Amaya Eshia - 0110224102 - 24TI06 - AI02

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

Load Data

```
# menghubungkan colab dengan google drive
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
# MEmanggil dataset via gdrive
path = "/content/drive/MyDrive/Praktikum Machine Learning_Amaya Eshia_0110224102_Ai02/Praktikum 7 (Review)/Data/dataset_satelit.csv"
```

```
df = pd.read_csv('/content/drive/MyDrive/Praktikum Machine Learning_Amaya Eshia_0110224102_Ai02/Praktikum 7 (Review)/Data/dataset_satelit.csv')
df.head()
```

	No	Longitude	Lattitude	N	P	K	Ca	Mg	Fe	Mn	...	b1	Sigma_VV	Sigma_VH	plia	lia	iafe	gamma0_vv	gamma0_vh	beta0_vv	beta0_vh
0	1	103.036658	-0.604417	2.64	0.15	0.415	0.51	0.31	119.96	463.23	...	0.0433	0.18183	0.04461	35.74446	35.79744	35.41161	0.22331	0.05479	0.31325	0.07686
1	2	103.037201	-0.604689	2.75	0.17	0.568	0.76	0.58	102.63	493.81	...	0.0465	0.22079	0.04640	35.12096	35.14591	35.41510	0.27116	0.05699	0.38033	0.07993
2	3	103.036359	-0.603012	1.77	0.12	0.339	0.49	0.6	107.37	460.93	...	0.0417	0.18926	0.03992	35.07724	35.07730	35.41135	0.23242	0.04902	0.32604	0.06876
3	4	103.036950	-0.603219	2.30	0.15	0.460	0.74	0.67	96.02	338.17	...	0.0367	0.14769	0.03622	36.08078	36.08469	35.41583	0.18138	0.04448	0.25440	0.06238
4	5	103.036802	-0.601969	2.05	0.14	0.308	0.64	0.72	87.01	384.33	...	0.0361	0.18205	0.03797	32.68855	32.69293	35.41592	0.22359	0.04664	0.31359	0.06541

5 rows × 34 columns

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 594 entries, 0 to 593
Data columns (total 34 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   No         594 non-null    int64  
 1   Longitude  594 non-null    float64
 2   Lattitude  594 non-null    float64
 3   N          594 non-null    float64
 4   P          594 non-null    float64
```

```
 5   K          593 non-null    float64
 6   Ca         594 non-null    float64
 7   Mg         594 non-null    object 
 8   Fe         594 non-null    float64
 9   Mn         594 non-null    float64
 10  Cu         594 non-null    float64
 11  Zn         594 non-null    float64
 12  B          594 non-null    float64
 13  b12        594 non-null    float64
 14  b11        594 non-null    float64
 15  b9         594 non-null    float64
 16  b8a        594 non-null    float64
 17  b8         594 non-null    float64
 18  b7         594 non-null    float64
 19  b6         594 non-null    float64
 20  b5         594 non-null    float64
 21  b4         594 non-null    float64
 22  b3         594 non-null    float64
 23  b2         594 non-null    float64
 24  b1         594 non-null    float64
 25  Sigma_VV   594 non-null    float64
 26  Sigma_VH   594 non-null    float64
 27  plia       594 non-null    float64
 28  lia        594 non-null    float64
 29  iafe       594 non-null    float64
 30  gamma0_vv  594 non-null    float64
 31  gamma0_vh  594 non-null    float64
 32  beta0_vv   594 non-null    float64
 33  beta0_vh   594 non-null    float64
dtypes: float64(32), int64(1), object(1)
memory usage: 157.9+ KB
```

```
df.describe()
```

	No	Longitude	Lattitude	N	P	K	Ca	Fe	Mn	Cu	...	b1	Sigma_VV	Sigma_VH	plia	lia	
count	594.000000	594.000000	594.000000	594.000000	594.000000	593.000000	594.000000	594.000000	594.000000	594.000000	...	594.000000	594.000000	594.000000	594.000000	594.000000	594
mean	297.500000	106.878644	-1.024933	2.259091	0.141380	0.582175	0.595094	74.613771	308.034697	2.391195	...	0.177291	0.234474	0.102789	28.640422	28.664891	28
std	171.617307	4.949840	0.965349	0.395499	0.019782	0.222567	0.366118	55.579655	241.731643	1.580296	...	0.155615	0.070516	0.112310	15.325347	15.380384	15
min	1.000000	102.760857	-2.333750	1.140000	0.090000	0.122000	0.050000	21.080000	3.160000	0.090000	...	0.014100	0.115170	0.021460	0.127000	0.098600	0
25%	149.250000	102.927811	-2.233338	1.982500	0.130000	0.429000	0.320000	40.705000	124.015000	1.172500	...	0.046925	0.183210	0.039535	31.959745	31.968948	33
50%	297.500000	103.581969	-0.602276	2.280000	0.140000	0.549000	0.540000	65.650000	239.445000	2.225000	...	0.072700	0.213385	0.046550	35.067930	35.110415	34
75%	445.750000	113.403797	-0.257349	2.570000	0.150000	0.710000	0.790000	87.372500	434.990000	3.357500	...	0.318900	0.262242	0.059190	38.319135	38.441065	39
max	594.000000	113.434700	0.069251	3.230000	0.220000	1.489000	2.820000	559.100000	2009.320000	8.170000	...	0.751400	0.512210	0.373000	47.592900	48.014640	39

8 rows × 33 columns

```
df.columns
```

```
Index(['No', 'Longitude', 'Lattitude', 'N', 'P', 'K', 'Ca', 'Mg', 'Fe', 'Mn',
       'Cu', 'Zn', 'B', 'b12', 'b11', 'b9', 'b8a', 'b8', 'b7', 'b6', 'b5',
       'b4', 'b3', 'b2', 'b1', 'Sigma_VV', 'Sigma_VH', 'plia', 'lia', 'iafe',
```

```
       'gamma0_vv', 'gamma0_vh', 'beta0_vv', 'beta0_vh'],
      dtype='object')
```

```
# Ubah kolom Mg ke float

df['Mg'] = pd.to_numeric(df['Mg'], errors='coerce')

# Hilangkan baris yang ada missing value
df = df.dropna()
```

Feature Selection

```
# x = df[['b2','b3','b4','b8','b11','Sigma_VV','Sigma_VH']]
# y = df['N']
```

```
x = df[['P', 'K', 'Ca', 'Mg', 'Fe', 'Mn',
       'Cu', 'Zn', 'B', 'b12', 'b11', 'b9', 'b8a', 'b8', 'b7', 'b6', 'b5',
       'b4', 'b3', 'b2', 'b1', 'Sigma_VV', 'Sigma_VH', 'plia', 'lia', 'iafe',
       'gamma0_vv', 'gamma0_vh', 'beta0_vv', 'beta0_vh']]

y = df['N']
```

Splitting Data

```
x_train, x_test, y_train, y_test = train_test_split(
    x, y, test_size=0.2, random_state=42)
```

```
model = LinearRegression()
model.fit(x_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

MACHINE

```
# Testing
y_pred = model.predict(x_test)

# EValuasi Model
r2 = r2_score(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)

print("R2 Score :", r2)
print("RMSE :", mse)
```

```
R2 Score : 0.7549955124484078
RMSE : 0.037605716475545996
```

```
coeff = pd.DataFrame({
    'Fitur' : x.columns,
    'Koefisien' : model.coef_
})

print(coeff)
```

```
        Fitur  Koefisien
0           P   8.570837
1           K   0.056014
2          Ca  -0.058380
3          Mg  -0.161095
4          Fe   0.000284
5          Mn   0.000177
6          Cu   0.023202
7          Zn   0.002968
8           B  -0.002092
9         b12   0.327312
10        b11  -0.619437
11         b9  -0.047586
12        b8a   0.064453
13         b8  -0.072659
14         b7   0.981186
15         b6  -0.864947
16         b5  -0.329397
17         b4   1.420614
18         b3  -0.449043
19         b2  -0.357454
20         b1  -0.033418
21   Sigma_VV   0.156595
22   Sigma_VH  -1.466200
23       plia   0.021315
24        lia  -0.021906
25       iafe  -0.078122
26  gamma0_vv   0.457327
27  gamma0_vh   2.946416
28   beta0_vv  -0.569281
29   beta0_vh  -0.677599
```

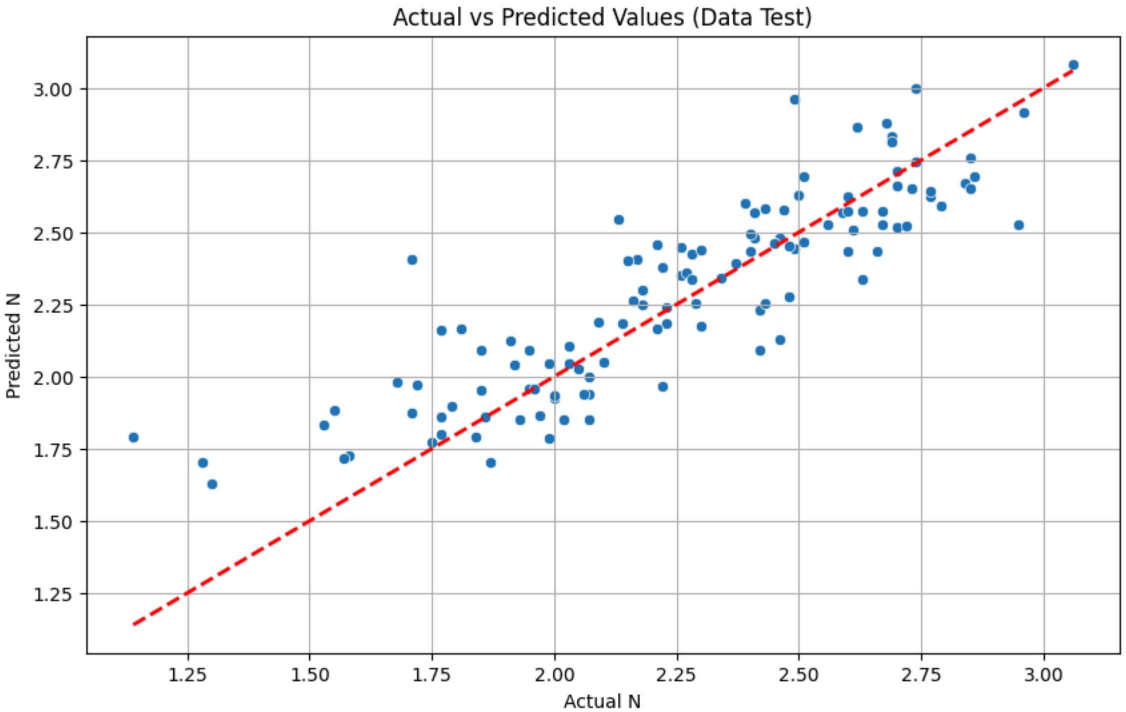
```
import statsmodels.api as sm

x_sm = sm.add_constant(x)
model_ols = sm.OLS(y, x_sm).fit()
print(model_ols.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      N   R-squared:                       0.779
Model:                            OLS   Adj. R-squared:                  0.768
Method:                 Least Squares   F-statistic:                     66.10
Date:                Sun, 09 Nov 2025   Prob (F-statistic):          6.69e-163
Time:                        14:45:07   Log-Likelihood:                 156.68
No. Observations:                 592   AIC:                            -251.4
Df Residuals:                     561   BIC:                            -115.5
Df Model:                          30
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          3.8681      0.864      4.479      0.000       2.172       5.564
P              8.5760      0.465     18.428      0.000       7.662       9.490
K              0.0273      0.051      0.530      0.596      -0.074       0.128
Ca            -0.0416      0.023     -1.808      0.071      -0.087       0.004
Mg            -0.2166      0.063     -3.464      0.001      -0.339      -0.094
Fe             0.0002      0.000      1.102      0.271      -0.000       0.001
Mn             0.0002   4.59e-05      4.083      0.000    9.72e-05       0.000
Cu             0.0229      0.006      4.046      0.000       0.012       0.034
Zn             0.0024      0.001      1.889      0.059   -9.52e-05       0.005
B             -0.0022      0.001     -1.476      0.141      -0.005       0.001
b12            0.2010      0.534      0.377      0.707      -0.848       1.250
b11           -0.9945      0.517     -1.922      0.055      -2.011       0.022
b9            -0.0802      0.067     -1.191      0.234      -0.212       0.052
b8a            0.0962      0.067      1.427      0.154      -0.036       0.229
b8            -0.0806      0.024     -3.362      0.001      -0.128      -0.034
b7             1.3059      0.542      2.409      0.016       0.241       2.371
b6            -0.9238      0.462     -2.001      0.046      -1.831      -0.017
b5            -0.5470      0.488     -1.120      0.263      -1.506       0.412
b4             1.2561      0.972      1.292      0.197      -0.653       3.166
b3             0.3085      1.639      0.188      0.851      -2.910       3.527
b2            -0.7075      0.942     -0.751      0.453      -2.559       1.144
b1             0.0023      0.352      0.006      0.995      -0.689       0.694
Sigma_VV       0.9543      0.889      1.074      0.283      -0.792       2.700
Sigma_VH      -1.1666      0.861     -1.356      0.176      -2.857       0.524
plia          -0.0113      0.071     -0.159      0.873      -0.150       0.128
lia            0.0102      0.071      0.144      0.886      -0.129       0.149
iafe          -0.0802      0.023     -3.475      0.001      -0.126      -0.035
gamma0_vv     -0.5040      2.180     -0.231      0.817      -4.785       3.777
gamma0_vh      3.1827      4.643      0.685      0.493      -5.938      12.303
beta0_vv      -0.2381      1.580     -0.151      0.880      -3.342       2.865
beta0_vh      -0.5472      3.536     -0.155      0.877      -7.493       6.399
==============================================================================
Omnibus:                       28.388   Durbin-Watson:                   1.527
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               53.216
Skew:                          -0.310   Prob(JB):                     2.78e-12
Kurtosis:                       4.332   Cond. No.                     2.98e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.98e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

```
import matplotlib.pyplot as plt

print("\nVisualisasi Hasil Model")
```

```
# 1. Scatter plot: Actual vs Predicted
plt.figure(figsize=(10, 6))
# Plot titik-titik data (aktual vs prediksi)
sns.scatterplot(x=y_test, y=y_pred)
# Plot garis diagonal merah (x=y) sebagai referensi
# Jika titik-titik mendekati garis ini, prediksinya bagus
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--', lw=2)
plt.title('Actual vs Predicted Values (Data Test)')
plt.xlabel('Actual N')
plt.ylabel('Predicted N')
plt.grid(True)
plt.show()
```

```
Visualisasi Hasil Model
```




```
# Analisis Residual (pada Data Training)
# Kita perlu prediksi pada data training untuk analisis residual
y_train_pred = model.predict(x_train)
residuals = y_train - y_train_pred

print("\n Analisis Residual (pada Data Training)")

# Plot Residuals vs Predicted
# Cek asumsi Homoskedastisitas (varian error konstan)
plt.figure(figsize=(10, 6))
```

```
sns.scatterplot(x=y_train_pred, y=residuals)
plt.axhline(0, color='red', linestyle='--') # Garis horizontal di y=0
plt.title('Residuals vs Predicted Values')
plt.xlabel('Predicted N (Training)')
plt.ylabel('Residuals')
plt.grid(True)
plt.show()

# Histogram Residuals
# Mengecek asumsi Normalitas (error terdistribusi normal)
plt.figure(figsize=(10, 6))
sns.histplot(residuals, kde=True)
plt.title('Histogram of Residuals')
plt.xlabel('Residual')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```

```
Analisis Residual (pada Data Training)
```