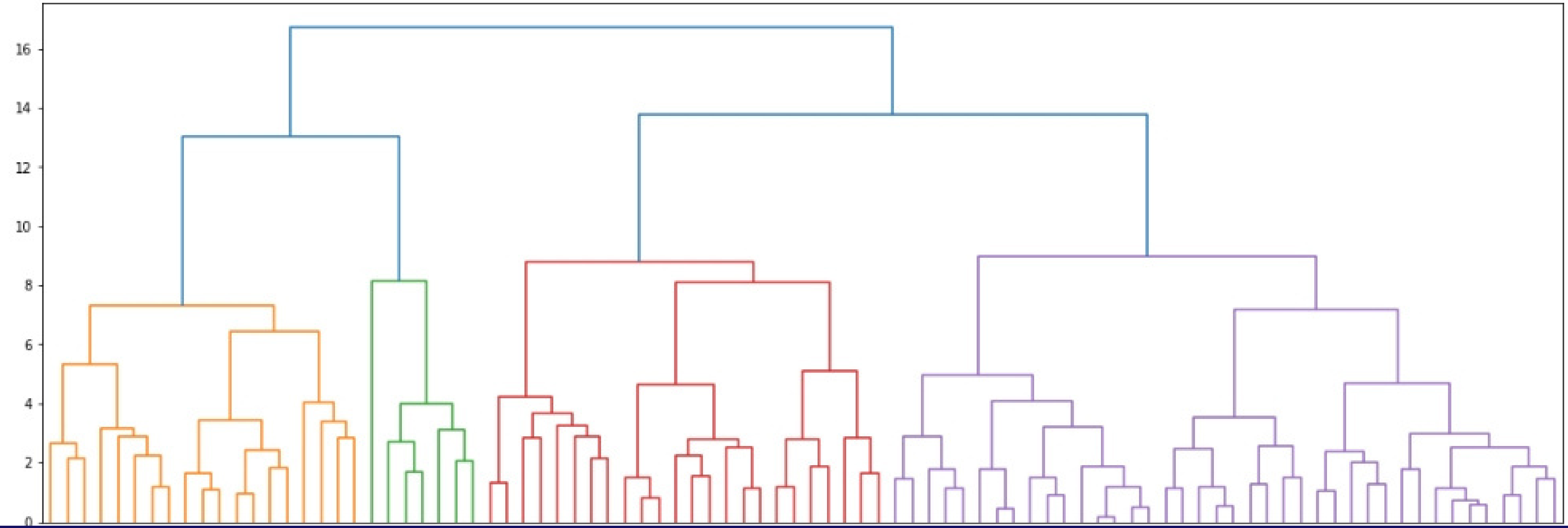
Dendrogram Average

```python
plt.figure(figsize=(20,7))
linkage_data = linkage(dfscaler, method='complete', metric='euclidean',)
dendrogram(linkage_data)
plt.show()
```



Dendrogram Complete

```
plt.figure(figsize=(20,7))
linkage_data = linkage(dfscaler, method='ward', metric='euclidean',)
dendrogram(linkage_data)
plt.show()
```



Dendrogram Ward

Kesimpulan

Kesimpulan yang saya dapat adalah bahwa KNN memiliki tingkat keakuraasian maksimal disusul dengan Naive Bayes lalu Logistic Regression. Dan menurut saya paling cocok menggunakan KNN karena keakurasian diperlukan dalam dunia medis