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Link Video: https://binusianorg-my.sharepoint.com/personal/rafael_tanaja_binus_ac_id/_layouts/15/guestaccess.aspx?docid=0758108b77a3b4863b713e6546755ebb2&authkey=AcnelikxZv9Tk5fLDaXPeOI&e=ptE78j (https://binusianorg-my.sharepoint.com/personal/rafael_tanaja_binus_ac_id/_layouts/15/guestaccess.aspx?docid=0758108b77a3b4863b713e6546755ebb2&authkey=AcnelikxZv9Tk5fLDaXPeOI&e=ptE78j)

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf

from tensorflow import keras
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Sequential
from tensorflow.keras import layers
from tensorflow.keras.layers import LSTM, Dense, GRU, Bidirectional
from sklearn.metrics import mean_absolute_error, mean_squared_error
from tensorflow.keras.wrappers.scikit_learn import KerasClassifier
from sklearn.model_selection import GridSearchCV, ParameterGrid
from tensorflow.keras.optimizers import SGD, Adam, RMSprop
from sklearn.preprocessing import MinMaxScaler
from tqdm import tqdm

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

Data Preprocessing

In [2]:
```
amd = pd.read_csv('AMD.csv')
aapl = pd.read_csv('AAPL.csv')
```

In [3]:
```
amd['Date'] = pd.to_datetime(amd['Date'])
aapl['Date'] = pd.to_datetime(aapl['Date'])
```

In [4]:
```
amdsqrt = amd.copy()

amdsqrt['Open'] = np.sqrt(amd['Open'])
amdsqrt['Close'] = np.sqrt(amd['Close'])
amdsqrt['High'] = np.sqrt(amd['High'])
amdsqrt['Low'] = np.sqrt(amd['Low'])
amdsqrt['Adj Close'] = np.sqrt(amd['Adj Close'])
amdsqrt['Volume'] = np.sqrt(amd['Volume'])
```

In [5]:
```
aaplsqrt = aapl.copy()

aaplsqrt['Open'] = np.sqrt(aapl['Open'])
aaplsqrt['Close'] = np.sqrt(aapl['Close'])
aaplsqrt['High'] = np.sqrt(aapl['High'])
aaplsqrt['Low'] = np.sqrt(aapl['Low'])
aaplsqrt['Adj Close'] = np.sqrt(aapl['Adj Close'])
aaplsqrt['Volume'] = np.sqrt(aapl['Volume'])
```

In [6]:
```
amdsqrt = amdsqrt.drop(['Open', 'High', 'Low', 'Adj Close', 'Volume'], axis = 1)
aaplsqrt = aaplsqrt.drop(['Open', 'High', 'Low', 'Adj Close', 'Volume'], axis = 1)
```

In [7]:
```
amdsqrt.head(5)
```

Out[7]:

	Date	Close
0	1980-03-17	1.773650
1	1980-03-18	1.741049
2	1980-03-19	1.744037
3	1980-03-20	1.735055
4	1980-03-21	1.707825

In [8]:
```
amdsqrt_close = amdsqrt['Close'].to_numpy()
aaplsqrt_close = aaplsqrt['Close'].to_numpy()
```

In [9]:
```
amdsqrt_close.shape
```

Out[9]:
```
(10098,)
```

In [10]:
```
amdsqrt_close = amdsqrt_close.reshape(-1,1)
aaplsqrt_close = aaplsqrt_close.reshape(-1,1)

scale = MinMaxScaler(feature_range= (0,1))
amdsqrt_close = scale.fit_transform(amdsqrt_close)
aaplsqrt_close = scale.fit_transform(aaplsqrt_close)
```

Window and Split Data

In [11]:
```
windowsize = 5
horizon = 5
```

In [12]:
```
def labelingwindow(x, horizon):
  return x[:, :-horizon], x[:, -horizon:]
```

In [13]:
```
def makewindows(x, window_size, horizon):
  step = np.expand_dims(np.arange(windowsize + horizon), axis=0)

  index = step + np.expand_dims(np.arange(len(x) - (windowsize+horizon-1)), axis=0).T

  arr = x[index]

  input, output = labelingwindow(arr, horizon)

  return input, output
```

In [14]:
```
amdinput, amdoutput = makewindows(amdsqrt_close, windowsize, horizon)

aaplinput, aaploutput = makewindows(aaplsqrt_close, windowsize, horizon)
```

In [15]:
```
for i in range(5):
  print(f"Window: {amdinput[i-3]} \n Label: {amdoutput[i-3]}")
```

```
Window: [[0.81206069]
 [0.77818329]
 [0.78688559]
 [0.784283  ]
 [0.80916001]]
 Label: [[0.86314808]
 [0.84472206]
 [0.87775248]
 [0.8672758 ]
 [0.88182441]]
Window: [[0.77818329]
 [0.78688559]
 [0.784283  ]
 [0.80916001]
 [0.86314808]]
 Label: [[0.84472206]
 [0.87775248]
 [0.8672758 ]
 [0.88182441]
 [0.85461253]]
Window: [[0.78688559]
 [0.784283  ]
 [0.80916001]
 [0.86314808]
 [0.84472206]]
 Label: [[0.87775248]
 [0.8672758 ]
 [0.88182441]
 [0.85461253]
 [0.83331948]]
Window: [[0.07823647]
 [0.07314401]
 [0.07361089]
 [0.07220783]
 [0.06795435]]
 Label: [[0.05626521]
 [0.05325825]
 [0.04557904]
 [0.04191158]
 [0.05021498]]
Window: [[0.07314401]
 [0.07361089]
 [0.07220783]
 [0.06795435]
 [0.05626521]]
 Label: [[0.05325825]
 [0.04557904]
 [0.04191158]
 [0.05021498]
 [0.05021498]]
```

In [16]:
```
for i in range(5):
  print(f"Window: {aaplinput[i-3]} \n Label: {aaploutput[i-3]}")
```

```
Window: [[0.87605324]
 [0.86495459]
 [0.86153815]
 [0.83293178]
 [0.82376859]]
 Label: [[0.8653334 ]
 [0.86287738]
 [0.8859423 ]
 [0.86688298]
 [0.87952138]]
Window: [[0.86495459]
 [0.86153815]
 [0.83293178]
 [0.82376859]
 [0.8653334 ]]
 Label: [[0.86287738]
 [0.8859423 ]
 [0.86688298]
 [0.87952138]
 [0.87859783]]
Window: [[0.86153815]
 [0.83293178]
 [0.82376859]
 [0.8653334 ]
 [0.86287738]]
 Label: [[0.8859423 ]
 [0.86688298]
 [0.87952138]
 [0.87859783]
 [0.85450117]]
Window: [[0.01548906]
 [0.01441558]
 [0.0129372 ]
 [0.01340529]
 [0.0139596 ]]
 Label: [[0.01513442]
 [0.01610235]
 [0.01696297]
 [0.01805614]
 [0.02000478]]
Window: [[0.01441558]
 [0.0129372 ]
 [0.01340529]
 [0.0139596 ]
 [0.01513442]]
 Label: [[0.01610235]
 [0.01696297]
 [0.01805614]
 [0.02000478]
 [0.02032143]]
```

In [17]:
```
def datasplit(input, output):
  train_size = int(0.8 * len(input))
  test_size = train_size + int(0.1 * len(input))

  X_train, y_train = input[:train_size], output[:train_size]

  X_test, y_test = input[train_size:test_size], output[train_size:test_size]

  X_val, y_val = input[test_size:], output[test_size:]

  return X_train, y_train, X_test, y_test, X_val, y_val
```

AMD

In [18]:
```
amd_Xtrain, amd_ytrain, amd_Xtest, amd_ytest, amd_Xval, amd_yval = datasplit(amdinput, amdou
```

In [19]:
```
print("AMD Split:")
print(len(amd_Xtrain))
print(len(amd_ytrain))

print(len(amd_Xtest))
print(len(amd_ytest))

print(len(amd_Xval))
print(len(amd_yval))
```

```
AMD Split:
8071
8071
1008
1008
1010
1010
```

In [20]:
```
amd_ytrain.shape
```

Out[20]:
```
(8071, 5, 1)
```

In [21]:
```
# amd_ytrain = amd_ytrain[:, 0, :]
# amd_yval = amd_yval[:, 0, :]
# amd_ytest = amd_ytest[:, 0, :]
```

In [22]:
```
print(amd_ytrain.shape)
print(amd_yval.shape)
print(amd_ytest.shape)
```

```
(8071, 5, 1)
(1010, 5, 1)
(1008, 5, 1)
```

In [23]:
```
amd_ytrain
```

Out[23]:
```
array([[[0.05626521],
        [0.05325825],
        [0.04557904],
        [0.04191158],
        [0.05021498]],

       [[0.05325825],
        [0.04557904],
        [0.04191158],
        [0.05021498],
        [0.05021498]],

       [[0.04557904],
        [0.04191158],
        [0.05021498],
        [0.05021498],
        [0.05972913]],

       ...,

       [[0.24984829],
        [0.24848662],
        [0.24794081],
        [0.24465176],
        [0.2441012 ]],

       [[0.24848662],
        [0.24794081],
        [0.24465176],
        [0.2441012 ],
        [0.24382566]],

       [[0.24794081],
        [0.24465176],
        [0.2441012 ],
        [0.24382566],
        [0.2454763 ]]])
```

AAPL

In [24]:
```
aapl_Xtrain, aapl_ytrain, aapl_Xtest, aapl_ytest, aapl_Xval, aapl_yval = datasplit(aaplinput
```

In [25]:
```
print("AAPL Split:")
print(len(aapl_Xtrain))
print(len(aapl_ytrain))

print(len(aapl_Xtest))
print(len(aapl_ytest))

print(len(aapl_Xval))
print(len(aapl_yval))
```

```
AAPL Split:
7920
7920
990
990
990
990
```

In [26]:
```
# aapl_ytrain = aapl_ytrain[:, 0, :]
# aapl_yval = aapl_yval[:, 0, :]
# aapl_ytest = aapl_ytest[:, 0, :]
```

In [27]:
```
print(aapl_ytrain.shape)
print(aapl_yval.shape)
print(aapl_ytest.shape)
```

```
(7920, 5, 1)
(990, 5, 1)
(990, 5, 1)
```

Dataset telah di windowing dengan window size = 5 dan horizon = 5, kolom yang diambil hanyalah kolom price dikarenakan feature lainnya tidak terlalu dibutuhkan didalam proses ini.

Transformer Baseline Model

In [28]:
```
def positional_encoding(input_dim, d_model):
    angle_rates = 1 / np.power(10000, (2 * (np.arange(d_model) // 2)) / np.float32(d_model))
    positional_encoding = np.zeros((input_dim, d_model))

    for position in range(input_dim):
        for i in range(d_model):
            if i % 2 == 0:
                positional_encoding[position, i] = np.sin(position * angle_rates[i])
            else:
                positional_encoding[position, i] = np.cos(position * angle_rates[i])

    return tf.cast(positional_encoding, dtype=tf.float32)
```

In [29]:
```
def transformerencoder(inputs, head_size, num_heads, ff_dim, dropout=0):
    length = inputs.shape[1]
    d_model = inputs.shape[2]

    x = inputs

    encoding = positional_encoding(length, d_model)
    x = x + encoding

    x = layers.MultiHeadAttention(key_dim=head_size, num_heads=num_heads, dropout=dropout)(x

    x = layers.Dropout(dropout)(x)
    res = x + inputs

    x = layers.Conv1D(filters=ff_dim, kernel_size=1, activation = "relu")(x)

    x = layers.Dropout(dropout)(x)

    return x + res
```

In [30]:
```
def buildmodel(
    input_shape,
    head_size,
    num_heads,
    ff_dim,
    num_transformer_blocks,
    mlp_units,
    dropout=0,
    mlp_dropout=0,
):
    inputs = keras.Input(shape=input_shape)
    x = inputs

    for _ in range(num_transformer_blocks):
        x = transformerencoder(x, head_size, num_heads, ff_dim, dropout)

    x = layers.GlobalAveragePooling1D(data_format="channels_first")(x)
    for dim in mlp_units:
        x = layers.Dense(dim, activation="elu")(x)
        x = layers.Dropout(mlp_dropout)(x)
    outputs = layers.Dense(horizon, activation="linear")(x)
    return keras.Model(inputs, outputs)

def lrscheduler(epoch, lr, warmup_epochs=30, decay_epochs=100, initial_lr=1e-6, base_lr=1e-3
    if epoch <= warmup_epochs:
        pct = epoch / warmup_epochs
        return ((base_lr - initial_lr) * pct) + initial_lr

    if epoch > warmup_epochs and epoch < warmup_epochs+decay_epochs:
        pct = 1 - ((epoch - warmup_epochs) / decay_epochs)
        return ((base_lr - min_lr) * pct) + min_lr

    return min_lr
```

In [31]:
```
callbacks = [keras.callbacks.EarlyStopping(patience=10, restore_best_weights=True), keras.ca
```

In [32]:
```
input_shape_amd = amd_Xtrain.shape[1:]
print(input_shape_amd)
```

```
(5, 1)
```

In [33]:
```
input_shape_aapl = aapl_Xtrain.shape[1:]
print(input_shape_aapl)
```

```
(5, 1)
```

In [45]:
```
def evaluatemodel(model, name, data, X_test, y_test):
    testpred = model.predict(X_test)
    testpred = testpred.flatten()

    y_test = y_test.flatten()

    testrmse = np.sqrt(np.mean((testpred - y_test)) ** 2)
    testmae = mean_absolute_error(y_test, testpred)

    print(f'\n{name} - Test:')
    print('RMSE: %.8f ' % (testrmse))
    print('MAE: %.8f ' % (testmae))

    plt.figure(figsize=(20, 10))
    plt.plot(testpred,color='red', label='Prediction Test Data')
    plt.plot(y_test,color='green', label='y_test')
    plt.title(f'{name} - Test')
    plt.xlabel('Number of Days')
    plt.ylabel('Close Price')
    plt.legend(loc='upper left')
    plt.show()
```

In [35]:
```
from tensorflow.keras import layers

model = buildmodel(
    input_shape_amd,
    head_size=46,
    num_heads=60,
    ff_dim=55,
    num_transformer_blocks=5,
    mlp_units=[256],
    mlp_dropout=0.4,
    dropout=0.14
)

model.compile(
    loss="mean_squared_error",
    optimizer=keras.optimizers.Adam(learning_rate=1e-4),
    metrics=["mean_squared_error"],
)

history = model.fit(
    amd_Xtrain,
    amd_ytrain,
    validation_split=0.2,
    epochs=20,
    batch_size=64,
    callbacks=callbacks
)
```

```
rror: 0.0025 - val_loss: 5.5496e-04 - val_mean_squared_error: 5.5496e-04 - lr: 3.3400e-04
Epoch 12/20
101/101 [==============================] - 18s 178ms/step - loss: 0.0023 - mean_squared_e
rror: 0.0023 - val_loss: 0.0010 - val_mean_squared_error: 0.0010 - lr: 3.6730e-04
Epoch 13/20
101/101 [==============================] - 18s 180ms/step - loss: 0.0020 - mean_squared_e
rror: 0.0020 - val_loss: 4.6277e-04 - val_mean_squared_error: 4.6277e-04 - lr: 4.0060e-04
Epoch 14/20
101/101 [==============================] - 18s 179ms/step - loss: 0.0019 - mean_squared_e
rror: 0.0019 - val_loss: 0.0015 - val_mean_squared_error: 0.0015 - lr: 4.3390e-04
Epoch 15/20
101/101 [==============================] - 18s 178ms/step - loss: 0.0021 - mean_squared_e
rror: 0.0021 - val_loss: 0.0012 - val_mean_squared_error: 0.0012 - lr: 4.6720e-04
Epoch 16/20
101/101 [==============================] - 18s 179ms/step - loss: 0.0018 - mean_squared_e
rror: 0.0018 - val_loss: 0.0016 - val_mean_squared_error: 0.0016 - lr: 5.0050e-04
Epoch 17/20
101/101 [==============================] - 18s 179ms/step - loss: 0.0026 - mean_squared_e
rror: 0.0026 - val_loss: 3.4837e-04 - val_mean_squared_error: 3.4837e-04 - lr: 5.3380e-04
```

In [36]:
```
model2 = buildmodel(
    input_shape_aapl,
    head_size=46,
    num_heads=60,
    ff_dim=55,
    num_transformer_blocks=5,
    mlp_units=[256],
    mlp_dropout=0.4,
    dropout=0.14,
)

model2.compile(
    loss="mean_squared_error",
    optimizer=keras.optimizers.Adam(learning_rate=1e-4),
    metrics=["mean_squared_error"],
)

history = model2.fit(
    aapl_Xtrain,
    aapl_ytrain,
    validation_split=0.2,
    epochs=20,
    batch_size=64,
    callbacks=callbacks
)
```

```
Epoch 16/20
99/99 [==============================] - 20s 204ms/step - loss: 1.1236e-04 - mean_squared
_error: 1.1236e-04 - val_loss: 2.8840e-04 - val_mean_squared_error: 2.8840e-04 - lr: 5.00
50e-04
Epoch 17/20
99/99 [==============================] - 21s 217ms/step - loss: 1.1072e-04 - mean_squared
_error: 1.1072e-04 - val_loss: 9.1685e-04 - val_mean_squared_error: 9.1685e-04 - lr: 5.33
80e-04
Epoch 18/20
99/99 [==============================] - 20s 207ms/step - loss: 1.2719e-04 - mean_squared
_error: 1.2719e-04 - val_loss: 3.2733e-04 - val_mean_squared_error: 3.2733e-04 - lr: 5.67
10e-04
Epoch 19/20
99/99 [==============================] - 18s 180ms/step - loss: 9.6154e-05 - mean_squared
_error: 9.6154e-05 - val_loss: 6.1412e-05 - val_mean_squared_error: 6.1412e-05 - lr: 6.00
40e-04
Epoch 20/20
99/99 [==============================] - 18s 177ms/step - loss: 9.4096e-05 - mean_squared
_error: 9.4096e-05 - val_loss: 9.9800e-05 - val_mean_squared_error: 9.9800e-05 - lr: 6.33
70e-04
```

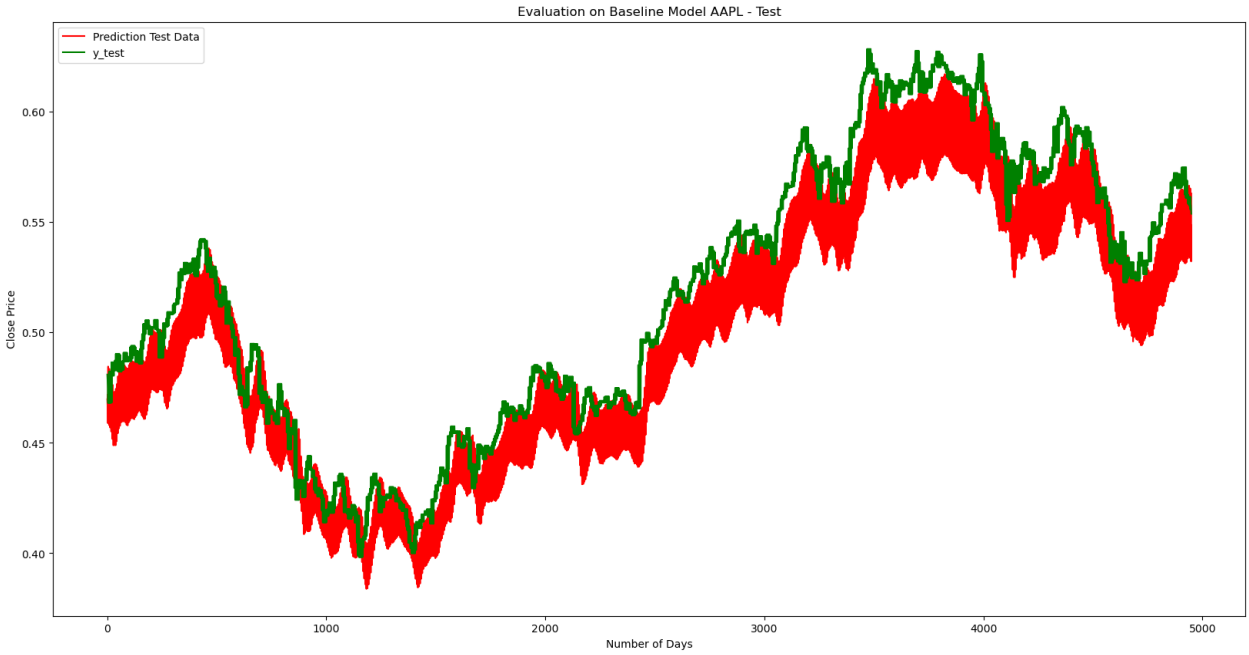
Evaluate Baseline Model

In [37]:
```
evaluatemodel(model, "Evaluation on Baseline Model AMD", amdsqrt_close, amd_Xtest, amd_ytest
```

```
32/32 [==============================] - 1s 34ms/step

Evaluation on Baseline Model AMD - Test:
RMSE: 0.00581307
MAE: 0.00884268
```

In [38]:
```
evaluatemodel(model2, "Evaluation on Baseline Model AAPL", aaplsqrt_close, aapl_Xtest, aapl_
```

```
31/31 [==============================] - 1s 32ms/step

Evaluation on Baseline Model AAPL - Test:
RMSE: 0.01837979
MAE: 0.01971346
```



Modified Model

In [39]:
```
def modifiedtransformerencoder(inputs, head_size, num_heads, ff_dim, dropout=0):
    length = inputs.shape[1]
    embed = inputs.shape[2]

    x = layers.LayerNormalization(epsilon=1e-6)(inputs)

    x = layers.MultiHeadAttention(key_dim=head_size, num_heads=num_heads, dropout=dropout)(x

    x = layers.Dropout(dropout)(x)
    res = x + inputs

    x = layers.LayerNormalization(epsilon=1e-6)(res)
    encoding = positional_encoding(length, embed)

    x = layers.Conv1D(ff_dim, kernel_size=1, activation = "relu")(x)

    x = layers.Dropout(dropout)(x)

    x = layers.Conv1D(inputs.shape[-1], kernel_size=1)(x)

    return x + res
```

Pada modified transformer, saya menambahkan Layer Normalization dan Convolutional layer. Hal ini dilakukan untuk mengatasi underfitting.

In [46]:
```
def buildmodel(
    input_shape,
    head_size,
    num_heads,
    ff_dim,
    num_transformer_blocks,
    mlp_units,
    dropout=0,
    mlp_dropout=0,
):
    inputs = keras.Input(shape=input_shape_amd)
    x = inputs

    for _ in range(num_transformer_blocks):
        x = modifiedtransformerencoder(x, head_size, num_heads, ff_dim, dropout)

    x = layers.GlobalAveragePooling1D(data_format="channels_first")(x)
    for dim in mlp_units:
        x = layers.Dense(dim, activation="elu")(x)
        x = layers.Dropout(mlp_dropout)(x)
    outputs = layers.Dense(5, activation="linear")(x)
    return keras.Model(inputs, outputs)
```

AMD

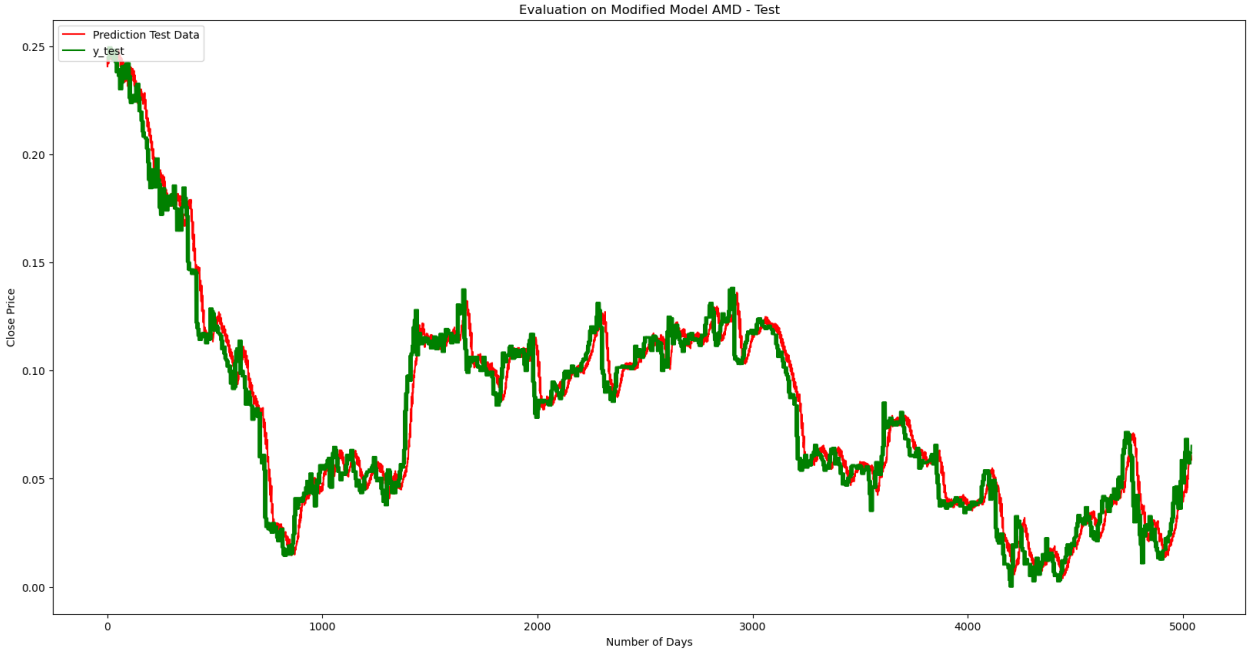
In [47]:
```
model1 = buildmodel(
    input_shape_amd,
    head_size=46,
    num_heads=60,
    ff_dim=55,
    num_transformer_blocks=5,
    mlp_units=[128],
    mlp_dropout=0.4,
    dropout=0.2,
)

model1.compile(
    loss="mean_squared_error",
    optimizer=keras.optimizers.Adam(learning_rate=1e-4),
    metrics=["mean_squared_error"],
)

history = model1.fit(
    amd_Xtrain,
    amd_ytrain,
    validation_split=0.2,
    epochs=20,
    batch_size=64,
    callbacks=callbacks
)
```

```
rror: 0.0033 - val_loss: 5.3682e-04 - val_mean_squared_error: 5.3682e-04 - lr: 4.3390e-04
Epoch 15/20
101/101 [==============================] - 14s 139ms/step - loss: 0.0029 - mean_squared_e
rror: 0.0029 - val_loss: 3.9674e-04 - val_mean_squared_error: 3.9674e-04 - lr: 4.6720e-04
Epoch 16/20
101/101 [==============================] - 14s 139ms/step - loss: 0.0027 - mean_squared_e
rror: 0.0027 - val_loss: 4.4490e-04 - val_mean_squared_error: 4.4490e-04 - lr: 5.0050e-04
Epoch 17/20
101/101 [==============================] - 14s 141ms/step - loss: 0.0025 - mean_squared_e
rror: 0.0025 - val_loss: 3.5612e-04 - val_mean_squared_error: 3.5612e-04 - lr: 5.3380e-04
Epoch 18/20
101/101 [==============================] - 14s 139ms/step - loss: 0.0024 - mean_squared_e
rror: 0.0024 - val_loss: 3.5953e-04 - val_mean_squared_error: 3.5953e-04 - lr: 5.6710e-04
Epoch 19/20
101/101 [==============================] - 14s 140ms/step - loss: 0.0022 - mean_squared_e
rror: 0.0022 - val_loss: 3.4129e-04 - val_mean_squared_error: 3.4129e-04 - lr: 6.0040e-04
Epoch 20/20
101/101 [==============================] - 14s 140ms/step - loss: 0.0021 - mean_squared_e
rror: 0.0021 - val_loss: 3.4987e-04 - val_mean_squared_error: 3.4987e-04 - lr: 6.3370e-04
```

Hyperparameter pada mlp_units dari 256 -> 128 agar mengurangi kemungkinan overfitting, dikarenakan sudah menambahkan layer pada transformer model.

In [48]:
```
evaluatemodel(model1, "Evaluation on Modified Model AMD", amdsqrt_close, amd_Xtest, amd_ytes
```

```
32/32 [==============================] - 1s 27ms/step

Evaluation on Modified Model AMD - Test:
RMSE: 0.00163976
MAE: 0.00710936
```



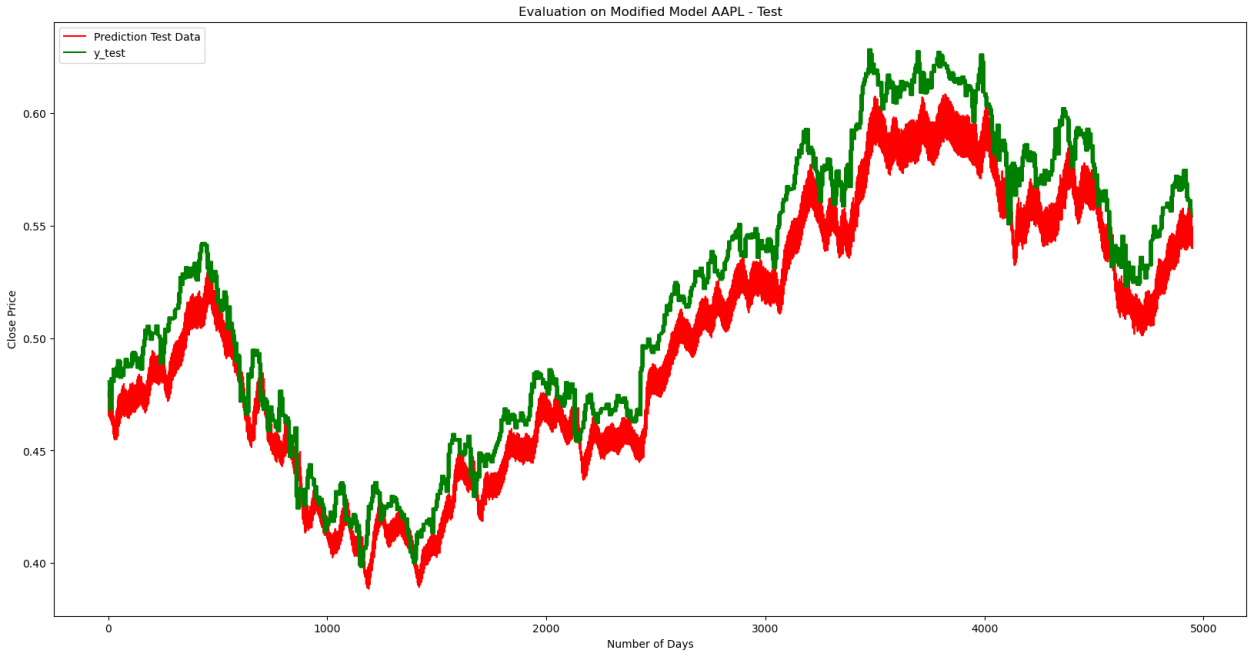
AAPL

In [49]:
```
model2 = buildmodel(
    input_shape_aapl,
    head_size=24,
    num_heads=32,
    ff_dim=45,
    num_transformer_blocks=5,
    mlp_units=[128],
    mlp_dropout=0.2,
    dropout=0.07,
)

model2.compile(
    loss="mean_squared_error",
    optimizer=keras.optimizers.Adam(learning_rate=1e-4),
    metrics=["mean_squared_error"],
)

history = model2.fit(
    aapl_Xtrain,
    aapl_ytrain,
    validation_split=0.2,
    epochs=20,
    batch_size=64,
    callbacks=callbacks
)
```

```
r: 0.0031 - val_loss: 0.1081 - val_mean_squared_error: 0.1081 - lr: 1.0000e-06
Epoch 2/20
99/99 [==============================] - 4s 38ms/step - loss: 0.0018 - mean_squared_erro
r: 0.0018 - val_loss: 0.0900 - val_mean_squared_error: 0.0900 - lr: 3.4300e-05
Epoch 3/20
99/99 [==============================] - 4s 36ms/step - loss: 0.0011 - mean_squared_erro
r: 0.0011 - val_loss: 0.0706 - val_mean_squared_error: 0.0706 - lr: 6.7600e-05
Epoch 4/20
99/99 [==============================] - 4s 36ms/step - loss: 6.3469e-04 - mean_squared_e
rror: 6.3469e-04 - val_loss: 0.0384 - val_mean_squared_error: 0.0384 - lr: 1.0090e-04
Epoch 5/20
99/99 [==============================] - 4s 37ms/step - loss: 3.1723e-04 - mean_squared_e
rror: 3.1723e-04 - val_loss: 0.0149 - val_mean_squared_error: 0.0149 - lr: 1.3420e-04
Epoch 6/20
99/99 [==============================] - 4s 37ms/step - loss: 1.3313e-04 - mean_squared_e
rror: 1.3313e-04 - val_loss: 0.0040 - val_mean_squared_error: 0.0040 - lr: 1.6750e-04
Epoch 7/20
99/99 [==============================] - 4s 36ms/step - loss: 6.4603e-05 - mean_squared_e
rror: 6.4603e-05 - val_loss: 8.2146e-04 - val_mean_squared_error: 8.2146e-04 - lr: 2.0080
e-04
```

In [50]:
```
evaluatemodel(model2, "Evaluation on Modified Model AAPL", aaplsqrt_close, aapl_Xtest, aapl_
```

```
31/31 [==============================] - 1s 9ms/step

Evaluation on Modified Model AAPL - Test:
RMSE: 0.01722986
MAE: 0.01780906
```



Conclusion

Berikut merupakan hasil dari evaluasi baseline:

Evaluation on Baseline Model AMD - Test:

- RMSE: 0.00581307
- MAE: 0.00884268

Evaluation on Baseline Model AAPL - Test:

- RMSE: 0.01837979
- MAE: 0.01971346

Berikut merupakan hasil dari modified baseline:

Evaluation on Modified Model AMD - Test:

- RMSE: 0.00163976
- MAE: 0.00710936

Evaluation on Modified Model AAPL - Test:

- RMSE: 0.01722986
- MAE: 0.01780906

Model modified pada kedua saham memiliki performa yang lebih baik daripada model baseline, hal ini dapat dilihat dari nilai RMSE dan MAE yang lebih kecil pada Modified Model.