UTS Deep Learning - No 1

Nama: Farren Angelica Dinzani

NIM: 2702243546

Dataset: 1A

Link video:

https://drive.google.com/file/d/1JV4M9mNmjGevwa4qRj6FSAwViduDzjDr/viev

usp=sharing

EDA & PREPROCESSING

```
In [1]: import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder, StandardScaler, OneHotEncode
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer

import warnings
warnings.filterwarnings('ignore')
```

Read data

```
In [2]: df = pd.read_parquet('dataset_1A.parquet')
    df.head()
```

Out[2]:		Month	Hour	DayOfWeek	Holiday	Temperature	Humidity	SquareFootage	Occupancy
	0	8	3	Sunday	Yes	24.492063	59.969085	1403.454805	7
	1	1	8	Wednesday	No	26.312114	51.408711	1220.547133	8
	2	1	19	Sunday	Yes	20.516186	40.918500	1114.230124	8
	3	7	3	Wednesday	Yes	20.879426	46.859237	1096.207227	7
	4	10	17	Saturday	No	23.015216	48.998158	1999.982252	1

Informasi data

```
In [3]: df.shape
Out[3]: (1232, 12)
In [4]: df.info()
```

> <class 'pandas.core.frame.DataFrame'> RangeIndex: 1232 entries, 0 to 1231 Data columns (total 12 columns):

#	Column	Non-Null Count	Dtype			
0	Month	1232 non-null	object			
1	Hour	1232 non-null	int64			
2	DayOfWeek	1232 non-null	object			
3	Holiday	1232 non-null	object			
4	Temperature	1232 non-null	float64			
5	Humidity	1232 non-null	float64			
6	SquareFootage	1232 non-null	float64			
7	Occupancy	1232 non-null	int64			
8	HVACUsage	1232 non-null	object			
9	LightingUsage	1232 non-null	object			
10	RenewableEnergy	1232 non-null	float64			
11	EnergyConsumption	1232 non-null	object			
dtyp	dtypes: float64(4), int64(2), object(6)					

memory usage: 115.6+ KB

- Dataset terdiri dari 12 kolom.
- Memua kolom memiliki nilai non-null yang cukup.
- Kolom EnergyConsumption yang perlu diubah menjadi tipe float.

```
df['EnergyConsumption'] = pd.to_numeric(df['EnergyConsumption'], errors='coe
        df['Month'].value_counts()
In [6]:
                       189
Out[6]:
                       119
         10
                       115
         3
                       100
         12
                        99
                        95
         6
                        93
         11
         8
                        90
         7
                        88
         5
                        84
         9
                        83
         2
                        64
         Sep
                         7
                         4
         July
                         2
         September
         Name: Month, dtype: int64
```

Pada kolom 'Month' terdapat data yang tidak sesuai dengan format yang diharapkan. Data tersebut adalah 'Sep', 'July', dan 'September'. Harus diubah menjadi '9', '7', dan '9'

agar sesuai dengan format.

```
In [ ]:
        df['Month'] = df['Month'].replace({'Sep': 9, 'July': 7, 'September': 9})
```

Ubah data type 'Month' menjadi int

```
In [8]:
        df['Month'] = df['Month'].astype(int)
In [9]:
        df.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1232 entries, 0 to 1231
Data columns (total 12 columns):

```
#
    Column
                       Non-Null Count
                                       Dtype
 0
    Month
                       1232 non-null
                                       int64
 1
    Hour
                       1232 non-null
                                       int64
 2
    DayOfWeek
                       1232 non-null
                                       object
 3
    Holiday
                       1232 non-null
                                       object
 4
    Temperature
                       1232 non-null
                                       float64
    Humidity
 5
                       1232 non-null
                                       float64
 6
                       1232 non-null
                                       float64
    SquareFootage
 7
    Occupancy
                       1232 non-null
                                       int64
 8
    HVACUsage
                       1232 non-null
                                       object
 9
    LightingUsage
                                       object
                       1232 non-null
 10 RenewableEnergy
                       1232 non-null
                                       float64
 11 EnergyConsumption 1229 non-null
                                       float64
dtypes: float64(5), int64(3), object(4)
```

```
memory usage: 115.6+ KB

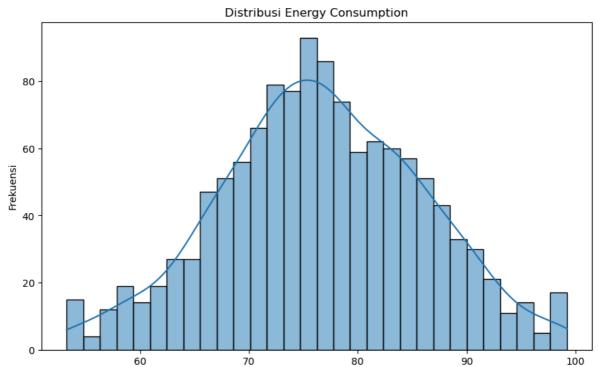
In [10]: df.columns
```

Prepare data (input & target)

```
In [ ]: df_input=df[['Month', 'Hour', 'Holiday', 'Temperature', 'Humidity','SquareFootdataget=df[['EnergyConsumption']]
```

Visualisasi distribusi kolom target: EnergyConsumption

```
In []: plt.figure(figsize=(10, 6))
    sns.histplot(df['EnergyConsumption'], bins=30, kde=True)
    plt.title('Distribusi Energy Consumption')
    plt.xlabel('Energy Consumption')
    plt.ylabel('Frekuensi')
    plt.show()
```



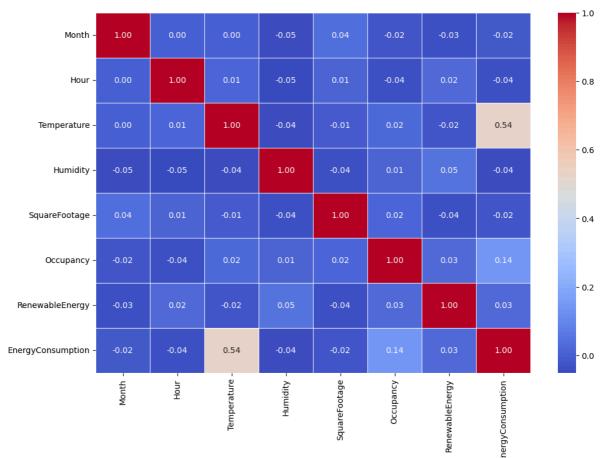
• Data terdistribusi hampir normal, dengan sebagian besar nilai EnergyConsumption berkisar antara 60 hingga 90.

Energy Consumption

• Menunjukkan bahwa sebagian besar gedung memiliki konsumsi energi yang serupa.

Visualisasi korelasi antar fitur

```
In []: plt.figure(figsize=(12, 8))
    correlation_matrix = df.corr()
    sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap="coolwarm", line
Out[]: <Axes: >
```



- Temperature memiliki korelasi yang cukup kuat dengan EnergyConsumption.
- Masuk akal karena suhu ruangan dapat mempengaruhi penggunaan energi untuk pendinginan atau pemanasan.

Data splitting

Menjadi train, val, dan test dengan proporsi 70:10:20

```
In [ ]: X_train, X_temp, y_train, y_temp = train_test_split(df_input, df_target, test_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.
```

Cek missing value

```
print(X_train.isnull().sum())
In []:
        Month
                             0
         Hour
                             0
         Holiday
         Temperature
                             0
         Humidity
                             0
                             0
         SquareFootage
                             0
         Occupancy
         HVACUsage
                             0
         LightingUsage
                             0
         RenewableEnergy
         dtype: int64
         Tidak ada missing value
```

```
In [16]: X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 862 entries, 2 to 1126
Data columns (total 10 columns):
#
     Column
                      Non-Null Count
                                      Dtype
 0
    Month
                      862 non-null
                                      int64
 1
    Hour
                      862 non-null
                                      int64
 2
    Holiday
                      862 non-null
                                      object
 3
    Temperature
                      862 non-null
                                      float64
                                      float64
    Humidity
                      862 non-null
 5
    SquareFootage
                      862 non-null
                                      float64
 6
     Occupancy
                      862 non-null
                                      int64
 7
    HVACUsage
                      862 non-null
                                      object
 8
    LightingUsage
                      862 non-null
                                      object
     RenewableEnergy 862 non-null
                                      float64
dtypes: float64(4), int64(3), object(3)
memory usage: 74.1+ KB
```

Encoding

Kolom Holiday, HVACUsage, dan LightingUsage adalah variabel kategorikal dengan nilai Yes/No atau On/Off yang perlu diubah menjadi 1/0 untuk dapat digunakan dalam model.

```
In []: X_train['Holiday'] = X_train['Holiday'].map({'Yes': 1, 'No': 0})
    X_test['Holiday'] = X_test['Holiday'].map({'Yes': 1, 'No': 0})
    X_val['Holiday'] = X_val['Holiday'].map({'Yes': 1, 'No': 0})

X_train['HVACUsage'] = X_train['HVACUsage'].map({'On': 1, 'Off': 0})
    X_test['HVACUsage'] = X_test['HVACUsage'].map({'On': 1, 'Off': 0})

X_train['LightingUsage'] = X_train['LightingUsage'].map({'On': 1, 'Off': 0})

X_test['LightingUsage'] = X_test['LightingUsage'].map({'On': 1, 'Off': 0})
    X_val['LightingUsage'] = X_val['LightingUsage'].map({'On': 1, 'Off': 0})
```

cek NaN

```
In []: print(np.any(np.isnan(X_train)))
    print(np.any(np.isnan(y_train)))

    print(np.any(np.isnan(X_test)))
    print(np.any(np.isnan(y_test)))

    print(np.any(np.isnan(X_val)))

    print(np.any(np.isnan(y_val)))

False
    True
    False
    False
```

Terdapat NaN pada y_train, dan lakukan fillna untuk mengisi nilai NaN dengan mean.

```
In [ ]: y_train = y_train.fillna(y_train.mean())
```

Standard Scaling

```
In []: standard_scaler = StandardScaler()

X_train_standardized = standard_scaler.fit_transform(X_train)
X_val_standardized = standard_scaler.transform(X_val)
X_test_standardized = standard_scaler.transform(X_test)
```

Cek data sebelum melakukan model

In [108 X_test.head()									
Out[108]:		Month	Hour	Holiday	Temperature	Humidity	SquareFootage	Occupancy	HVACU
	1219	8	12	1	20.126991	51.408470	1492.203415	7	
	355	2	1	1	26.823037	39.000664	1998.439525	3	
	415	3	15	0	29.998671	43.798996	1404.058579	3	
	310	2	5	1	28.295123	42.784629	1141.161725	1	
	344	11	15	1	27.558304	35.324520	1206.614730	1	
<pre>In [23]: import tensorflow as tf # Mendapatkan daftar perangkat fisik GPU physical_devices = tf.config.list_physical_devices('GPU') # Nonaktifkan GPU dengan menyembunyikan GPU if len(physical_devices) > 0: tf.config.set_visible_devices([], 'GPU')</pre>									

SEQUENTIAL MODEL

Dalam model ini, setiap lapisan (layer) tersambung secara berurutan dari lapisan input hingga lapisan output.

Pembuatan model Sequential

- Input layer: Jumlah fitur = 10
- Hidden layer: Jumlah neuron untuk setiap layer adalah 20, karena input memiliki 10 fitur
- Output layer: Memiliki 1 neuron karena kita melakukan regresi, di mana kita ingin memprediksi EnergyConsumption, yang merupakan nilai kontinu.
- Compile model: Fungsi loss yang digunakan adalah mean_squared_error (MSE), ideal untuk regresi.

```
import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras import layers, Input, Model
import tensorflow as tf

input_dim = X_train.shape[1]

model_sequential = Sequential()

model_sequential.add(tf.keras.Input(shape=(input_dim,)))
```

Model: "sequential"

Layer (type)	Output Shape	Para
dense (Dense)	(None, 20)	
dense_1 (Dense)	(None, 20)	
dense_2 (Dense)	(None, 1)	

Total params: 661 (2.58 KB)

Trainable params: 661 (2.58 KB)

Non-trainable params: 0 (0.00 B)

Training: Model dilatih menggunakan 15 epoch.

```
In [ ]: model_sequential.fit(X_train, y_train, epochs=15, validation_data=(X_val, y_
```

```
Epoch 1/15
                      --- 0s 3ms/step - loss: 61.7545 - mae: 6.2082 - map
27/27 -
e: 8.2447 - root_mean_squared_error: 7.8521 - val_loss: 85.4363 - val_mae:
7.6835 - val_mape: 10.1452 - val_root_mean_squared_error: 9.2432
Epoch 2/15
27/27 -
                      Os 2ms/step - loss: 65.4547 - mae: 6.3566 - map
e: 8.4657 - root mean squared error: 8.0886 - val loss: 90.0275 - val mae:
7.9099 - val_mape: 10.3797 - val_root_mean_squared_error: 9.4883
Epoch 3/15
                      Os 2ms/step - loss: 68.3369 - mae: 6.5088 - map
27/27 -
e: 8.5728 - root_mean_squared_error: 8.2646 - val_loss: 75.2581 - val_mae:
6.5077 - val_mape: 9.1421 - val_root_mean_squared_error: 8.6751
Epoch 4/15
27/27 -
                      Os 2ms/step - loss: 69.7819 - mae: 6.5294 - map
e: 8.7844 - root mean squared error: 8.3510 - val loss: 73.7685 - val mae:
6.8928 - val mape: 9.3496 - val root mean squared error: 8.5889
Epoch 5/15
27/27 -
                      Os 2ms/step - loss: 61.5166 - mae: 6.3112 - map
e: 8.4263 - root_mean_squared_error: 7.8409 - val_loss: 72.8996 - val_mae:
6.7872 - val_mape: 9.2489 - val_root_mean_squared_error: 8.5381
Epoch 6/15
                       — 0s 2ms/step - loss: 63.2037 - mae: 6.4156 - map
e: 8.5357 - root mean squared error: 7.9429 - val loss: 76.2150 - val mae:
6.5231 - val mape: 9.1875 - val root mean squared error: 8.7301
Epoch 7/15
                        — 0s 2ms/step - loss: 70.2456 - mae: 6.6787 - map
27/27 -
e: 9.0003 - root mean squared error: 8.3802 - val loss: 76.0833 - val mae:
7.1066 - val_mape: 9.5585 - val_root_mean_squared_error: 8.7226
Epoch 8/15
27/27 —
                     Os 2ms/step - loss: 66.8895 - mae: 6.6280 - map
e: 8.7517 - root_mean_squared_error: 8.1770 - val_loss: 76.8982 - val_mae:
7.1688 - val_mape: 9.6198 - val_root_mean_squared_error: 8.7692
Epoch 9/15
27/27 -
                  Os 2ms/step - loss: 62.1864 - mae: 6.3153 - map
e: 8.4618 - root mean squared error: 7.8813 - val loss: 72.0271 - val mae:
6.5605 - val_mape: 9.0662 - val_root_mean_squared_error: 8.4869
Epoch 10/15
27/27 -
                      Os 2ms/step - loss: 61.1945 - mae: 6.1599 - map
e: 8.2370 - root_mean_squared_error: 7.8028 - val_loss: 77.4493 - val_mae:
7.2085 - val_mape: 9.6609 - val_root_mean_squared_error: 8.8005
Epoch 11/15
                    Os 2ms/step - loss: 67.2476 - mae: 6.4562 - map
27/27 -
e: 8.5270 - root_mean_squared_error: 8.1993 - val_loss: 72.0824 - val_mae:
6.5429 - val_mape: 9.0601 - val_root_mean_squared_error: 8.4901
Epoch 12/15
                        — 0s 2ms/step - loss: 67.4649 - mae: 6.4994 - map
e: 8.7797 - root_mean_squared_error: 8.2021 - val_loss: 75.9357 - val_mae:
6.5116 - val_mape: 9.1648 - val_root_mean_squared_error: 8.7141
Epoch 13/15
                      Os 2ms/step - loss: 74.9500 - mae: 6.9464 - map
27/27 -
e: 9.2348 - root_mean_squared_error: 8.6511 - val_loss: 73.9596 - val mae:
6.5101 - val_mape: 9.1131 - val_root_mean_squared_error: 8.6000
Epoch 14/15
                 Os 2ms/step - loss: 69.6439 - mae: 6.6325 - map
27/27 ——
e: 8.9266 - root_mean_squared_error: 8.3440 - val_loss: 77.9204 - val_mae:
7.2403 - val_mape: 9.6944 - val_root_mean_squared_error: 8.8273
Epoch 15/15
27/27 -
                      Os 2ms/step - loss: 63.9658 - mae: 6.4420 - map
e: 8.5346 - root_mean_squared_error: 7.9923 - val_loss: 71.8889 - val_mae:
6.5792 - val_mape: 9.0749 - val_root_mean_squared_error: 8.4787
<keras.src.callbacks.history.History at 0x2d2c18850>
```

Out[]:

FUNCTIONAL MODEL

Lebih fleksibel dibandingkan Sequential Model. Functional memungkinkan pembuatan model yang lebih kompleks dengan berbagai input, output, dan koneksi yang lebih rumit.

Pembuatan model Functional

- Input layer: Jumlah fitur = 10
- Hidden layer: Jumlah neuron untuk setiap layer adalah 20, karena input memiliki 10 fitur
- Output layer: Memiliki 1 neuron karena kita melakukan regresi, di mana kita ingin memprediksi EnergyConsumption, yang merupakan nilai kontinu.
- Compile model: Fungsi loss yang digunakan adalah mean_squared_error (MSE), ideal untuk regresi.

Functional Model Summary:
Model: "functional_3"

Layer (type)	Output Shape	Para
<pre>input_layer_1 (InputLayer)</pre>	(None, 10)	
dense_3 (Dense)	(None, 20)	
dense_4 (Dense)	(None, 20)	
dense_5 (Dense)	(None, 1)	

Total params: 661 (2.58 KB)

Trainable params: 661 (2.58 KB)

Non-trainable params: 0 (0.00 B)

Training: Model dilatih menggunakan 15 epoch.

```
In [ ]: model_functional.fit(X_train, y_train, epochs=15, validation_data=(X_val, y_
```

```
Epoch 1/15
27/27 - 0s - 4ms/step - loss: 72.3171 - mae: 6.9013 - mape: 9.1790 - root_m
ean_squared_error: 8.5039 - val_loss: 73.0154 - val_mae: 6.6162 - val_mape:
9.1384 - val_root_mean_squared_error: 8.5449
Epoch 2/15
27/27 - 0s - 3ms/step - loss: 73.3371 - mae: 6.8222 - mape: 9.0588 - root m
ean_squared_error: 8.5637 - val_loss: 77.4449 - val_mae: 7.1628 - val_mape:
9.6364 - val root mean squared error: 8.8003
Epoch 3/15
27/27 - 0s - 3ms/step - loss: 67.1327 - mae: 6.4978 - mape: 8.6627 - root m
ean_squared_error: 8.1935 - val_loss: 74.3012 - val_mae: 6.5541 - val_mape:
9.1479 - val_root_mean_squared_error: 8.6198
Epoch 4/15
27/27 - 0s - 3ms/step - loss: 66.4327 - mae: 6.4879 - mape: 8.6473 - root_m
ean squared error: 8.1506 - val loss: 74.0580 - val mae: 6.8401 - val mape:
9.3212 - val root mean squared error: 8.6057
Epoch 5/15
27/27 - 0s - 3ms/step - loss: 71.4347 - mae: 6.7012 - mape: 8.9125 - root_m
ean_squared_error: 8.4519 - val_loss: 74.7921 - val_mae: 6.9241 - val_mape:
9.3999 - val_root_mean_squared_error: 8.6482
Epoch 6/15
27/27 - 0s - 3ms/step - loss: 68.2584 - mae: 6.5547 - mape: 8.6917 - root m
ean squared error: 8.2619 - val loss: 73.0159 - val mae: 6.6657 - val mape:
9.1734 - val root mean squared error: 8.5449
Epoch 7/15
27/27 - 0s - 3ms/step - loss: 79.8708 - mae: 7.0246 - mape: 9.3411 - root_m
ean squared error: 8.9370 - val loss: 90.9948 - val mae: 7.9256 - val mape:
10.4097 - val_root_mean_squared_error: 9.5391
27/27 - 0s - 3ms/step - loss: 77.6849 - mae: 7.0689 - mape: 9.4095 - root_m
ean_squared_error: 8.8139 - val_loss: 88.8695 - val_mae: 7.8216 - val_mape:
10.3017 - val_root_mean_squared_error: 9.4271
Epoch 9/15
27/27 - 0s - 3ms/step - loss: 74.4918 - mae: 6.9592 - mape: 9.2541 - root m
ean squared error: 8.6309 - val loss: 79.4793 - val mae: 7.3051 - val mape:
9.7764 - val_root_mean_squared_error: 8.9151
Epoch 10/15
27/27 - 0s - 3ms/step - loss: 66.9765 - mae: 6.5214 - mape: 8.6914 - root_m
ean_squared_error: 8.1839 - val_loss: 74.2450 - val_mae: 6.8601 - val_mape:
9.3406 - val_root_mean_squared_error: 8.6166
Epoch 11/15
27/27 - 0s - 3ms/step - loss: 67.0780 - mae: 6.5162 - mape: 8.6833 - root_m
ean_squared_error: 8.1901 - val_loss: 72.9884 - val_mae: 6.6516 - val_mape:
9.1614 - val_root_mean_squared_error: 8.5433
Epoch 12/15
27/27 - 0s - 3ms/step - loss: 70.3250 - mae: 6.6899 - mape: 8.9025 - root_m
ean_squared_error: 8.3860 - val_loss: 73.7768 - val_mae: 6.5607 - val_mape:
9.1340 - val_root_mean_squared_error: 8.5893
Epoch 13/15
27/27 - 0s - 3ms/step - loss: 69.2405 - mae: 6.5967 - mape: 8.7707 - root_m
ean squared error: 8.3211 - val loss: 77.5449 - val mae: 7.1711 - val mape:
9.6444 - val_root_mean_squared_error: 8.8060
27/27 - 0s - 3ms/step - loss: 73.3149 - mae: 6.7915 - mape: 9.0519 - root_m
ean_squared_error: 8.5624 - val_loss: 92.4336 - val_mae: 7.9924 - val_mape:
10.4810 - val_root_mean_squared_error: 9.6142
Epoch 15/15
27/27 - 0s - 3ms/step - loss: 67.8459 - mae: 6.5494 - mape: 8.7061 - root_m
ean_squared_error: 8.2369 - val_loss: 73.1494 - val_mae: 6.7027 - val_mape:
9.2019 - val_root_mean_squared_error: 8.5527
<keras.src.callbacks.history.History at 0x2d4d08ed0>
```

file:///Users/farrenangelica/Desktop/binus/Data Science/sem 4/Deep Learning/2702243546/NOMOR 1.html

Out[]:

MODIFIKASI SEQUENTIAL MODEL

- 1. Input layer: sesuai dengan jumlah fitur input = 10
- 2. Hidden layer pertama:
 - menambah jumlah neuron menjadi tiga kali lipat dimensi input untuk meningkatkan kapasitas model.
 - Leaky ReLU mencegah masalah "dying neurons" dengan memberikan nilai kecil untuk nilai negatif (alpha=0.3).
 - Batch Normalization untuk membantu model belajar lebih cepat dan stabil.
 - Menggunakan Dropout sebesar 30% untuk mencegah overfitting.
- 3. Hidden layer kedua: Neuron lebih banyak lagi, konfigurasi sama.
- 4. Hidden layer ketiga: 2x jumlah neuron dari dimensi input.
- 5. Output layer: 1 neuron, karena kita melakukan tugas regresi untuk memprediksi nilai kontinu dari EnergyConsumption.

```
In []: from tensorflow.keras.models import Sequential
        from tensorflow.keras.layers import Dense, Dropout, BatchNormalization, Leal
        from tensorflow.keras.optimizers import Adam
        from tensorflow.keras.callbacks import EarlyStopping
        import tensorflow as tf
        model sequential modif = Sequential()
        # Input layer
        model sequential modif.add(tf.keras.Input(shape=(X train.shape[1],)))
        # Hidden layer pertama
        model_sequential_modif.add(Dense(3 * X_train.shape[1]))
        model_sequential_modif.add(LeakyReLU(alpha=0.3))
        model sequential modif.add(BatchNormalization())
        model_sequential_modif.add(Dropout(0.3))
        # Hidden layer kedua
        model_sequential_modif.add(Dense(3 * X_train.shape[1]))
        model_sequential_modif.add(LeakyReLU(alpha=0.3))
        model_sequential_modif.add(BatchNormalization())
        model_sequential_modif.add(Dropout(0.3))
        # Hidden layer ketiga
        model_sequential_modif.add(Dense(2 * X_train.shape[1]))
        model_sequential_modif.add(LeakyReLU(alpha=0.3))
        model_sequential_modif.add(BatchNormalization())
        model_sequential_modif.add(Dropout(0.3))
        # Output layer
        model_sequential_modif.add(Dense(1))
        optimizer = Adam(learning_rate=0.0005)
        model_sequential_modif.compile(optimizer=optimizer, loss='mean_squared_error
                                         metrics=[tf.keras.metrics.RootMeanSquaredEri
        model_sequential_modif.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Para
dense_6 (Dense)	(None, 30)	
leaky_re_lu (LeakyReLU)	(None, 30)	
batch_normalization (BatchNormalization)	(None, 30)	
dropout (Dropout)	(None, 30)	
dense_7 (Dense)	(None, 30)	
leaky_re_lu_1 (LeakyReLU)	(None, 30)	
batch_normalization_1 (BatchNormalization)	(None, 30)	
dropout_1 (Dropout)	(None, 30)	
dense_8 (Dense)	(None, 20)	
leaky_re_lu_2 (LeakyReLU)	(None, 20)	
batch_normalization_2 (BatchNormalization)	(None, 20)	
dropout_2 (Dropout)	(None, 20)	
dense_9 (Dense)	(None, 1)	

Total params: 2,221 (8.68 KB)

Trainable params: 2,061 (8.05 KB)

Non-trainable params: 160 (640.00 B)

- Early stopping: Menghentikan training jika tidak ada perbaikan pada val_loss dalam 5 epoch berturut-turut.
- Training: Dilatih selama 50 epoch, dengan validation data untuk memantau overfitting. Early stopping memastikan bahwa pelatihan berhenti saat model mulai mengalami overfitting.

```
In [ ]: early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_
model_sequential_modif.fit(X_train, y_train, epochs=50, verbose=2, validation
```

```
Epoch 1/50
27/27 - 0s - 4ms/step - loss: 181.4971 - mae: 10.6602 - mape: 14.0420 - roo
t_mean_squared_error: 13.4721 - val_loss: 69.4552 - val_mae: 6.5999 - val_m
ape: 9.0207 - val_root_mean_squared_error: 8.3340
Epoch 2/50
27/27 - 0s - 3ms/step - loss: 195.4977 - mae: 11.2098 - mape: 14.8383 - roo
t_mean_squared_error: 13.9820 - val_loss: 69.0139 - val_mae: 6.5700 - val_m
ape: 8.9823 - val_root_mean_squared_error: 8.3075
Epoch 3/50
27/27 - 0s - 3ms/step - loss: 197.6206 - mae: 11.2334 - mape: 14.8261 - roo
t_mean_squared_error: 14.0578 - val_loss: 72.7347 - val_mae: 6.5698 - val_m
ape: 9.0922 - val_root_mean_squared_error: 8.5285
Epoch 4/50
27/27 - 0s - 3ms/step - loss: 198.1405 - mae: 11.1424 - mape: 14.6385 - roo
t mean squared error: 14.0762 - val loss: 72.2332 - val mae: 6.5568 - val m
ape: 9.0599 - val_root_mean_squared_error: 8.4990
Epoch 5/50
27/27 - 0s - 3ms/step - loss: 217.8742 - mae: 11.5849 - mape: 15.2590 - roo
t_mean_squared_error: 14.7606 - val_loss: 73.9926 - val_mae: 6.9924 - val_m
ape: 9.3582 - val_root_mean_squared_error: 8.6019
Epoch 6/50
27/27 - 0s - 3ms/step - loss: 204.9069 - mae: 11.3801 - mape: 14.9843 - roo
t mean squared error: 14.3146 - val loss: 77.0719 - val mae: 7.2365 - val m
ape: 9.5728 - val root mean squared error: 8.7791
Epoch 7/50
27/27 - 0s - 3ms/step - loss: 194.1683 - mae: 11.3432 - mape: 14.9572 - roo
t mean squared error: 13.9344 - val loss: 72.1202 - val mae: 6.8550 - val m
ape: 9.2419 - val_root_mean_squared_error: 8.4924
<keras.src.callbacks.history.History at 0x2db0d98d0>
```

MODIFIKASI FUNCTIONAL MODEL

- 1. Input layer: disesuaikan dengan dimensi input.
- 2. Hidden layer pertama:
 - Leaky ReLU untuk meningkatkan kapasitas model dan mencegah "dying neurons".
 - Batch Normalization dan Dropout untuk membantu pelatihan dan mencegah overfitting.
- 3. Hidden layer kedua: Neuron lebih banyak untuk menjaga generalisasi model.
- 4. Hidden layer ketiga: Neuron lebih banyak dan menerapkan Leaky ReLU, Batch Normalization, dan Dropout untuk layer tambahan.
- 5. Output layer: tetap 1 neuron karena kita melakukan regresi.

```
In []: from tensorflow.keras import Input, Model
    from tensorflow.keras.layers import Dense, Dropout, LeakyReLU, BatchNormaliz
    from tensorflow.keras.optimizers import Adam
    from tensorflow.keras.callbacks import EarlyStopping

inputs = Input(shape=(X_train.shape[1],))

# Hidden layer pertama
    x = Dense(3 * X_train.shape[1])(inputs)
    x = LeakyReLU(alpha=0.3)(x)
    x = BatchNormalization()(x)
    x = Dropout(0.3)(x)
```

```
# Hidden layer kedua
x = Dense(3 * X_train.shape[1])(x)
x = LeakyReLU(alpha=0.3)(x)
x = BatchNormalization()(x)
x = Dropout(0.3)(x)
# Hidden layer ketiga
x = Dense(2 * X_train.shape[1])(x)
x = LeakyReLU(alpha=0.3)(x)
x = BatchNormalization()(x)
x = Dropout(0.3)(x)
# Output layer
outputs = Dense(1)(x)
model_functional_modif = Model(inputs=inputs, outputs=outputs)
optimizer = Adam(learning_rate=0.0005) # Learning rate lebih rendah
model_functional_modif.compile(optimizer=optimizer, loss='mean_squared_error
                                metrics=[tf.keras.metrics.RootMeanSquaredEri
model_functional_modif.summary()
```

Model: "functional_17"

Layer (type)	Output Shape	Para
<pre>input_layer_3 (InputLayer)</pre>	(None, 10)	
dense_10 (Dense)	(None, 30)	
leaky_re_lu_3 (LeakyReLU)	(None, 30)	
batch_normalization_3 (BatchNormalization)	(None, 30)	
dropout_3 (Dropout)	(None, 30)	
dense_11 (Dense)	(None, 30)	
leaky_re_lu_4 (LeakyReLU)	(None, 30)	
batch_normalization_4 (BatchNormalization)	(None, 30)	
dropout_4 (Dropout)	(None, 30)	
dense_12 (Dense)	(None, 20)	
leaky_re_lu_5 (LeakyReLU)	(None, 20)	
batch_normalization_5 (BatchNormalization)	(None, 20)	
dropout_5 (Dropout)	(None, 20)	
dense_13 (Dense)	(None, 1)	

Total params: 2,221 (8.68 KB)

Trainable params: 2,061 (8.05 KB)

Non-trainable params: 160 (640.00 B)

Model dilatih selama 50 epoch dengan early stopping dan validation data untuk memantau performa.

```
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best]
In []:
        model_functional_modif.fit(X_train, y_train, epochs=50, verbose=2, validation
        Epoch 1/50
        27/27 - 0s - 4ms/step - loss: 195.3911 - mae: 10.9776 - mape: 14.4857 - roo
        t_mean_squared_error: 13.9782 - val_loss: 77.2608 - val_mae: 7.2373 - val_m
        ape: 9.5553 - val_root_mean_squared_error: 8.7898
        27/27 - 0s - 3ms/step - loss: 193.9443 - mae: 11.1688 - mape: 14.7077 - roo
        t_mean_squared_error: 13.9264 - val_loss: 112.9375 - val_mae: 8.9133 - val_
        mape: 11.3218 - val root mean squared error: 10.6272
        Epoch 3/50
        27/27 - 0s - 3ms/step - loss: 205.4549 - mae: 11.4398 - mape: 15.1007 - roo
        t_mean_squared_error: 14.3337 - val_loss: 71.8089 - val_mae: 6.6250 - val_m
        ape: 9.0282 - val_root_mean_squared_error: 8.4740
        Epoch 4/50
        27/27 - 0s - 3ms/step - loss: 194.7201 - mae: 10.9918 - mape: 14.5293 - roo
        t_mean_squared_error: 13.9542 - val_loss: 75.7124 - val_mae: 7.0928 - val_m
        ape: 9.4203 - val_root_mean_squared_error: 8.7013
        27/27 - 0s - 3ms/step - loss: 194.6088 - mae: 10.9449 - mape: 14.3597 - roo
        t_mean_squared_error: 13.9502 - val_loss: 91.6898 - val_mae: 8.0257 - val_m
        ape: 10.3717 - val_root_mean_squared_error: 9.5755
        Epoch 6/50
        27/27 - 0s - 3ms/step - loss: 186.6893 - mae: 10.9832 - mape: 14.4922 - roo
        t mean squared error: 13.6634 - val loss: 72.5401 - val mae: 6.6850 - val m
        ape: 9.1311 - val_root_mean_squared_error: 8.5170
        Epoch 7/50
        27/27 - 0s - 3ms/step - loss: 211.4969 - mae: 11.5716 - mape: 15.2949 - roo
        t_mean_squared_error: 14.5429 - val_loss: 74.1374 - val_mae: 6.8945 - val_m
        ape: 9.2877 - val_root_mean_squared_error: 8.6103
        Epoch 8/50
        27/27 - 0s - 3ms/step - loss: 197.5047 - mae: 11.1061 - mape: 14.6413 - roo
        t_mean_squared_error: 14.0536 - val_loss: 74.8698 - val_mae: 6.9946 - val_m
        ape: 9.3507 - val_root_mean_squared_error: 8.6527
        <keras.src.callbacks.history.History at 0x2d88d8310>
Out[]:
```

EVALUASI 4 MODEL

```
In []: from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_scol
# Evaluasi untuk Sequential Model (Original)
y_pred_sequential = model_sequential.predict(X_test)
mse_sequential = mean_squared_error(y_test, y_pred_sequential)
mae_sequential = mean_absolute_error(y_test, y_pred_sequential)
r2_sequential = r2_score(y_test, y_pred_sequential)

# Evaluasi untuk Functional Model (Original)
y_pred_functional = model_functional.predict(X_test)
mse_functional = mean_squared_error(y_test, y_pred_functional)
mae_functional = mean_absolute_error(y_test, y_pred_functional)
r2_functional = r2_score(y_test, y_pred_functional)

# Evaluasi untuk Sequential Model (Modified)
y_pred_sequential_modif = model_sequential_modif.predict(X_test)
mse_sequential_modif = mean_squared_error(y_test, y_pred_sequential_modif)
```

```
mae_sequential_modif = mean_absolute_error(y_test, y_pred_sequential_modif)
r2_sequential_modif = r2_score(y_test, y_pred_sequential_modif)
# Evaluasi untuk Functional Model (Modified)
y_pred_functional_modif = model_functional_modif.predict(X_test)
mse_functional_modif = mean_squared_error(y_test, y_pred_functional_modif)
mae_functional_modif = mean_absolute_error(y_test, y_pred_functional_modif)
r2_functional_modif = r2_score(y_test, y_pred_functional_modif)
# Menampilkan hasil evaluasi
print("Evaluasi Model:")
# Evaluasi Original Sequential Model
print("\n0riginal Sequential Model:")
print(f"MSE: {mse_sequential}, MAE: {mae_sequential}, R<sup>2</sup>: {r2_sequential}")
# Evaluasi Original Functional Model
print("\n0riginal Functional Model:")
print(f"MSE: {mse_functional}, MAE: {mae_functional}, R<sup>2</sup>: {r2_functional}")
# Evaluasi Modified Sequential Model
print("\nModified Sequential Model:")
print(f"MSE: {mse_sequential_modif}, MAE: {mae_sequential_modif}, R2: {r2_se
# Evaluasi Modified Functional Model
print("\nModified Functional Model:")
print(f"MSE: {mse_functional_modif}, MAE: {mae_functional_modif}, R2: {r2_functional_modif}
```

> 8/8 0s 5ms/step - 0s 5ms/step 8/8

WARNING:tensorflow:5 out of the last 17 calls to <function TensorFlowTraine r.make predict function.<locals>.one step on data distributed at 0x2daa5804 0> triggered tf.function retracing. Tracing is expensive and the excessive number of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2) passing tensors with different shapes, (3) passing Python objec ts instead of tensors. For (1), please define your @tf.function outside of the loop. For (2), @tf.function has reduce_retracing=True option that can a void unnecessary retracing. For (3), please refer to https://www.tensorflo w.org/guide/function#controlling_retracing and https://www.tensorflow.org/a pi_docs/python/tf/function for more details.

- 0s 9ms/step WARNING:tensorflow:5 out of the last 17 calls to <function TensorFlowTraine r.make predict function.<locals>.one step on data distributed at 0x2daa5a2a 0> triggered tf.function retracing. Tracing is expensive and the excessive number of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2) passing tensors with different shapes, (3) passing Python objec ts instead of tensors. For (1), please define your @tf.function outside of the loop. For (2), @tf.function has reduce_retracing=True option that can a void unnecessary retracing. For (3), please refer to https://www.tensorflo w.org/guide/function#controlling_retracing and https://www.tensorflow.org/a pi docs/python/tf/function for more details.

8/8 - 0s 9ms/step

Evaluasi Model:

Original Sequential Model:

MSE: 61.860305743374, MAE: 6.252115019364708, R²: 0.1754854133067154

Original Functional Model:

MSE: 62.45223043036776, MAE: 6.266800704254569, R²: 0.16759585419792467

Modified Sequential Model:

MSE: 57.56914201211439, MAE: 5.9893836617507645, R²: 0.23268084821113644

Modified Functional Model:

MSE: 57.59351134368601, MAE: 5.957974902223641, R²: 0.23235603783221392

Evaluasi Model dan Analisis

1. Original Sequential Model: MSE: 61.86, MAE: 6.25, R²: 0.175

Analisis: Model ini memiliki kesalahan prediksi yang tinggi dengan R² rendah, hanya menjelaskan 17.5% variasi dalam data.

2. Original Functional Model: MSE: 62.45, MAE: 6.27, R²: 0.168

Analisis: Performa hampir identik dengan Sequential Model. R² lebih rendah, yang menunjukkan bahwa model ini sedikit lebih buruk dalam menjelaskan variasi target.

3. Modified Sequential Model: MSE: 57.57, MAE: 5.99, R2: 0.233

Analisis: Modifikasi menunjukkan peningkatan signifikan dalam mengurangi kesalahan dan meningkatkan R² menjadi 23.3%, lebih baik dibandingkan model original.

4. Modified Functional Model: MSE: 57.59, MAE: 5.96, R2: 0.232

Analisis: Hasilnya sangat mirip dengan Modified Sequential Model, dengan sedikit perbedaan di MSE dan R².

Kesimpulan:

- Modified Sequential Model adalah yang paling optimal dengan MSE lebih rendah dan R^2 lebih tinggi dibandingkan model original dan Functional Model.

 Modifikasi dengan Leaky ReLU, Batch Normalization, dan Dropout meningkatkan kinerja model secara keseluruhan.