Import Libraries such as numpy,seaborn, pandas, and matplotlib.pyplot

Link onedrive(video penjelasan semua nomor):
https://binusianorg-my.sharepoint.com/personal/nicholas_javier_binus_ac_id/_layouts/15/guestaccess.aspx?share=ER_SwVOgwr1GgVXre8eBkjQBs8GBPpUdQTa-12VatGVNXw

Link onedrive(backup):
https://binusianorg-my.sharepoint.com/personal/nicholas_javier_binus_ac_id/_layouts/15/guestaccess.aspx?share=ER_SwVOgwr1GgVXre8eBkjQBs8GBPpUdQTa-12VatGVNXw&nav=eyJyZWZlcnJhbEluZm8iOnsicmVmZXJyYWxBcHAiOiJPbmVEcml2ZUZvckJ1c2luZXNzIiwicmVmZXJyYWxBcHBQbGF0Zm9ybSI6IldlYiIsInJlZmVycmFsTW9kZSI6InZpZXciLCJyZWZlcnJhbFZpZXciOiJNeUZpbGVzTGlua0NvcHkifX0&e=EZxLJy

Link youtube(video penjelasan semua nomor): https://youtu.be/IEJqxwOFtPM

```
import numpy as np
import seaborn as sns
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
```

Import library seperti numpy, seaborn, pandas, dan matplotlib pyplot.

NIM - Nama - Kelas : 2502041956 - Nicholas Javier - LA05

1. [LO 1, LO 2, LO 3, LO4 45 poin] You are an AI Engineer at a company working in the finance sector. Your team has been tasked with predicting the stock performance of Company "X". The provided dataset, stored as "X.csv", contains several important details about each column. For this task, you will be focusing solely on the 'Date' and 'Close' columns. Here are the key considerations you need to keep in mind while developing the Deep Learning architecture:

a. Before delving into the data analysis, it is essential to conduct an initial exploration of the dataset to comprehend the challenges inherent within it. The provided dataset is a time series, and it necessitates appropriate preprocessing to resolve any issues that may be present. The time series data should then be divided into two segments: input and output. This division should be structured with a window size of 5 and a horizon of 1, effectively setting up the framework for subsequent analysis.

Import X.csv

```
df = pd.read_csv("X.csv")
df.head(10)
```

```
         Date        Open        High         Low       Close    Adj
Close  \
0  2005-09-29  432.588074  436.787964  407.388763  432.588074
304.904572
1  2005-09-30  457.787384  457.787384  432.588074  457.787384
322.666016
2  2005-10-03  470.387024  474.586914  440.987854  470.387024
331.546692
3  2005-10-04  474.586914  482.986694  466.187164  474.586914
334.506927
4  2005-10-05  482.986694  482.986694  466.187164  482.986694
340.427429
```

```
5  2005-10-06  466.187164  482.986694  461.987274  466.187164
328.586487
6  2005-10-07  470.387024  470.387024  457.787384  470.387024
331.546692
7  2005-10-10  466.187164  470.387024  457.787384  466.187164
328.586487
8  2005-10-11  466.187164  466.187164  461.987274  466.187164
328.586487
9  2005-10-12  470.387024  474.586914  466.187164  470.387024
331.546692

        Volume
0   76180670.0
1  105493978.0
2   59712955.0
3   56236668.0
4   31319315.0
5    8107366.0
6    6577562.0
7   23223854.0
8   13497395.0
9   29804392.0
```

Find the info df

```
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3808 entries, 0 to 3807
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       3808 non-null   object
 1   Open       3807 non-null   float64
 2   High       3807 non-null   float64
 3   Low        3807 non-null   float64
 4   Close      3807 non-null   float64
 5   Adj Close  3807 non-null   float64
 6   Volume     3807 non-null   float64
dtypes: float64(6), object(1)
memory usage: 208.4+ KB
```

Find the missing data of each columns

```
df.isnull().sum()

Date         0
Open         1
High         1
```

```
Low          1
Close        1
Adj Close    1
Volume       1
dtype: int64
```

Drop the missing data of each columns

```
df1 = df.dropna()
df1.isnull().sum()
```

```
Date         0
Open         0
High         0
Low          0
Close        0
Adj Close    0
Volume       0
dtype: int64
```

Drop the duplicate data of each columns

```
df2 = df1.drop_duplicates()
df2
```

```
            Date         Open         High          Low
Close  \
0     2005-09-29   432.588074   436.787964   407.388763   432.588074

1     2005-09-30   457.787384   457.787384   432.588074   457.787384

2     2005-10-03   470.387024   474.586914   440.987854   470.387024

3     2005-10-04   474.586914   482.986694   466.187164   474.586914

4     2005-10-05   482.986694   482.986694   466.187164   482.986694

...          ...          ...          ...          ...          ...

3803  2021-01-28  2470.000000  2570.000000  2380.000000  2380.000000

3804  2021-01-29  2370.000000  2440.000000  2220.000000  2220.000000

3805  2021-02-01  2090.000000  2640.000000  2070.000000  2600.000000

3806  2021-02-02  2600.000000  2630.000000  2420.000000  2420.000000

3807  2021-02-03  2390.000000  2520.000000  2290.000000  2330.000000
```

```
        Adj Close        Volume
0      304.904572  7.618067e+07
1      322.666016  1.054940e+08
2      331.546692  5.971296e+07
3      334.506927  5.623667e+07
4      340.427429  3.131932e+07
...           ...           ...
3803  2380.000000  7.318549e+08
3804  2220.000000  4.503212e+08
3805  2600.000000  2.186653e+09
3806  2420.000000  9.424343e+08
3807  2330.000000  9.480310e+08

[3807 rows x 7 columns]
```

The code parses the 'Date' column into a datetime format and cleans numeric columns (Open, High, Low, Close, Adj Close, Volume) in the DataFrame df2 by removing dots and converting to float.

```
df2['Date'] = pd.to_datetime(df2['Date'], format='%Y/%m/%d')
columns_to_convert = ['Open', 'High', 'Low', 'Close', 'Adj Close',
'Volume']
df2[columns_to_convert] = df2[columns_to_convert].replace('\.', '',
regex=True).astype(float)
df2.head()
```

```
        Date        Open        High         Low       Close    Adj
Close  \
0 2005-09-29  432.588074  436.787964  407.388763  432.588074
304.904572
1 2005-09-30  457.787384  457.787384  432.588074  457.787384
322.666016
2 2005-10-03  470.387024  474.586914  440.987854  470.387024
331.546692
3 2005-10-04  474.586914  482.986694  466.187164  474.586914
334.506927
4 2005-10-05  482.986694  482.986694  466.187164  482.986694
340.427429

        Volume
0   76180670.0
1  105493978.0
2   59712955.0
3   56236668.0
4   31319315.0
```

Make a graph about Date throughout close

```
date_column = 'Date'
close_column = 'Close'

plt.plot_date(df2[date_column], df2[close_column], fmt='-',
color='green')
plt.gcf().autofmt_xdate()
plt.title(f'{date_column} throughout {close_column}')
plt.xlabel(date_column)
plt.ylabel(close_column)
plt.show()
```

This code normalizes (scales) the values in the 'Close' column of the DataFrame df2 using Min-Max scaling, transforming the values to a range between 0 and 1.

```
column_to_scale = 'Close'
df2[column_to_scale] =
MinMaxScaler().fit_transform(df2[[column_to_scale]])
print(df2)

           Date        Open        High         Low     Close
Adj Close  \
0    2005-09-29  432.588074  436.787964  407.388763  0.036812
304.904572
1    2005-09-30  457.787384  457.787384  432.588074  0.043184
```

```
322.666016
2    2005-10-03   470.387024   474.586914   440.987854  0.046370
331.546692
3    2005-10-04   474.586914   482.986694   466.187164  0.047432
334.506927
4    2005-10-05   482.986694   482.986694   466.187164  0.049556
340.427429
...         ...          ...          ...          ...        ...
...
3803 2021-01-28  2470.000000  2570.000000  2380.000000  0.529219
2380.000000
3804 2021-01-29  2370.000000  2440.000000  2220.000000  0.488763
2220.000000
3805 2021-02-01  2090.000000  2640.000000  2070.000000  0.584847
2600.000000
3806 2021-02-02  2600.000000  2630.000000  2420.000000  0.539333
2420.000000
3807 2021-02-03  2390.000000  2520.000000  2290.000000  0.516577
2330.000000

            Volume
0     7.618067e+07
1     1.054940e+08
2     5.971296e+07
3     5.623667e+07
4     3.131932e+07
...            ...
3803  7.318549e+08
3804  4.503212e+08
3805  2.186653e+09
3806  9.424343e+08
3807  9.480310e+08

[3807 rows x 7 columns]
```

Kode ini mendefinisikan fungsi makewindow yang mengambil DataFrame, membuat jendela berurutan dengan ukuran tertentu dari kolom yang dipilih, dan mengekstrak nilai target yang sesuai, lalu mendemonstrasikan fungsi pada DataFrame df2 yang berfokus pada kolom 'Close'.

```
def makewindow(df):
    x = []
    y = []
    window_size = 5
    target_column_index = 0

    for i in range(window_size, len(df)):
        window_data = df.iloc[i - window_size:i, target_column_index]
        target_value = df.iloc[i, target_column_index]
```

```
        x.append(window_data)
        y.append(target_value)

    return np.array(x), np.array(y)

x_df2, y_df2 = makewindow(df2[['Close']])
print(x_df2.shape)
print(y_df2.shape)
print(y_df2)
```

```
(3802, 5)
(3802,)
[0.04530783 0.04636977 0.04530783 ... 0.58484659 0.53933323
0.51657656]
```

b. [LO 1, LO 2, LO 3, LO4 5 point] Separate data into train, validation and test (80:10:10)

Seperating data into train, validation and test

```
from sklearn.model_selection import train_test_split

df2 = df2.sort_values(by="Date")


x_train,x_temp,y_train,y_temp = train_test_split(x_df2,
                                                 y_df2,
                                                 test_size = 0.2,
                                                 shuffle = False)

x_val,x_test,y_val,y_test = train_test_split(x_temp,
                                             y_temp,
                                             test_size = 0.5,
                                             shuffle = False)

print("Train set shape:", x_train.shape)
print("Val set shape:", x_val.shape)
print("Test set shape:", x_test.shape)
```

```
Train set shape: (3041, 5)
Val set shape: (380, 5)
Test set shape: (381, 5)
```

Reshape input features for a sequential model

```
def reshape_input(data):
    return data.reshape(data.shape[0], data.shape[1], 1)
```

```
x_train_reshaped = reshape_input(x_train)
x_val_reshaped = reshape_input(x_val)
x_test_reshaped = reshape_input(x_test)

print("Reshaped Train set shape:", x_train_reshaped.shape)
print("Reshaped Val set shape:", x_val_reshaped.shape)
print("Reshaped Test set shape:", x_test_reshaped.shape)
print("Reshaped Train set shape:", y_train.shape)
print("Reshaped Val set shape:", y_val.shape)
print("Reshaped Test set shape:", y_test.shape)
```

```
Reshaped Train set shape: (3041, 5, 1)
Reshaped Val set shape: (380, 5, 1)
Reshaped Test set shape: (381, 5, 1)
Reshaped Train set shape: (3041,)
Reshaped Val set shape: (380,)
Reshaped Test set shape: (381,)
```

c. [LO 1, LO 2, LO 3, LO 4 10 point] Create base architecture based on Table 1

```
import tensorflow as tf
from tensorflow import keras

from keras.models import Sequential
from keras.layers import Dense, Dropout, SimpleRNN

model = Sequential([
    SimpleRNN(units=512, activation = "relu",return_sequences=True,
input_shape=(5, 1)),
    SimpleRNN(units=256, activation = "relu",return_sequences=True),
    SimpleRNN(units=128, activation = "relu",return_sequences=False),
    Dropout(0.1),
    Dense(1 , activation = "relu")
])


model.compile(optimizer = 'adam', loss='mean_squared_error', metrics =
['mean_absolute_error'])
model.summary()
```

```
Model: "sequential_6"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 simple_rnn_18 (SimpleRNN)   (None, 5, 512)            263168

 simple_rnn_19 (SimpleRNN)   (None, 5, 256)            196864

 simple_rnn_20 (SimpleRNN)   (None, 128)               49280
```

```
 dropout_6 (Dropout)         (None, 128)               0

 dense_8 (Dense)             (None, 1)                 129

=================================================================
Total params: 509441 (1.94 MB)
Trainable params: 509441 (1.94 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
model_result = model.fit(x_train,
                         y_train,
                         epochs = 35,
                         batch_size = 25,
                         validation_data=(x_val,y_val),
                         verbose = 1)
```

```
Epoch 1/35
122/122 [==============================] - 107s 30ms/step - loss:
0.0021 - mean_absolute_error: 0.0279 - val_loss: 5.7801e-05 -
val_mean_absolute_error: 0.0057
Epoch 2/35
122/122 [==============================] - 4s 29ms/step - loss:
6.9705e-04 - mean_absolute_error: 0.0175 - val_loss: 1.1357e-04 -
val_mean_absolute_error: 0.0093
Epoch 3/35
122/122 [==============================] - 5s 41ms/step - loss:
7.0283e-04 - mean_absolute_error: 0.0175 - val_loss: 5.5593e-05 -
val_mean_absolute_error: 0.0061
Epoch 4/35
122/122 [==============================] - 3s 26ms/step - loss:
6.8446e-04 - mean_absolute_error: 0.0173 - val_loss: 4.6068e-05 -
val_mean_absolute_error: 0.0052
Epoch 5/35
122/122 [==============================] - 3s 27ms/step - loss:
5.2042e-04 - mean_absolute_error: 0.0149 - val_loss: 3.2839e-05 -
val_mean_absolute_error: 0.0041
Epoch 6/35
122/122 [==============================] - 3s 29ms/step - loss:
5.1495e-04 - mean_absolute_error: 0.0149 - val_loss: 3.8086e-05 -
val_mean_absolute_error: 0.0045
Epoch 7/35
122/122 [==============================] - 5s 42ms/step - loss:
5.0178e-04 - mean_absolute_error: 0.0147 - val_loss: 4.9347e-04 -
val_mean_absolute_error: 0.0214
Epoch 8/35
122/122 [==============================] - 3s 26ms/step - loss:
4.8999e-04 - mean_absolute_error: 0.0146 - val_loss: 9.0932e-05 -
val_mean_absolute_error: 0.0078
```

```
Epoch 9/35
122/122 [==============================] - 3s 26ms/step - loss:
4.4574e-04 - mean_absolute_error: 0.0137 - val_loss: 3.8196e-05 -
val_mean_absolute_error: 0.0046
Epoch 10/35
122/122 [==============================] - 3s 26ms/step - loss:
5.5892e-04 - mean_absolute_error: 0.0152 - val_loss: 3.8409e-05 -
val_mean_absolute_error: 0.0047
Epoch 11/35
122/122 [==============================] - 5s 42ms/step - loss:
4.8660e-04 - mean_absolute_error: 0.0143 - val_loss: 1.2762e-04 -
val_mean_absolute_error: 0.0102
Epoch 12/35
122/122 [==============================] - 3s 28ms/step - loss:
4.3163e-04 - mean_absolute_error: 0.0141 - val_loss: 5.5410e-05 -
val_mean_absolute_error: 0.0058
Epoch 13/35
122/122 [==============================] - 3s 26ms/step - loss:
4.1908e-04 - mean_absolute_error: 0.0132 - val_loss: 4.1791e-05 -
val_mean_absolute_error: 0.0049
Epoch 14/35
122/122 [==============================] - 3s 26ms/step - loss:
3.5404e-04 - mean_absolute_error: 0.0124 - val_loss: 6.1050e-05 -
val_mean_absolute_error: 0.0066
Epoch 15/35
122/122 [==============================] - 5s 38ms/step - loss:
3.6592e-04 - mean_absolute_error: 0.0126 - val_loss: 3.4787e-05 -
val_mean_absolute_error: 0.0043
Epoch 16/35
122/122 [==============================] - 4s 31ms/step - loss:
4.2049e-04 - mean_absolute_error: 0.0131 - val_loss: 3.9808e-05 -
val_mean_absolute_error: 0.0047
Epoch 17/35
122/122 [==============================] - 3s 26ms/step - loss:
4.3486e-04 - mean_absolute_error: 0.0142 - val_loss: 4.5360e-05 -
val_mean_absolute_error: 0.0050
Epoch 18/35
122/122 [==============================] - 3s 26ms/step - loss:
3.4308e-04 - mean_absolute_error: 0.0120 - val_loss: 5.4903e-05 -
val_mean_absolute_error: 0.0057
Epoch 19/35
122/122 [==============================] - 4s 35ms/step - loss:
3.6513e-04 - mean_absolute_error: 0.0125 - val_loss: 3.9815e-05 -
val_mean_absolute_error: 0.0048
Epoch 20/35
122/122 [==============================] - 4s 34ms/step - loss:
4.6701e-04 - mean_absolute_error: 0.0146 - val_loss: 1.0315e-04 -
val_mean_absolute_error: 0.0084
Epoch 21/35
```

```
122/122 [==============================] - 3s 26ms/step - loss: 
3.0572e-04 - mean_absolute_error: 0.0116 - val_loss: 1.6412e-04 - 
val_mean_absolute_error: 0.0115
Epoch 22/35
122/122 [==============================] - 3s 26ms/step - loss: 
3.5037e-04 - mean_absolute_error: 0.0120 - val_loss: 3.9073e-05 - 
val_mean_absolute_error: 0.0047
Epoch 23/35
122/122 [==============================] - 4s 33ms/step - loss: 
3.4648e-04 - mean_absolute_error: 0.0116 - val_loss: 4.3989e-05 - 
val_mean_absolute_error: 0.0049
Epoch 24/35
122/122 [==============================] - 4s 37ms/step - loss: 
3.4085e-04 - mean_absolute_error: 0.0121 - val_loss: 1.9651e-04 - 
val_mean_absolute_error: 0.0129
Epoch 25/35
122/122 [==============================] - 3s 26ms/step - loss: 
3.4730e-04 - mean_absolute_error: 0.0122 - val_loss: 5.1108e-05 - 
val_mean_absolute_error: 0.0059
Epoch 26/35
122/122 [==============================] - 3s 26ms/step - loss: 
3.4865e-04 - mean_absolute_error: 0.0125 - val_loss: 5.5171e-05 - 
val_mean_absolute_error: 0.0058
Epoch 27/35
122/122 [==============================] - 4s 30ms/step - loss: 
3.2968e-04 - mean_absolute_error: 0.0119 - val_loss: 3.7894e-05 - 
val_mean_absolute_error: 0.0045
Epoch 28/35
122/122 [==============================] - 6s 51ms/step - loss: 
3.0776e-04 - mean_absolute_error: 0.0115 - val_loss: 5.1120e-05 - 
val_mean_absolute_error: 0.0058
Epoch 29/35
122/122 [==============================] - 3s 26ms/step - loss: 
3.2103e-04 - mean_absolute_error: 0.0118 - val_loss: 6.0415e-05 - 
val_mean_absolute_error: 0.0064
Epoch 30/35
122/122 [==============================] - 3s 27ms/step - loss: 
3.0337e-04 - mean_absolute_error: 0.0114 - val_loss: 7.0513e-05 - 
val_mean_absolute_error: 0.0067
Epoch 31/35
122/122 [==============================] - 4s 32ms/step - loss: 
3.1502e-04 - mean_absolute_error: 0.0117 - val_loss: 4.8855e-05 - 
val_mean_absolute_error: 0.0051
Epoch 32/35
122/122 [==============================] - 5s 38ms/step - loss: 
3.1415e-04 - mean_absolute_error: 0.0114 - val_loss: 1.0177e-04 - 
val_mean_absolute_error: 0.0085
Epoch 33/35
122/122 [==============================] - 3s 27ms/step - loss: 
```

```
4.5169e-04 - mean_absolute_error: 0.0138 - val_loss: 1.2904e-04 -
val_mean_absolute_error: 0.0099
Epoch 34/35
122/122 [==============================] - 3s 27ms/step - loss:
3.5116e-04 - mean_absolute_error: 0.0120 - val_loss: 5.4161e-05 -
val_mean_absolute_error: 0.0057
Epoch 35/35
122/122 [==============================] - 4s 32ms/step - loss:
3.6635e-04 - mean_absolute_error: 0.0120 - val_loss: 3.6617e-05 -
val_mean_absolute_error: 0.0046
```

d. [LO 1, LO 2, LO 3, LO 4 10 point] Adding Sequential Self-Attention Mechanism and explain how the sequential self-attention mechanism works.

```
!pip install keras-self-attention
```

```
Requirement already satisfied: keras-self-attention in
/usr/local/lib/python3.10/dist-packages (0.51.0)
Requirement already satisfied: numpy in
/usr/local/lib/python3.10/dist-packages (from keras-self-attention)
(1.23.5)
```

```
from keras.models import Sequential
from keras.layers import SimpleRNN, Dropout, Dense, Flatten
from keras_self_attention import SeqSelfAttention

model_ssa = Sequential([
    SimpleRNN(units=512, return_sequences=True, input_shape=(5, 1)),
    SeqSelfAttention(attention_activation='sigmoid'),
    SimpleRNN(units=256, return_sequences=True),
    SeqSelfAttention(attention_activation='sigmoid'),
    SimpleRNN(units=128, return_sequences=False),
    Dropout(0.1),
    Flatten(),
    Dense(1, activation="relu")
])

model_ssa.summary()
```

```
Model: "sequential_8"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 simple_rnn_24 (SimpleRNN)   (None, 5, 512)            263168

 seq_self_attention_2 (SeqS  (None, 5, 512)            32833
 elfAttention)
```

```
 simple_rnn_25 (SimpleRNN)   (None, 5, 256)            196864

 seq_self_attention_3 (SeqS  (None, 5, 256)            16449
 elfAttention)

 simple_rnn_26 (SimpleRNN)   (None, 128)               49280

 dropout_8 (Dropout)         (None, 128)               0

 flatten_1 (Flatten)         (None, 128)               0

 dense_11 (Dense)            (None, 1)                 129

=================================================================
Total params: 558723 (2.13 MB)
Trainable params: 558723 (2.13 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
model_ssa.compile(optimizer='adam', loss='mean_squared_error', metrics
= ['mean_absolute_error'])
model_ssa_epoch = model_ssa.fit(x_train,
                         y_train,
                         epochs = 34,
                         batch_size = 25,
                         validation_data=(x_val,y_val))
```

```
Epoch 1/34
122/122 [==============================] - 11s 54ms/step - loss:
0.0946 - mean_absolute_error: 0.2324 - val_loss: 0.0026 -
val_mean_absolute_error: 0.0504
Epoch 2/34
122/122 [==============================] - 4s 33ms/step - loss: 0.0028
- mean_absolute_error: 0.0337 - val_loss: 5.1077e-05 -
val_mean_absolute_error: 0.0053
Epoch 3/34
122/122 [==============================] - 4s 32ms/step - loss:
8.5674e-04 - mean_absolute_error: 0.0204 - val_loss: 6.9223e-05 -
val_mean_absolute_error: 0.0067
Epoch 4/34
122/122 [==============================] - 5s 42ms/step - loss:
9.3264e-04 - mean_absolute_error: 0.0207 - val_loss: 4.9154e-05 -
val_mean_absolute_error: 0.0054
Epoch 5/34
122/122 [==============================] - 5s 37ms/step - loss:
7.5533e-04 - mean_absolute_error: 0.0186 - val_loss: 2.7337e-04 -
val_mean_absolute_error: 0.0152
Epoch 6/34
122/122 [==============================] - 4s 31ms/step - loss:
8.3150e-04 - mean_absolute_error: 0.0200 - val_loss: 2.3391e-04 -
```

```
val_mean_absolute_error: 0.0137
Epoch 7/34
122/122 [==============================] - 4s 33ms/step - loss:
8.6040e-04 - mean_absolute_error: 0.0202 - val_loss: 2.1565e-04 -
val_mean_absolute_error: 0.0131
Epoch 8/34
122/122 [==============================] - 6s 48ms/step - loss:
6.3978e-04 - mean_absolute_error: 0.0172 - val_loss: 1.0071e-04 -
val_mean_absolute_error: 0.0083
Epoch 9/34
122/122 [==============================] - 4s 31ms/step - loss:
9.0746e-04 - mean_absolute_error: 0.0202 - val_loss: 9.7810e-05 -
val_mean_absolute_error: 0.0084
Epoch 10/34
122/122 [==============================] - 4s 31ms/step - loss:
5.7731e-04 - mean_absolute_error: 0.0163 - val_loss: 9.1440e-05 -
val_mean_absolute_error: 0.0078
Epoch 11/34
122/122 [==============================] - 8s 63ms/step - loss:
7.7839e-04 - mean_absolute_error: 0.0192 - val_loss: 6.9128e-05 -
val_mean_absolute_error: 0.0065
Epoch 12/34
122/122 [==============================] - 4s 32ms/step - loss:
5.2148e-04 - mean_absolute_error: 0.0156 - val_loss: 6.2724e-05 -
val_mean_absolute_error: 0.0062
Epoch 13/34
122/122 [==============================] - 4s 32ms/step - loss:
5.6324e-04 - mean_absolute_error: 0.0161 - val_loss: 9.7550e-05 -
val_mean_absolute_error: 0.0085
Epoch 14/34
122/122 [==============================] - 5s 41ms/step - loss:
5.9432e-04 - mean_absolute_error: 0.0161 - val_loss: 3.5279e-04 -
val_mean_absolute_error: 0.0177
Epoch 15/34
122/122 [==============================] - 5s 40ms/step - loss:
5.6971e-04 - mean_absolute_error: 0.0161 - val_loss: 9.7380e-05 -
val_mean_absolute_error: 0.0085
Epoch 16/34
122/122 [==============================] - 4s 33ms/step - loss:
4.5730e-04 - mean_absolute_error: 0.0144 - val_loss: 3.5860e-04 -
val_mean_absolute_error: 0.0179
Epoch 17/34
122/122 [==============================] - 4s 34ms/step - loss:
5.4379e-04 - mean_absolute_error: 0.0156 - val_loss: 4.0526e-05 -
val_mean_absolute_error: 0.0047
Epoch 18/34
122/122 [==============================] - 6s 52ms/step - loss:
5.2152e-04 - mean_absolute_error: 0.0154 - val_loss: 7.8617e-05 -
val_mean_absolute_error: 0.0073
```

```
Epoch 19/34
122/122 [==============================] - 4s 35ms/step - loss:
5.9606e-04 - mean_absolute_error: 0.0166 - val_loss: 4.0584e-05 -
val_mean_absolute_error: 0.0047
Epoch 20/34
122/122 [==============================] - 4s 31ms/step - loss:
5.5566e-04 - mean_absolute_error: 0.0158 - val_loss: 4.1492e-05 -
val_mean_absolute_error: 0.0047
Epoch 21/34
122/122 [==============================] - 6s 47ms/step - loss:
4.8310e-04 - mean_absolute_error: 0.0146 - val_loss: 8.2524e-05 -
val_mean_absolute_error: 0.0078
Epoch 22/34
122/122 [==============================] - 4s 32ms/step - loss:
7.1630e-04 - mean_absolute_error: 0.0177 - val_loss: 1.5634e-04 -
val_mean_absolute_error: 0.0113
Epoch 23/34
122/122 [==============================] - 4s 32ms/step - loss:
4.5234e-04 - mean_absolute_error: 0.0144 - val_loss: 4.9810e-05 -
val_mean_absolute_error: 0.0056
Epoch 24/34
122/122 [==============================] - 5s 38ms/step - loss:
4.5598e-04 - mean_absolute_error: 0.0143 - val_loss: 1.1280e-04 -
val_mean_absolute_error: 0.0093
Epoch 25/34
122/122 [==============================] - 5s 42ms/step - loss:
5.7772e-04 - mean_absolute_error: 0.0166 - val_loss: 8.4287e-05 -
val_mean_absolute_error: 0.0078
Epoch 26/34
122/122 [==============================] - 4s 33ms/step - loss:
3.8454e-04 - mean_absolute_error: 0.0127 - val_loss: 5.9940e-05 -
val_mean_absolute_error: 0.0060
Epoch 27/34
122/122 [==============================] - 4s 32ms/step - loss:
4.1294e-04 - mean_absolute_error: 0.0135 - val_loss: 5.3071e-05 -
val_mean_absolute_error: 0.0055
Epoch 28/34
122/122 [==============================] - 6s 50ms/step - loss:
5.8906e-04 - mean_absolute_error: 0.0164 - val_loss: 5.3446e-05 -
val_mean_absolute_error: 0.0055
Epoch 29/34
122/122 [==============================] - 4s 33ms/step - loss:
4.0900e-04 - mean_absolute_error: 0.0134 - val_loss: 5.0118e-05 -
val_mean_absolute_error: 0.0054
Epoch 30/34
122/122 [==============================] - 4s 32ms/step - loss:
4.0343e-04 - mean_absolute_error: 0.0134 - val_loss: 8.2392e-05 -
val_mean_absolute_error: 0.0073
Epoch 31/34
```

```
122/122 [==============================] - 5s 42ms/step - loss:
4.1869e-04 - mean_absolute_error: 0.0137 - val_loss: 4.6987e-05 -
val_mean_absolute_error: 0.0052
Epoch 32/34
122/122 [==============================] - 5s 40ms/step - loss:
4.6346e-04 - mean_absolute_error: 0.0143 - val_loss: 9.7791e-05 -
val_mean_absolute_error: 0.0081
Epoch 33/34
122/122 [==============================] - 4s 33ms/step - loss:
5.3848e-04 - mean_absolute_error: 0.0157 - val_loss: 7.2155e-05 -
val_mean_absolute_error: 0.0070
Epoch 34/34
122/122 [==============================] - 7s 58ms/step - loss:
4.8679e-04 - mean_absolute_error: 0.0143 - val_loss: 5.4982e-05 -
val_mean_absolute_error: 0.0058
```

e. [LO 1, LO 2 & LO 3, LO 4 10 points] Please proceed to evaluate the architecture outlined above on the test set, utilizing evaluation metrics that are congruent with the architecture specified in number 1c and 1d. Include a justification for the choice of these evaluation metrics. Subsequently, provide a detailed explanation of the results obtained.

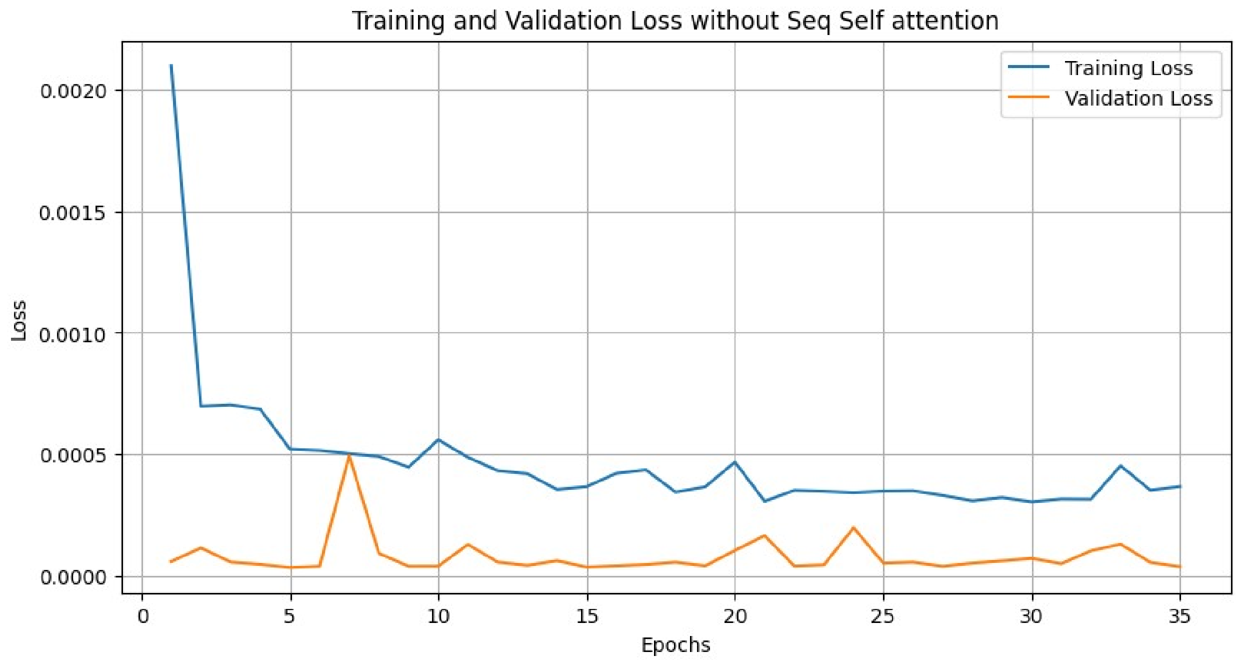
Alasan pemilihan metrik evaluasi:

Mean Squared Error adalah metrik umum untuk masalah regresi, dan mengukur perbedaan kuadrat rata-rata antara nilai prediksi dan nilai aktual. Ini memberikan hukuman yang lebih berat terhadap kesalahan yang lebih besar daripada kesalahan yang lebih kecil, sehingga memberikan ukuran yang baik untuk akurasi prediksi secara keseluruhan.

```python
def plot1_training_history(history):
    train_loss = history.history['loss']
    val_loss = history.history['val_loss']
    epochs = range(1, len(train_loss) + 1)

    plt.figure(figsize=(10, 5))
    plt.plot(epochs, train_loss, label='Training Loss')
    plt.plot(epochs, val_loss, label='Validation Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.title('Training and Validation Loss without Seq Self 
attention')
    plt.legend()
    plt.grid(True)
    plt.show()

plot1_training_history(model_result)
```

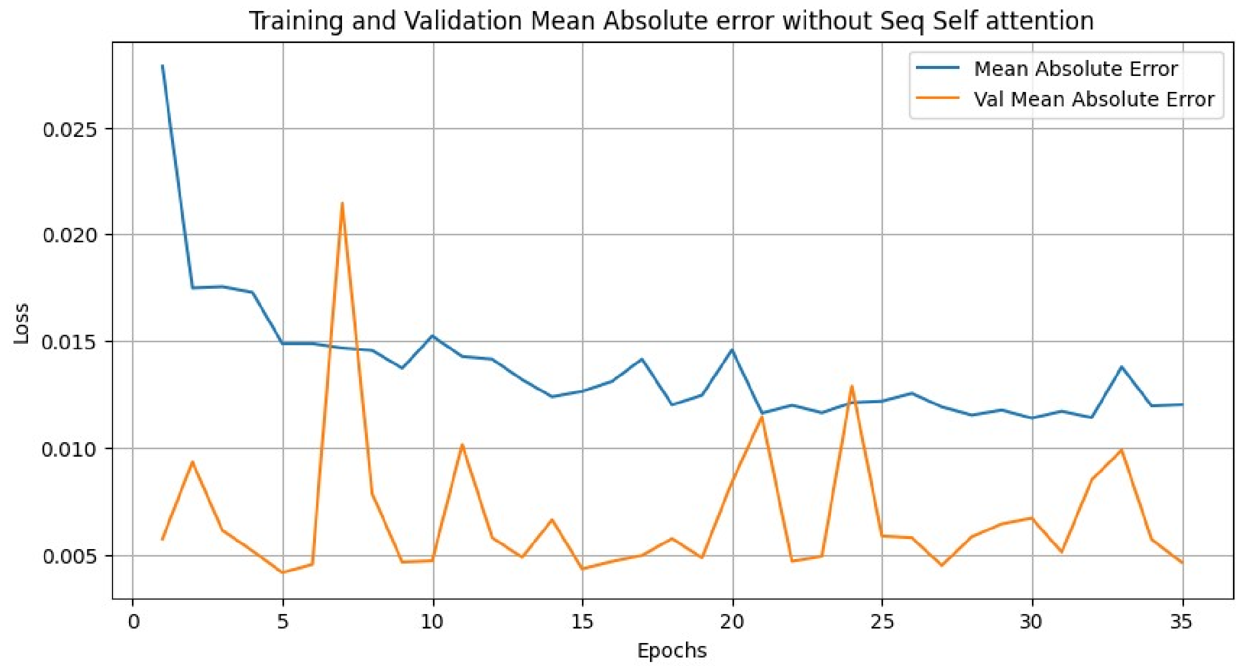


Penjelasan untuk training dan validation loss sebelum ditambah Sequential self-attention mechanism adalah dapat dilihat bahwa training loss dan validation loss belum menyentuh titik terendahnya. Sehingga test loss belum begitu rendah sehingga model belum begitu maksimal dan dapat terlihat bahwa validation loss dan training lossnya belum begitu dekat sehingga masih sangat berpeluang untuk dibaguskan

```
def plot1_training_history(history):
    train_loss = history.history['mean_absolute_error']
    val_loss = history.history['val_mean_absolute_error']
    epochs = range(1, len(train_loss) + 1)

    plt.figure(figsize=(10, 5))
    plt.plot(epochs, train_loss, label='Mean Absolute Error')
    plt.plot(epochs, val_loss, label='Val Mean Absolute Error')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.title('Training and Validation Mean Absolute error without Seq 
Self attention')
    plt.legend()
    plt.grid(True)
    plt.show()

plot1_training_history(model_result)
```



Sama seperti gambar training loss da validation, perbandingan antara training dan validation mean squared error belom rendah sehingga tanpa sequential self attention mechanism, model yang dilakukan masih dapat dibaguskan terlebih lagi. Dan dapat dilihat perbandingan mean absolute error dan val mean absolute error belum stabil dikarenakan beberapa faktor dimana salah satunya adalah sequential self-attention mechanism.

```
def plot1_training_history(history):
    train_loss = history.history['loss']
    val_loss = history.history['val_loss']
    epochs = range(1, len(train_loss) + 1)

    plt.figure(figsize=(10, 5))
    plt.plot(epochs, train_loss, label='Training Loss')
    plt.plot(epochs, val_loss, label='Validation Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.title('Training and Validation Loss with adding Seq Self
attention')
    plt.legend()
    plt.grid(True)
    plt.show()

plot1_training_history(model_ssa_epoch)
```

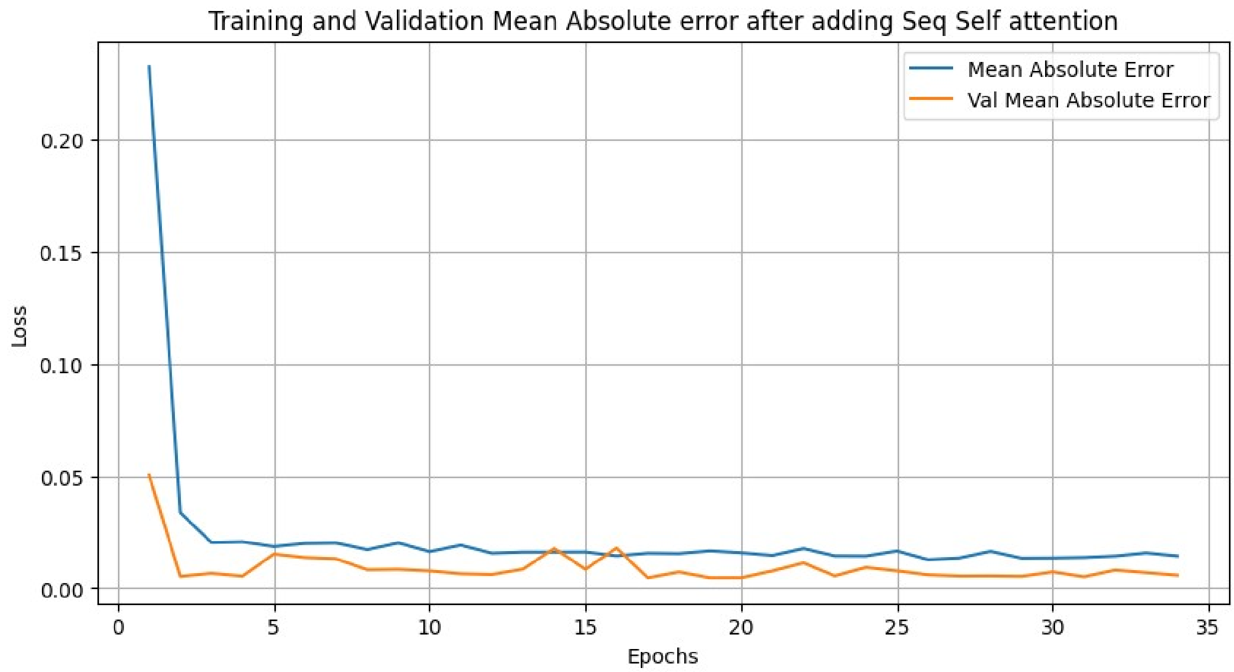
Sequential Self attention adalah varian mekanisme perhatian yang dirancang untuk pemrosesan data berurutan, menekankan urutan elemen dalam suatu urutan. Tidak seperti perhatian diri standar, ini menghitung bobot perhatian secara berurutan untuk setiap posisi dalam urutan, dengan mempertimbangkan ketergantungan dari waktu ke waktu dengan cara autoregresif.

Setelah modelnya diberikan sequential self attention, hasil dari training dan validation loss semakin rendah dan semakin dekat dengan angka 0. Berarti model ini sudah lebih baik dibandingkan dengan training loss dan validation sebelum ditambahkan sequential self attention. Maka dari itu, model sudah membaik karena lossnya sudah rendah.

```
def plot1_training_history(history):
    train_loss = history.history['mean_absolute_error']
    val_loss = history.history['val_mean_absolute_error']
    epochs = range(1, len(train_loss) + 1)

    plt.figure(figsize=(10, 5))
    plt.plot(epochs, train_loss, label='Mean Absolute Error')
    plt.plot(epochs, val_loss, label='Val Mean Absolute Error')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.title('Training and Validation Mean Absolute error after
adding Seq Self attention')
    plt.legend()
    plt.grid(True)
    plt.show()

plot1_training_history(model_ssa_epoch)
```



Sama dengan training dan validation loss diatas, training dan validation MSE sudah rendah juga dimana berarti jika dibandingkan diatas, model sudah improve cukup drastis dimana MSE juga stabil dibawah dan tidak ada spiking pada grafik tersebut. Maka dari itu, model sudah jauh lebih baik dengan adanya Sequential self mechanism .

f. Create a line chart that displays a comparison between the prediction results from models 1d and 1c, and the actual values

```
predict = model.predict(x_test)
predict[:10]

12/12 [==============================] - 0s 18ms/step

array([[0.1560337 ],
       [0.16814432],
       [0.16420013],
       [0.1691059 ],
       [0.16489679],
       [0.1663259 ],
       [0.16310611],
       [0.15511772],
       [0.15623161],
       [0.16529438]], dtype=float32)

predict_ssa = model_ssa.predict(x_test)
predict_ssa[:10]

12/12 [==============================] - 0s 18ms/step
```

```
array([[0.1547901 ],
       [0.16354364],
       [0.16505295],
       [0.17001423],
       [0.17009759],
       [0.17073536],
       [0.16895717],
       [0.16284648],
       [0.16156232],
       [0.16395769]], dtype=float32)
```

```
df_actual = pd.read_csv('X.csv')
df_actual.head(5)
```

```
         Date        Open        High         Low       Close   Adj
Close  \
0  2005-09-29  432.588074  436.787964  407.388763  432.588074
304.904572
1  2005-09-30  457.787384  457.787384  432.588074  457.787384
322.666016
2  2005-10-03  470.387024  474.586914  440.987854  470.387024
331.546692
3  2005-10-04  474.586914  482.986694  466.187164  474.586914
334.506927
4  2005-10-05  482.986694  482.986694  466.187164  482.986694
340.427429

        Volume
0   76180670.0
1  105493978.0
2   59712955.0
3   56236668.0
4   31319315.0
```

```
df_actual['Date'] = pd.to_datetime(df_actual['Date'],
format='%Y/%m/%d')
columns_to_convert = ['Open', 'High', 'Low', 'Close', 'Adj Close',
'Volume']
df_actual[columns_to_convert] =
df_actual[columns_to_convert].replace('\.', '',
regex=True).astype(float)
df_actual.head()
```

```
        Date        Open        High         Low       Close   Adj
Close  \
0 2005-09-29  432.588074  436.787964  407.388763  432.588074
304.904572
1 2005-09-30  457.787384  457.787384  432.588074  457.787384
322.666016
2 2005-10-03  470.387024  474.586914  440.987854  470.387024
```

```
331.546692
3 2005-10-04  474.586914  482.986694  466.187164  474.586914
334.506927
4 2005-10-05  482.986694  482.986694  466.187164  482.986694
340.427429

       Volume
0   76180670.0
1  105493978.0
2   59712955.0
3   56236668.0
4   31319315.0
```

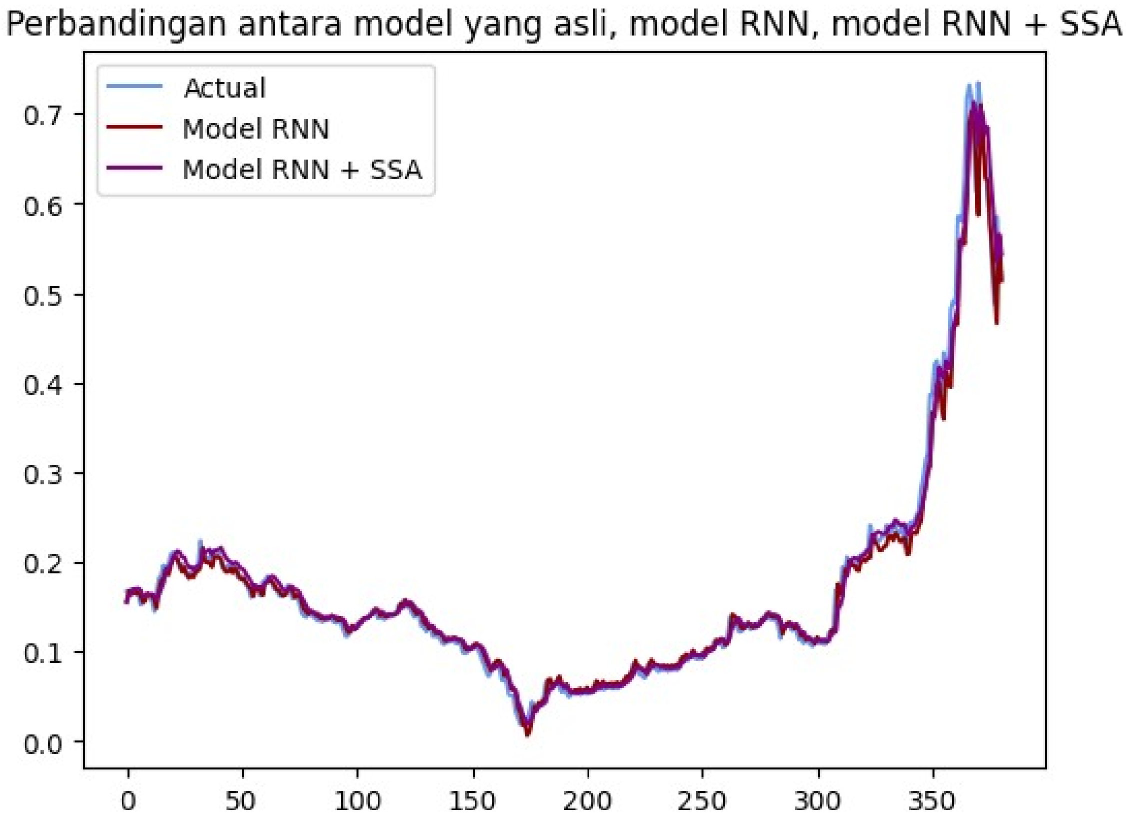
```
y_true = np.array(df2['Close'].tail(381))
y_true
```

```
array([0.16764085, 0.16511233, 0.17016937, 0.16511233, 0.16637659,
       0.16258381, 0.15246973, 0.15373399, 0.16384807, 0.16384807,
       0.16131955, 0.15499825, 0.14488417, 0.16511233, 0.18154771,
       0.18534049, 0.19671883, 0.18913327, 0.19671883, 0.20809716,
       0.21062568, 0.21062568, 0.20177587, 0.19292605, 0.19798309,
       0.19039753, 0.18407623, 0.18786901, 0.18534049, 0.19292605,
       0.19419031, 0.19798309, 0.22326828, 0.20809716, 0.20556864,
       0.20556864, 0.19924735, 0.21062568, 0.2131542 , 0.21188994,
       0.21062568, 0.19798309, 0.19292605, 0.19292605, 0.19671883,
       0.19166179, 0.19671883, 0.19419031, 0.18407623, 0.18281197,
       0.18407623, 0.17775493, 0.17396215, 0.16890511, 0.16005529,
       0.17143363, 0.17016937, 0.16890511, 0.16258381, 0.17775493,
       0.17901919, 0.18407623, 0.18028345, 0.17649067, 0.17016937,
       0.16890511, 0.16384807, 0.16131955, 0.16258381, 0.16890511,
       0.17396215, 0.16890511, 0.15879103, 0.16131955, 0.16258381,
       0.15246973, 0.14361991, 0.13982713, 0.13856287, 0.14235565,
       0.14109139, 0.13856287, 0.13729862, 0.1347701 , 0.1347701 ,
       0.13350584, 0.13603436, 0.1347701 , 0.13856287, 0.13603436,
       0.13350584, 0.13224158, 0.13350584, 0.13224158, 0.12465602,
       0.11707046, 0.11707046, 0.12718454, 0.12339176, 0.12592028,
       0.13097732, 0.13224158, 0.13603436, 0.13603436, 0.13603436,
       0.13856287, 0.14235565, 0.14614843, 0.14488417, 0.13729862,
       0.13856287, 0.13729862, 0.13603436, 0.13982713, 0.13856287,
       0.13982713, 0.13982713, 0.14235565, 0.15120547, 0.14867695,
       0.15626251, 0.14994121, 0.15120547, 0.14741269, 0.14235565,
       0.13856287, 0.14109139, 0.13982713, 0.1284488 , 0.1284488 ,
       0.1221275 , 0.12465602, 0.12592028, 0.11707046, 0.11707046,
       0.11707046, 0.11454194, 0.1094849 , 0.10822064, 0.11201342,
       0.11074916, 0.11327768, 0.11201342, 0.1094849 , 0.1094849 ,
       0.10822064, 0.09937082, 0.09810656, 0.09937082, 0.10189934,
       0.10569212, 0.10695638, 0.10442786, 0.10063508, 0.09431378,
       0.08672822, 0.07914266, 0.07282136, 0.07534988, 0.08293544,
       0.08672822, 0.08672822, 0.08167118, 0.06776433, 0.07282136,
       0.06397155, 0.05132895, 0.05132895, 0.05132895, 0.0326179 ,
```

```
       0.02553805, 0.0189639 , 0.02199812, 0.01542397, 0.0194696 ,
       0.0326179 , 0.04374339, 0.03666353, 0.04121487, 0.03767494,
       0.04172057, 0.0447548 , 0.06397155, 0.06776433, 0.05891451,
       0.05891451, 0.06270729, 0.06776433, 0.06017877, 0.05512173,
       0.05891451, 0.05385747, 0.04930613, 0.05183465, 0.05335176,
       0.05234036, 0.05512173, 0.05183465, 0.05335176, 0.05638599,
       0.05234036, 0.05385747, 0.05385747, 0.06270729, 0.06144303,
       0.05765025, 0.06270729, 0.05765025, 0.05891451, 0.06017877,
       0.06017877, 0.05891451, 0.06144303, 0.05891451, 0.06017877,
       0.06270729, 0.06776433, 0.06776433, 0.07155711, 0.07661414,
       0.08672822, 0.08167118, 0.0778784 , 0.07408562, 0.07408562,
       0.07029285, 0.08167118, 0.08799248, 0.0841997 , 0.08167118,
       0.08040692, 0.0778784 , 0.08040692, 0.07914266, 0.08040692,
       0.0778784 , 0.08040692, 0.07914266, 0.08167118, 0.07914266,
       0.08925674, 0.09178526, 0.09431378, 0.09178526, 0.090521  ,
       0.09810656, 0.09431378, 0.09304952, 0.09178526, 0.09431378,
       0.09178526, 0.10063508, 0.10063508, 0.10189934, 0.10063508,
       0.11074916, 0.1094849 , 0.11201342, 0.11201342, 0.10442786,
       0.10569212, 0.11707046, 0.13856287, 0.13982713, 0.13603436,
       0.12971306, 0.1221275 , 0.1221275 , 0.12592028, 0.13097732,
       0.1284488 , 0.12465602, 0.12718454, 0.12592028, 0.1284488 ,
       0.1347701 , 0.1347701 , 0.13982713, 0.14235565, 0.13729862,
       0.13603436, 0.13603436, 0.13603436, 0.1284488 , 0.11454194,
       0.12339176, 0.12971306, 0.13097732, 0.1284488 , 0.12339176,
       0.12718454, 0.12086324, 0.11327768, 0.11707046, 0.1094849 ,
       0.11201342, 0.11074916, 0.10822064, 0.10569212, 0.11327768,
       0.11074916, 0.1094849 , 0.1094849 , 0.10822064, 0.1094849 ,
       0.12086324, 0.12465602, 0.12086324, 0.16890511, 0.16384807,
       0.16511233, 0.19419031, 0.18913327, 0.20556864, 0.20177587,
       0.20177587, 0.19545457, 0.19419031, 0.20556864, 0.20809716,
       0.2068329 , 0.21188994, 0.21188994, 0.24096792, 0.23085384,
       0.22958958, 0.22326828, 0.22326828, 0.22706106, 0.22832532,
       0.24096792, 0.23970366, 0.23338236, 0.2447607 , 0.23970366,
       0.2321181 , 0.23338236, 0.2384394 , 0.21694698, 0.2194755 ,
       0.24223218, 0.2447607 , 0.24223218, 0.251082  , 0.25613904,
       0.28015997, 0.29406683, 0.31303073, 0.32188055, 0.3863578 ,
       0.3863578 , 0.42049281, 0.42428559, 0.39141484, 0.3800365 ,
       0.43313541, 0.41922855, 0.41670003, 0.48117728, 0.49129136,
       0.48876284, 0.58484659, 0.58484659, 0.57978955, 0.62783142,
       0.71632961, 0.73150072, 0.71632961, 0.66323069, 0.6126603 ,
       0.73402924, 0.70874405, 0.65564514, 0.65311662, 0.60254622,
       0.57220399, 0.52921916, 0.48876284, 0.58484659, 0.53933323,
       0.51657656])
```

```
plt.plot(y_true, label='Actual',color = 'cornflowerblue')
plt.plot(predict, label='Model RNN',color = 'darkred')
plt.plot(predict_ssa, label='Model RNN + SSA',color = 'purple')
plt.legend(loc='upper left')
plt.title('Perbandingan antara model yang asli, model RNN, model RNN +
```

```
SSA')
plt.show()
```


Perbandingan antara model yang asli, model RNN, model RNN + SSA
Actual
Model RNN
Model RNN + SSA
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0
50
100
150
200
250
300
350