```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from scipy import stats
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import metrics

#Input Data
src =pd.read_excel("C:/Users/asus/Downloads/Stunt dataset.xlsx")
src.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 520 entries, 0 to 519
Data columns (total 23 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   Kabupaten/Kota Prov Indonesia   520 non-null    object
 1   Prevalensi Stunting (TB/U) %    520 non-null    float64
 2   K4                              520 non-null    float64
 3   Persalinan FASYANKES            520 non-null    float64
 4   KF Lengkap                      520 non-null    float64
 5   Vit A Ibu                       520 non-null    float64
 6   bumil TTD                       520 non-null    float64
 7   BBLR                            520 non-null    float64
 8   IMD                             520 non-null    float64
 9   ASI                             520 non-null    float64
 10  CPKB                            520 non-null    float64
 11  IDL                             520 non-null    float64
 12  A 611                           520 non-null    float64
 13  A 1259                          520 non-null    float64
 14  A 659                           520 non-null    float64
 15  mCPR                            520 non-null    float64
 16  Air Minum Layak                 520 non-null    float64
 17  Sanitasi Layak                  520 non-null    float64
 18  IKP                             520 non-null    float64
 19  BPNT 40%                        520 non-null    float64
 20  KKS 40%                         520 non-null    float64
 21  APK PAUD                        520 non-null    float64
 22  UMK                             520 non-null    float64
dtypes: float64(22), object(1)
memory usage: 93.6+ KB
```

```python
#Describe
src.describe
```

```
       Prevalensi Stunting (TB/U) %          K4  Persalinan FASYANKES
\
count                    520.000000  520.000000            520.000000
```

```
mean                        15.677481   78.308056                 82.466731
std                         24.280961   23.551987                 23.143235
min                          0.000000    1.470000                  1.530000
25%                          6.150000   70.600000                 74.250000
50%                         13.000000   85.949571                 89.100000
75%                         21.125000   93.425000                 97.450000
max                        457.000000  125.300000                140.040000

       KF Lengkap   Vit A Ibu   bumil TTD        BBLR         IMD
ASI  \
count  520.000000  520.000000  520.000000  520.000000  520.000000
520.000000
mean    81.209170   83.740662   73.637825   13.821921   70.264076
55.203190
std     25.594245   28.895392   30.833068   22.008760   26.841913
25.199897
min      0.000000    0.000000    0.000000    0.000000    0.000000
0.000000
25%     74.287500   78.000000   65.875000    1.445000   57.900000
40.055000
50%     87.800000   89.620000   83.265000    4.700000   76.750000
60.000000
75%     97.247500   98.400000   93.122500   15.045000   89.450000
75.425000
max    138.100000  172.440000  139.900000  123.810000  127.800000
100.000000

             CPKB  ...      A 1259       A 659        mCPR  Air Minum
Layak  \
count  520.000000  ...  520.000000  520.000000  520.000000
520.000000
mean    83.438263  ...   81.544438   81.303483   60.058127
75.103154
std     28.803060  ...   24.113321   22.471708   28.824597
23.060407
min      0.000000  ...    0.000000    0.000000    0.000000
1.880000
25%     80.775000  ...   74.500000   75.660000   43.675000
61.872500
50%     92.350000  ...   87.760000   87.680000   67.000000
82.395000
75%     99.525000  ...   96.925000   96.400000   78.057881
```

```
93.920000
max    129.800000  ...  141.630000  126.060000  141.600000
100.000000

       Sanitasi Layak         IKP    BPNT 40%     KKS 40%    APK PAUD
\
count      520.000000  520.000000  520.000000  520.000000  520.000000

mean        72.193742   69.585019   20.431157   30.450234   46.817000

std         20.685373   16.964203   17.009022   31.213710   20.750632

min          3.290000   16.000000    0.000000    0.000000    0.710000

25%         63.770000   61.682500    8.925000    8.015000   31.930000

50%         77.220000   75.055000   17.325000   16.400000   44.915000

75%         86.982500   81.125000   26.302500   40.370000   62.032500

max         99.080000   94.200000   93.400000   98.720000   96.650000


                UMK
count  5.200000e+02
mean   2.809076e+06
std    7.999891e+05
min    0.000000e+00
25%    2.440486e+06
50%    2.862231e+06
75%    3.200000e+06
max    4.816921e+06

[8 rows x 22 columns]

#Cek missing value
src.isna().sum()

Kabupaten/Kota Prov Indonesia    0
Prevalensi Stunting (TB/U) %     0
K4                               0
Persalinan FASYANKES             0
KF Lengkap                       0
Vit A Ibu                        0
bumil TTD                        0
BBLR                             0
IMD                              0
ASI                              0
CPKB                             0
IDL                              0
A 611                            0
```

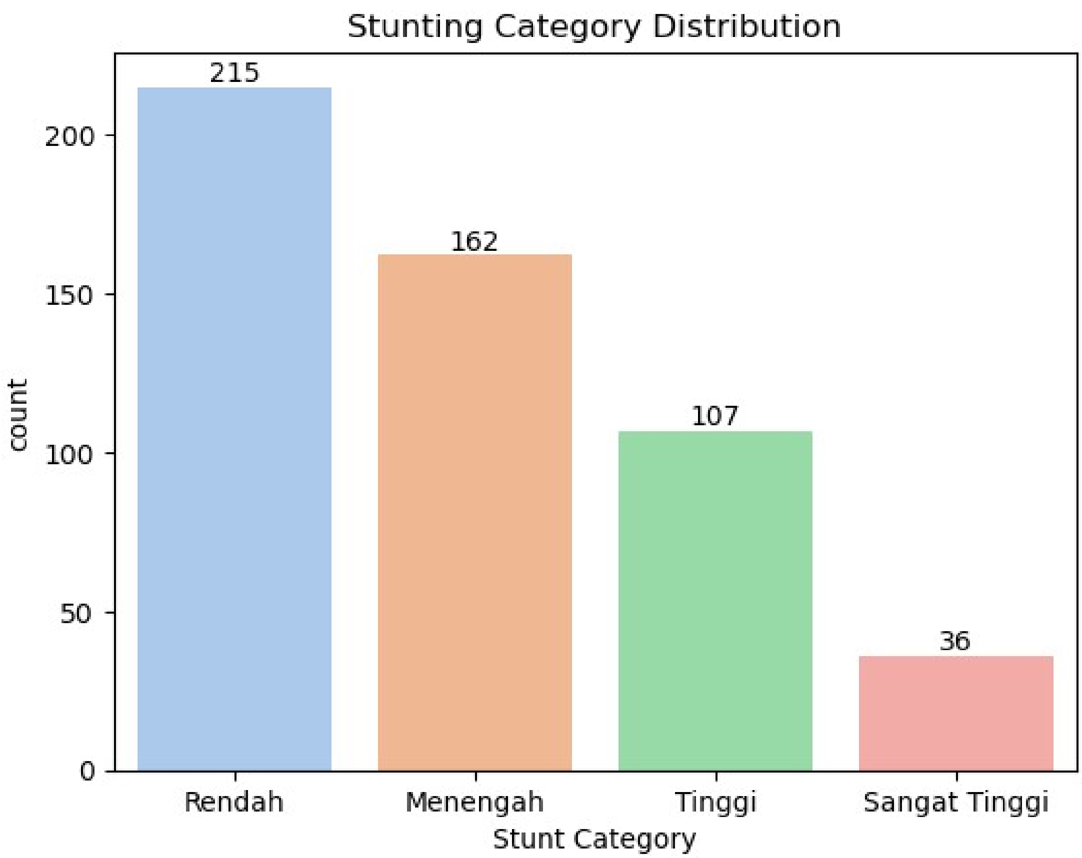
```
A 1259                              0
A 659                               0
mCPR                                0
Air Minum Layak                     0
Sanitasi Layak                      0
IKP                                 0
BPNT 40%                            0
KKS 40%                             0
APK PAUD                            0
UMK                                 0
dtype: int64
```

Tidak ada missing value pada dataset

```
#Binning menurut WHO
categories = ['Rendah','Menengah', 'Tinggi','Sangat Tinggi']
src['Stunt Category'] = pd.cut(src['Prevalensi Stunting (TB/U) %'],
bins=[-float('inf'), 10, 20, 30, float('inf')], labels=categories)


#Encoding
category_mapping = {'Rendah': 1, 'Menengah': 2, 'Tinggi': 3, 'Sangat
Tinggi': 4}
src['Stunt CatNum'] = src['Stunt Category'].map(category_mapping)
print(src[['Kabupaten/Kota Prov Indonesia','Prevalensi Stunting (TB/U)
%', 'Stunt Category', 'Stunt CatNum']])

      Kabupaten/Kota Prov Indonesia  Prevalensi Stunting (TB/U) %  \
0                Kabupaten Bangkalan                          26.2
1               Kabupaten Banyuwangi                          18.1
2                   Kabupaten Blitar                          14.3
3               Kabupaten Bojonegoro                          24.3
4                Kabupaten Bondowoso                          32.0
..                               ...                           ...
515       Kabupaten Sumba Barat Daya                          13.0
516           Kabupaten Sumba Tengah                          12.0
517            Kabupaten Sumba Timur                          10.0
518   Kabupaten Timor Tengah Selatan                          13.0
519     Kabupaten Timor Tengah Utara                          23.0

    Stunt Category Stunt CatNum
0           Tinggi            3
1         Menengah            2
2         Menengah            2
3           Tinggi            3
4    Sangat Tinggi            4
..             ...          ...
515       Menengah            2
516       Menengah            2
```

```
517          Rendah              1
518        Menengah              2
519          Tinggi              3

[520 rows x 4 columns]
```

```
sns.countplot(x='Stunt Category', data=src,
palette=sns.color_palette('pastel')[0:5])

# Adding data labels
for i, value in enumerate(src['Stunt Category'].value_counts()):
    plt.text(i, value + 0.1, str(value), ha='center', va='bottom',
fontsize=10)

plt.title('Stunting Category Distribution')
plt.show()
```



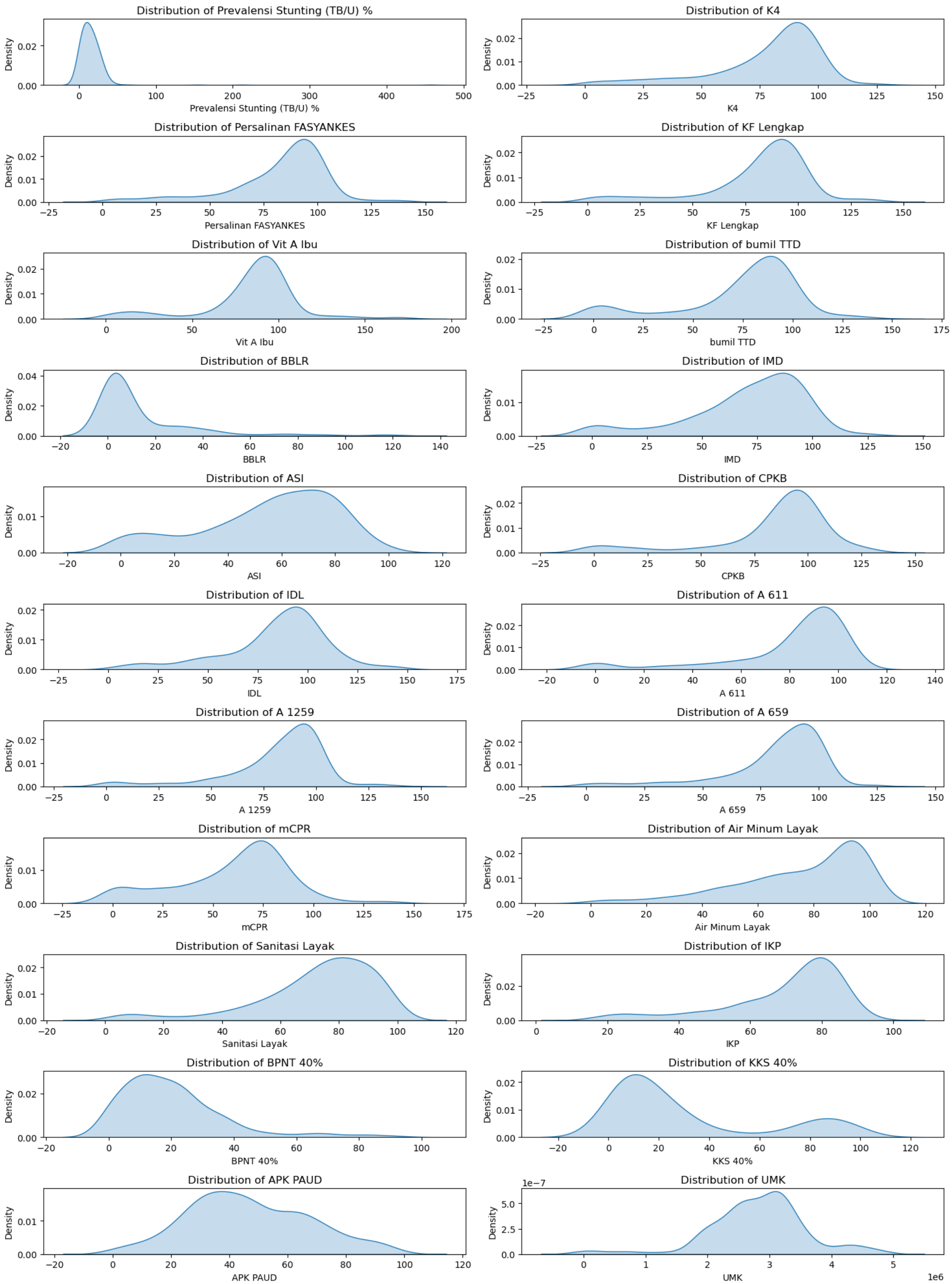

```
srcnokab = src.drop(['Kabupaten/Kota Prov Indonesia','Stunt
Category','Stunt CatNum'], axis=1)
print(srcnokab.head(5))

   Prevalensi Stunting (TB/U) %    K4  Persalinan FASYANKES  KF
Lengkap  \
```

```
0                          26.2  85.9                  88.0
86.2
1                          18.1  94.8                  97.4
84.9
2                          14.3  77.2                  80.2
80.0
3                          24.3  85.6                  93.5
90.4
4                          32.0  84.9                 103.3
103.1

   Vit A Ibu  bumil TTD  BBLR   IMD   ASI   CPKB  ...  A 1259  A 659
mCPR  \
0       94.1       62.8  14.0  92.1  31.8   66.2  ...    76.7   75.6
71.6
1       89.9       81.8  19.8  75.5  76.3   96.8  ...    96.4   95.9
70.0
2       80.3       78.7  24.3  60.6  57.5   83.5  ...    89.5   89.9
75.1
3       93.5       87.3  33.0  78.7  93.9   97.8  ...    99.6   98.8
72.1
4      105.7       89.2  57.8  96.8  82.7  104.8  ...    98.1   98.0
73.4

   Air Minum Layak  Sanitasi Layak    IKP  BPNT 40%  KKS 40%  APK PAUD
\
0            93.91           53.48  70.59    19.515   10.035     61.52

1            95.97           78.07  83.82    23.645   26.890     45.71

2            96.37           80.11  84.34    25.115   31.645     67.86

3            96.51           91.01  83.55    23.600   31.055     86.76

4            93.31           51.64  73.78    23.365   31.720     64.60


          UMK
0  1956773.48
1  2328899.12
2  2015071.18
3  2079568.07
4  1958640.12

[5 rows x 22 columns]

#cek outlier
Q1 = srcnokab.quantile(q=.25)
Q3 = srcnokab.quantile(q=.75)
IQR = Q3-Q1
```

```
data_iqr = srcnokab[-((srcnokab < (Q1-1.5*IQR)) | (srcnokab
>(Q3+1.5*IQR))).any(axis=1)]
data_iqr.shape

print("Dimensi dataset awal", srcnokab.shape)
print("Dimensi dataset setelah pengecekan outlier", data_iqr.shape)
```

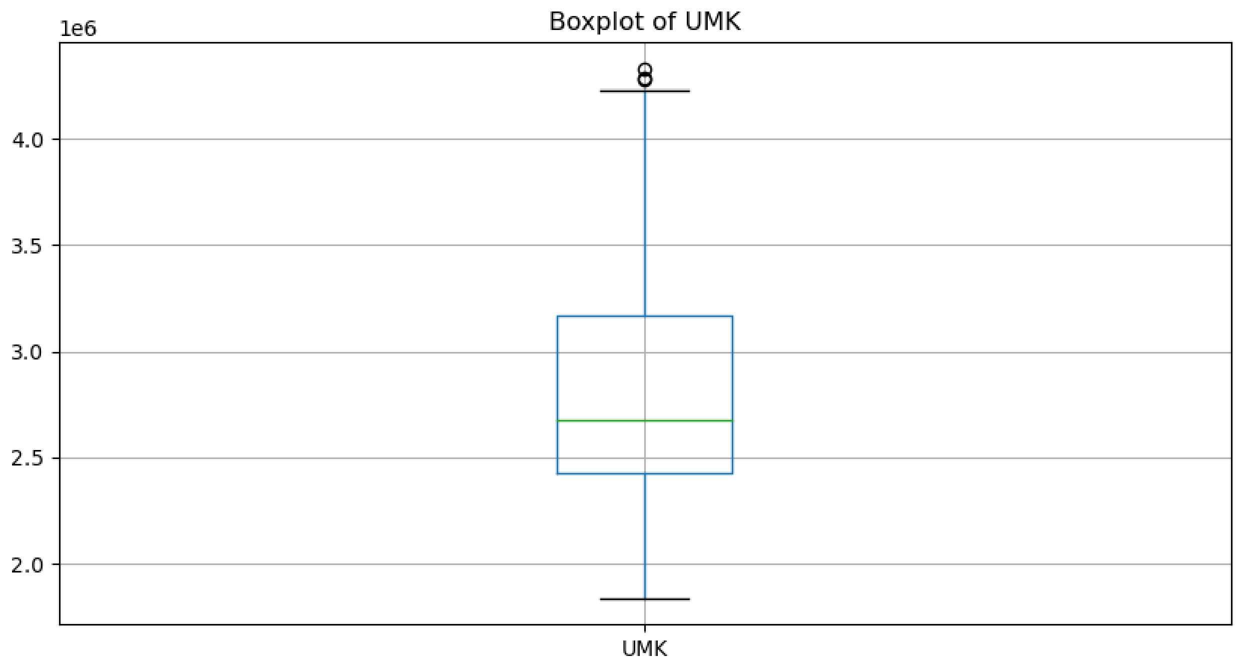
```
Dimensi dataset awal (520, 22)
Dimensi dataset setelah pengecekan outlier (274, 22)
```

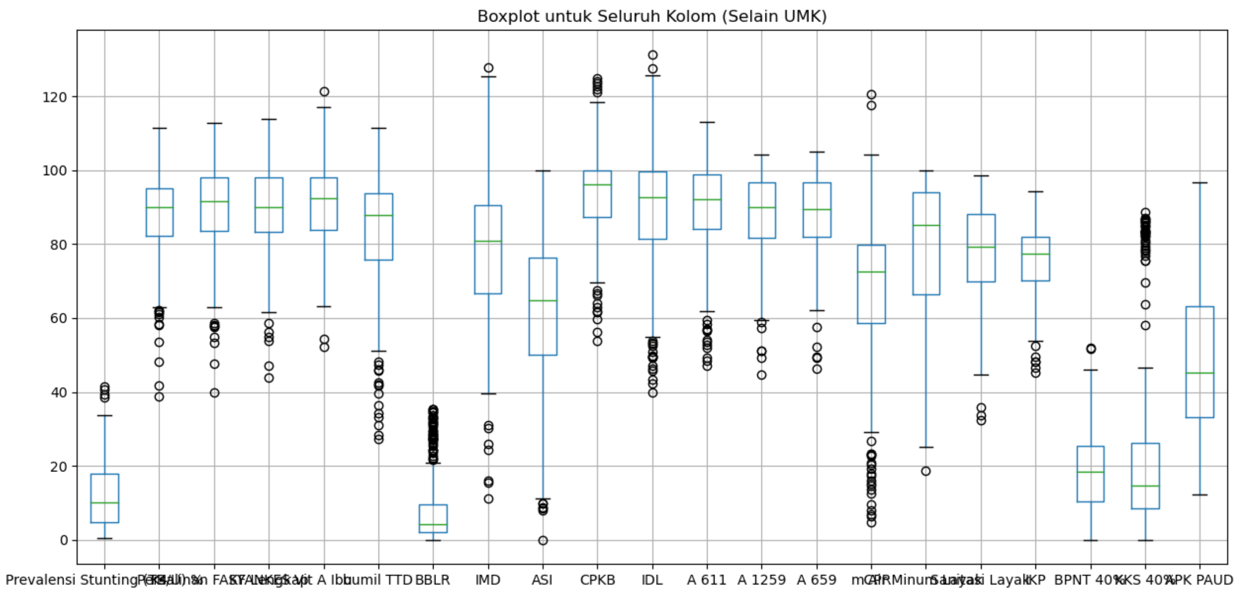
```
#cek distribusi

nrows = 11
ncols = 2

fig, axes = plt.subplots(nrows, ncols, figsize=(15, 20))

for i, var in enumerate(srcnokab):
    row = i // ncols
    col = i % ncols
    sns.kdeplot(data=srcnokab, x=var, ax=axes[row, col], fill=True)
    axes[row, col].set_title(f'Distribution of {var}')

plt.tight_layout()
plt.show()
```



Distribution of Prevalensi Stunting (TB/U) %
Prevalensi Stunting (TB/U) %
Distribution of K4
K4
Distribution of Persalinan FASYANKES
Persalinan FASYANKES
Distribution of KF Lengkap
KF Lengkap
Distribution of Vit A Ibu
Vit A Ibu
Distribution of bumil TTD
bumil TTD
Distribution of BBLR
BBLR
Distribution of IMD
IMD
Distribution of ASI
ASI
Distribution of CPKB
CPKB
Distribution of IDL
IDL
Distribution of A 611
A 611
Distribution of A 1259
A 1259
Distribution of A 659
A 659
Distribution of mCPR
mCPR
Distribution of Air Minum Layak
Air Minum Layak
Distribution of Sanitasi Layak
Sanitasi Layak
Distribution of IKP
IKP
Distribution of BPNT 40%
BPNT 40%
Distribution of KKS 40%
KKS 40%
Distribution of APK PAUD
APK PAUD
Distribution of UMK
UMK
1e−7
1e6
Density

```
#cek outlier menggunakan boxplot

# Membuat boxplot untuk kolom 'UMK'
data_iqr[['UMK']].boxplot(figsize=(10, 5))
plt.title('Boxplot of UMK')
plt.show()

# Memilih semua kolom kecuali 'UMK'
data_iqr_without_UMK = data_iqr.drop('UMK', axis=1)

# Membuat boxplot untuk seluruh kolom (selain 'UMK')
data_iqr_without_UMK.boxplot(figsize=(15, 7), vert=True)  # vert=False
agar boxplot horizontal
plt.title('Boxplot untuk Seluruh Kolom (Selain UMK)')
plt.show()
```





Terdapat outlier yang terdeteksi pada masing-masing fitur jika menggunakan perhitungan IQR sehingga perlu dilakukan penanganan outlier. Sebelum itu akan dilakukan pengecekan distribusi data

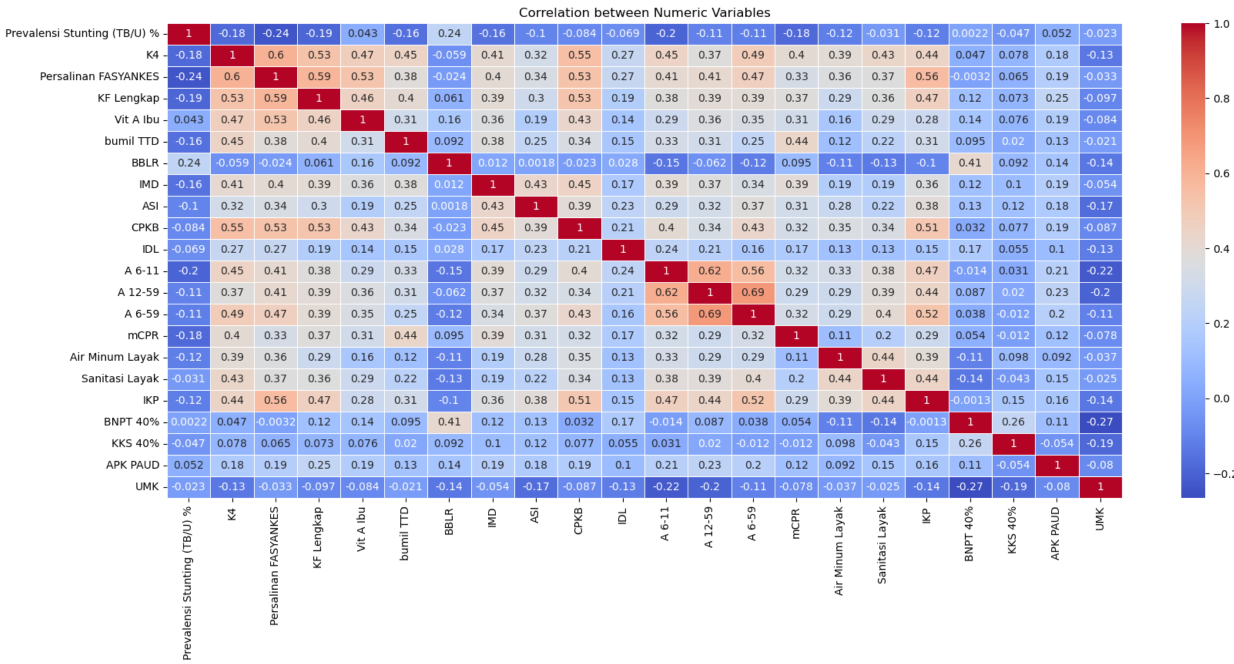
```
#cek skewness
for var_name in srcnokab:
    skewness = round(srcnokab[var_name].skew(), 3)
    print(f'Skewness of {var_name}: {skewness}')

Skewness of Prevalensi Stunting (TB/U) %: 13.017
Skewness of K4: -1.401
Skewness of Persalinan FASYANKES: -1.307
Skewness of KF Lengkap: -1.381
Skewness of Vit A Ibu: -0.849
Skewness of bumil TTD: -1.131
Skewness of BBLR: 2.633
Skewness of IMD: -1.027
Skewness of ASI: -0.681
Skewness of CPKB: -1.633
Skewness of IDL: -0.878
Skewness of A 611: -1.836
Skewness of A 1259: -1.513
Skewness of A 659: -1.733
Skewness of mCPR: -0.428
Skewness of Air Minum Layak: -1.1
Skewness of Sanitasi Layak: -1.383
Skewness of IKP: -1.382
Skewness of BPNT 40%: 1.64
Skewness of KKS 40%: 1.09
Skewness of APK PAUD: 0.242
Skewness of UMK: -0.638
```

Fitur-fitur dengan skewness negatif menunjukkan persebaran data yang besar ke arah kanan, menunjukkan bahwa nilai-nilai tersebut cenderung besar. Oleh karena itu, untuk mengatasi adanya pencilan (outlier), akan dilakukan standardisasi.

```
#standardization
from sklearn import preprocessing
srcz = preprocessing.scale(srcnokab)
srcz
```

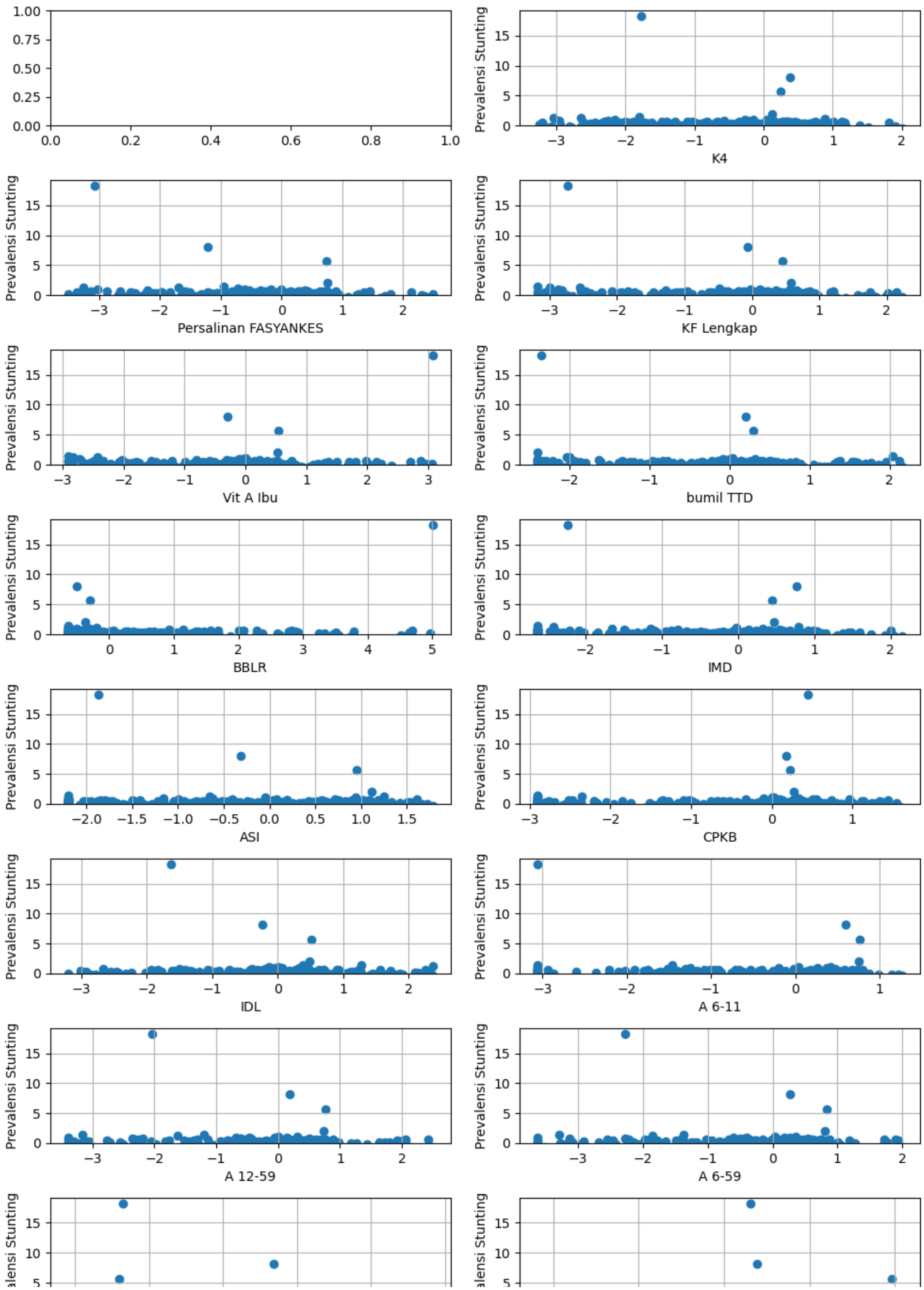
```
array([[ 0.43378231,  0.32265872,  0.2393182 , ..., -0.65467682,
         0.70923903, -1.06641861],
       [ 0.09986639,  0.70091003,  0.64587553, ..., -0.11416977,
        -0.05339914, -0.60080731],
       [-0.05678553, -0.04709256, -0.09803787, ...,  0.03831383,
         1.0150661 , -0.99347532],
       ...,
       [-0.23404954, -2.77560203, -1.27445906, ...,  2.16618955,
        -1.53477918, -0.02977162],
       [-0.11037697,  1.89941419, -0.49594504, ..., -0.75200336,
         0.0088275 ,  0.58191388],
       [ 0.30186491, -1.33059702,  1.45034002, ...,  1.7813729 ,
        -0.71473813, -0.31955558]])
```

```
#feature selection using correlation
srcz_df = pd.DataFrame(srcz, columns=['Prevalensi Stunting (TB/U) %',
'K4',
                                      'Persalinan FASYANKES', 'KF
Lengkap', 'Vit A Ibu', 'bumil TTD', 'BBLR',
                                      'IMD', 'ASI', 'CPKB', 'IDL', 'A
6-11', 'A 12-59', 'A 6-59', 'mCPR',
                                      'Air Minum Layak', 'Sanitasi
Layak', 'IKP', 'BNPT 40%', 'KKS 40%',
                                      'APK PAUD','UMK'])

correlation = srcz_df.corr()

# Plot heatmap
plt.figure(figsize=(20, 8))
sns.heatmap(correlation, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title("Correlation between Numeric Variables")
plt.show()
```



Pemilihan fitur didasarkan pada korelasi yang mendekati nilai 0,5, menunjukkan hubungan yang kuat. Fitur lainnya tidak dipertimbangkan karena memiliki korelasi yang mendekati 0.

```python
# Plotting scatterplots in a grid

fig, axes = plt.subplots(11, 2, figsize=(10, 20))

for i, ax in enumerate(axes.flatten()):
    if i == 0:
        continue  # Skip the first subplot

    x = srcz_df.iloc[:, i]
    y = srcz_df['Prevalensi Stunting (TB/U) %']

    ax.scatter(x, y, marker='o')
    ax.grid()
    ax.set_ylim(ymin=0)
    ax.set_xlabel(srcz_df.columns[i])
    ax.set_ylabel('Prevalensi Stunting')

plt.tight_layout()
plt.show()
```



Prevalensi Stunting
K4
Persalinan FASYANKES
KF Lengkap
Vit A Ibu
bumil TTD
BBLR
IMD
ASI
CPKB
IDL
A 6-11
A 12-59
A 6-59

```python
#K-means Clustering
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

import os

# Set OMP_NUM_THREADS to 1 to avoid memory leak warning
os.environ['OMP_NUM_THREADS'] = '1'

silhouette_scores = []
for n_clusters in range(2, 11):
    kmeans = KMeans(n_clusters=n_clusters, n_init=100)
    kmeans.fit(srcz)
    silhouette_scores.append(silhouette_score(srcz, kmeans.labels_))

plt.plot(range(2, 11), silhouette_scores, marker='o')
plt.xlabel('Jumlah Cluster')
plt.ylabel('Silhouette Score')
plt.title('Silhouette Score untuk Berbagai Jumlah Cluster')
plt.show()

for i, score in enumerate(silhouette_scores, 2):
    print(f"Silhouette Score for {i} clusters: {score:.3f}")
```

```
C:\Users\asus\anaconda3\Lib\site-packages\sklearn\cluster\
_kmeans.py:1436: UserWarning: KMeans is known to have a memory leak on
Windows with MKL, when there are less chunks than available threads.
You can avoid it by setting the environment variable
OMP_NUM_THREADS=1.
  warnings.warn(
C:\Users\asus\anaconda3\Lib\site-packages\sklearn\cluster\
_kmeans.py:1436: UserWarning: KMeans is known to have a memory leak on
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C:\Users\asus\anaconda3\Lib\site-packages\sklearn\cluster\
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C:\Users\asus\anaconda3\Lib\site-packages\sklearn\cluster\
_kmeans.py:1436: UserWarning: KMeans is known to have a memory leak on
```

```
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C:\Users\asus\anaconda3\Lib\site-packages\sklearn\cluster\
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C:\Users\asus\anaconda3\Lib\site-packages\sklearn\cluster\
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Windows with MKL, when there are less chunks than available threads.
You can avoid it by setting the environment variable
OMP_NUM_THREADS=1.
  warnings.warn(
```

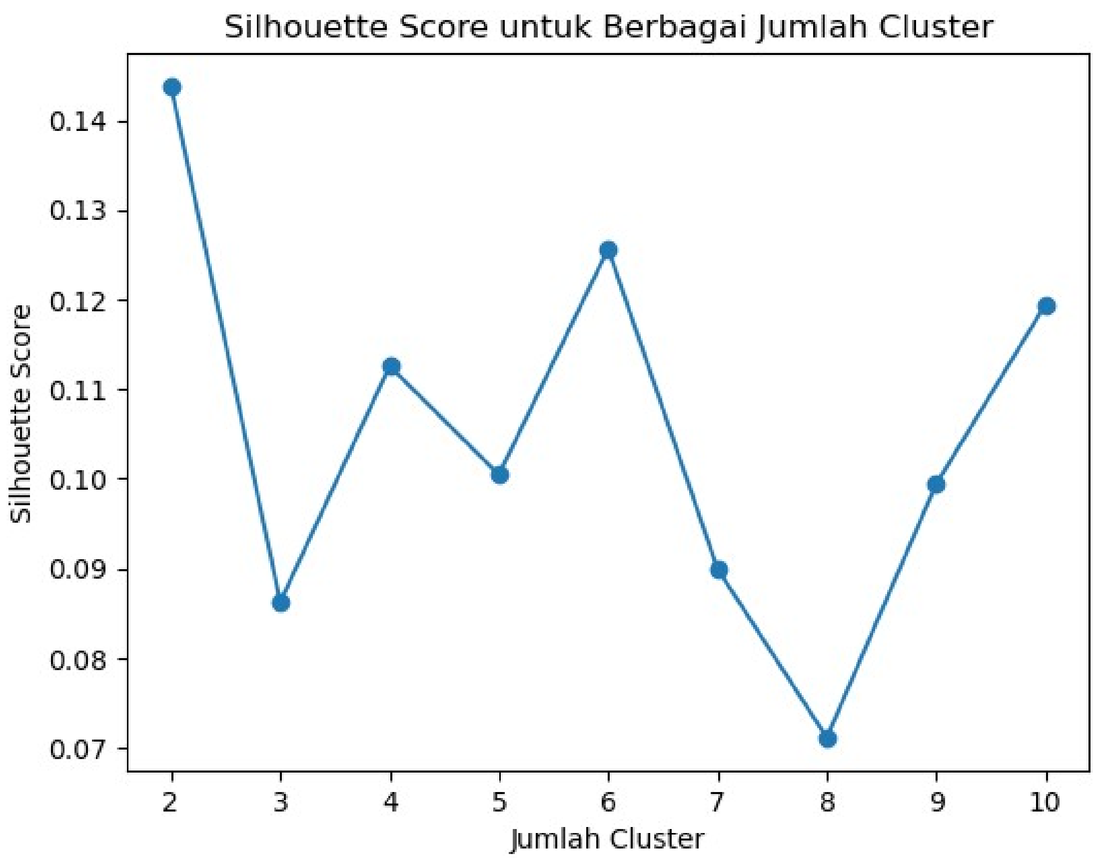


```
Silhouette Score for 2 clusters: 0.144
Silhouette Score for 3 clusters: 0.086
Silhouette Score for 4 clusters: 0.113
Silhouette Score for 5 clusters: 0.100
Silhouette Score for 6 clusters: 0.126
Silhouette Score for 7 clusters: 0.090
Silhouette Score for 8 clusters: 0.071
Silhouette Score for 9 clusters: 0.099
Silhouette Score for 10 clusters: 0.119
```

Berdasarkan grafik di atas dapat diketahui bahwa jumlah cluster yang optimal adalah 2 (dua). Hal ini disebabkan oleh nilai silhouette yang paling tinggi terjadi ketika jumlah cluster = 2.

```
#feature selected based on corr
X = srcz[:, [1, 2, 3, 6, 11, 14]]
Y = srcz[:, 0]

# Suppress warnings:
def warn(*args, **kwargs):
    pass
import warnings
warnings.warn = warn
```

```
k_means = KMeans(init="k-means++", n_clusters=2, n_init=100)
labels = k_means.fit_predict(X)
print((labels))

[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0
 0 0 1 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0
0 0
 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
0 0
 1 0 0 1 0 0 0 1 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0
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0 1
 0 1]

#menambahkan labels sebagai kolom baru
src['Cluster']=labels
src.head()

  Kabupaten/Kota Prov Indonesia  Prevalensi Stunting (TB/U) %    K4  \
0           Kabupaten Bangkalan                          26.2  85.9
1          Kabupaten Banyuwangi                          18.1  94.8
2              Kabupaten Blitar                          14.3  77.2
3          Kabupaten Bojonegoro                          24.3  85.6
4           Kabupaten Bondowoso                          32.0  84.9

   Persalinan FASYANKES  KF Lengkap  Vit A Ibu  bumil TTD  BBLR   IMD
ASI  \
0                  88.0        86.2       94.1       62.8  14.0  92.1
31.8
1                  97.4        84.9       89.9       81.8  19.8  75.5
```
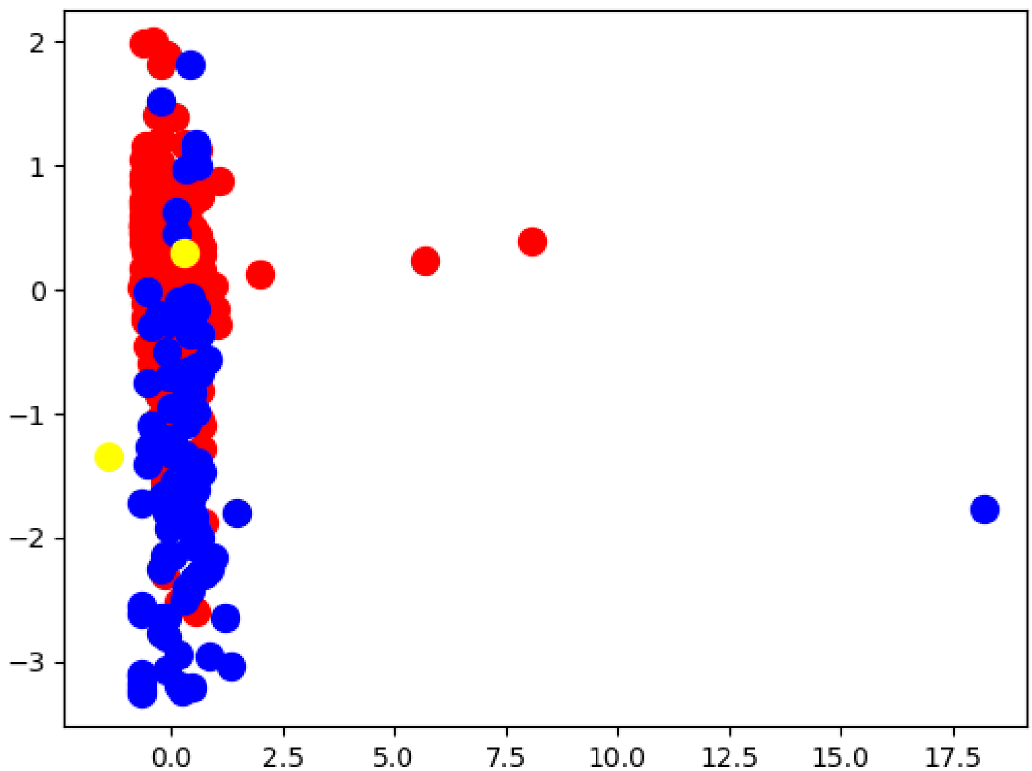

```
76.3
2                  80.2        80.0       80.3       78.7  24.3  60.6
57.5
3                  93.5        90.4       93.5       87.3  33.0  78.7
93.9
4                 103.3       103.1      105.7       89.2  57.8  96.8
82.7

   ...  Air Minum Layak  Sanitasi Layak    IKP  BPNT 40%  KKS 40%  APK
PAUD  \
0  ...            93.91           53.48  70.59    19.515   10.035
61.52
1  ...            95.97           78.07  83.82    23.645   26.890
45.71
2  ...            96.37           80.11  84.34    25.115   31.645
67.86
3  ...            96.51           91.01  83.55    23.600   31.055
86.76
4  ...            93.31           51.64  73.78    23.365   31.720
64.60

          UMK  Stunt Category  Stunt CatNum  Cluster
0  1956773.48          Tinggi             3        0
1  2328899.12        Menengah             2        0
2  2015071.18        Menengah             2        0
3  2079568.07          Tinggi             3        0
4  1958640.12   Sangat Tinggi             4        0

[5 rows x 26 columns]

# Plotting the results
plt.scatter(srcz[labels==0, 0], srcz[labels==0, 1], s=100, c='red',
label ='Cluster 1')
plt.scatter(srcz[labels==1, 0], srcz[labels==1, 1], s=100, c='blue',
label ='Cluster 2')

plt.scatter(k_means.cluster_centers_[:, 0],
k_means.cluster_centers_[:, 1], s=100, c='yellow', label =
'Centroids')
plt.show()
```




```
#Keanggotaan Kabupaten/Kota berdasarkan Cluster
grouped_data = src.groupby('Cluster')

for cluster, group_data in grouped_data:
    print(f"Cluster {cluster}:")
    print(group_data.iloc[:, 0])
    print("\n")
```

```
Cluster 0:
0                  Kabupaten Bangkalan
1                 Kabupaten Banyuwangi
2                     Kabupaten Blitar
3                 Kabupaten Bojonegoro
4                  Kabupaten Bondowoso
                         ...
511                Kabupaten Rote Ndao
513                    Kabupaten Sikka
515        Kabupaten Sumba Barat Daya
516            Kabupaten Sumba Tengah
518    Kabupaten Timor Tengah Selatan
Name: Kabupaten/Kota Prov Indonesia, Length: 425, dtype: object


Cluster 1:
113                            Dairi
115               Humbang Hasundutan
```

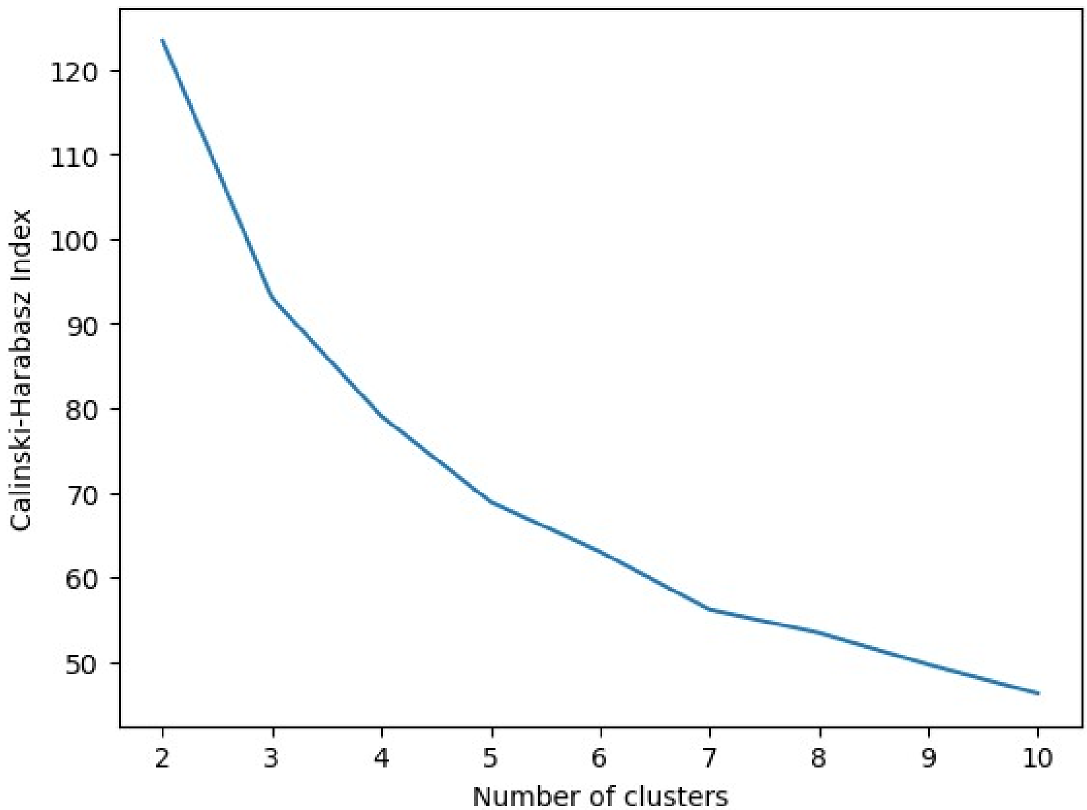
```
118                  Kota Gunungsitoli
131                         Nias Barat
132                       Nias Selatan
                       ...
510                    Kabupaten Ngada
512            Kabupaten Sabu Raijua
514            Kabupaten Sumba Barat
517            Kabupaten Sumba Timur
519     Kabupaten Timor Tengah Utara
Name: Kabupaten/Kota Prov Indonesia, Length: 95, dtype: object



#karakteristik tiap kluster
grouped_data.mean()

         Prevalensi Stunting (TB/U) %         K4  Persalinan FASYANKES
\
Cluster

0                          13.549106  85.723528             89.462871

1                          25.199158  45.133579             51.168211


         KF Lengkap  Vit A Ibu  bumil TTD       BBLR        IMD
ASI  \
Cluster

0         88.440703  89.325953  78.991178  12.382318  75.381052
58.998319
1         48.857571  58.753832  49.688618  20.262249  47.372343
38.224983

              CPKB  ...     A 1259      A 659       mCPR  Air Minum
Layak  \
Cluster             ...

0        90.666832  ...  86.327267  86.259544  66.536660
78.740400
1        51.099929  ...  60.147572  59.131630  31.075215
58.831263

         Sanitasi Layak        IKP   BPNT 40%    KKS 40%   APK PAUD  \
Cluster
0             76.437388  73.836659  19.930721  30.665827  48.514235
1             53.209007  50.564526  22.669947  29.485736  39.224105

                  UMK
Cluster
0        2.789366e+06
```

```
1        2.897253e+06

[2 rows x 22 columns]
```

Cluster 0 memiliki rata-rata prevalensi stunting yang lebih tinggi daripada cluster 1, sehingga Kabupaten/Kota yang tergabung pada cluster 0 memiliki rata-rata prevalensi stunting yang lebih tinggi daripada Kabupaten/Kota di Cluster 1.

```
# Cluster performance
import sklearn
results = {}

for i in range(2, 11):
    kmeans = KMeans(n_clusters=i, random_state=100)
    labels = kmeans.fit_predict(srcz)
    db_index = sklearn.metrics.calinski_harabasz_score(srcz, labels)
    results.update({i: db_index})

# Menampilkan hasil dan menambahkan data label
for k, v in results.items():
    print(f"Number of clusters: {k}, Calinski-Harabasz Index:
{v:.2f}")

# Plotting
plt.plot(list(results.keys()), list(results.values()))
plt.xlabel("Number of clusters")
plt.ylabel("Calinski-Harabasz Index")
plt.show()
```

```
Number of clusters: 2, Calinski-Harabasz Index: 123.42
Number of clusters: 3, Calinski-Harabasz Index: 93.02
Number of clusters: 4, Calinski-Harabasz Index: 79.04
Number of clusters: 5, Calinski-Harabasz Index: 68.89
Number of clusters: 6, Calinski-Harabasz Index: 63.00
Number of clusters: 7, Calinski-Harabasz Index: 56.16
Number of clusters: 8, Calinski-Harabasz Index: 53.41
Number of clusters: 9, Calinski-Harabasz Index: 49.67
Number of clusters: 10, Calinski-Harabasz Index: 46.25
```



Kualitas pengelompokkan Kabupaten/Kota berdasarkan variabel prediktor menjadi 2 klaster dapat dinilai melalui nilai Silhouette dan Calinski-Harabasz Index. Kedua metrik ini menunjukkan bahwa pemilihan 2 klaster adalah keputusan yang optimal, karena keduanya mencapai titik tertinggi pada jumlah klaster tersebut.

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report

#splitting training & testing + all scalling
srcz_df['Cluster']=labels
srcz_df['StuntCatNum']= src['Stunt CatNum']

Xc = srcz_df.iloc[:, list(range(1, 21))]
Yc = srcz_df.iloc[:, 22]
xc_train, xc_test, yc_train, yc_test = train_test_split(Xc, Yc,
test_size=0.2, random_state=1)
print ('Train set:',xc_train.shape, yc_train.shape)
print ('Test set:', xc_test.shape, yc_test.shape)

Train set: (416, 20) (416,)
Test set: (104, 20) (104,)

from sklearn import svm
model_SVM = svm.SVC(kernel='linear')
```

```
model_SVM.fit(xc_train, yc_train)
yc_pred_SVM = model_SVM.predict(xc_test)
print(classification_report(yc_test, yc_pred_SVM))
```

```
              precision    recall  f1-score   support

           0       1.00      0.80      0.89        20
           1       0.83      0.83      0.83         6
           2       0.67      1.00      0.80         2
           3       0.88      1.00      0.93         7
           4       0.88      0.94      0.91        31
           6       0.89      0.89      0.89         9
           7       1.00      0.86      0.92         7
           8       1.00      0.71      0.83         7
           9       0.78      0.93      0.85        15

    accuracy                           0.88       104
   macro avg       0.88      0.88      0.87       104
weighted avg       0.90      0.88      0.88       104
```

```
from sklearn import svm
model_SVM = svm.SVC(kernel='rbf')
model_SVM.fit(xc_train, yc_train)
yc_pred_SVM = model_SVM.predict(xc_test)
print(classification_report(yc_test, yc_pred_SVM))
```

```
              precision    recall  f1-score   support

           0       1.00      0.80      0.89        20
           1       1.00      0.83      0.91         6
           2       1.00      1.00      1.00         2
           3       0.70      1.00      0.82         7
           4       0.90      0.90      0.90        31
           6       0.90      1.00      0.95         9
           7       1.00      0.71      0.83         7
           8       1.00      0.71      0.83         7
           9       0.75      1.00      0.86        15

    accuracy                           0.88       104
   macro avg       0.92      0.89      0.89       104
weighted avg       0.91      0.88      0.89       104
```

```
from sklearn import svm
model_SVM = svm.SVC(kernel='sigmoid')
model_SVM.fit(xc_train, yc_train)
yc_pred_SVM = model_SVM.predict(xc_test)
print(classification_report(yc_test, yc_pred_SVM))
```

```
              precision    recall  f1-score   support

           0       1.00      0.80      0.89        20
           1       1.00      0.33      0.50         6
           2       0.06      0.50      0.10         2
           3       0.80      0.57      0.67         7
           4       0.90      0.90      0.90        31
           6       0.90      1.00      0.95         9
           7       1.00      0.71      0.83         7
           8       0.00      0.00      0.00         7
           9       0.76      0.87      0.81        15

    accuracy                           0.75       104
   macro avg       0.71      0.63      0.63       104
weighted avg       0.83      0.75      0.77       104
```

```python
from sklearn import svm
model_SVM = svm.SVC(kernel='poly')
model_SVM.fit(xc_train, yc_train)
yc_pred_SVM = model_SVM.predict(xc_test)
print(classification_report(yc_test, yc_pred_SVM))
```

```
              precision    recall  f1-score   support

           0       1.00      0.50      0.67        20
           1       1.00      0.67      0.80         6
           2       1.00      1.00      1.00         2
           3       1.00      0.86      0.92         7
           4       0.49      1.00      0.66        31
           6       1.00      0.44      0.62         9
           7       1.00      0.43      0.60         7
           8       1.00      0.86      0.92         7
           9       0.50      0.20      0.29        15

    accuracy                           0.66       104
   macro avg       0.89      0.66      0.72       104
weighted avg       0.78      0.66      0.65       104
```