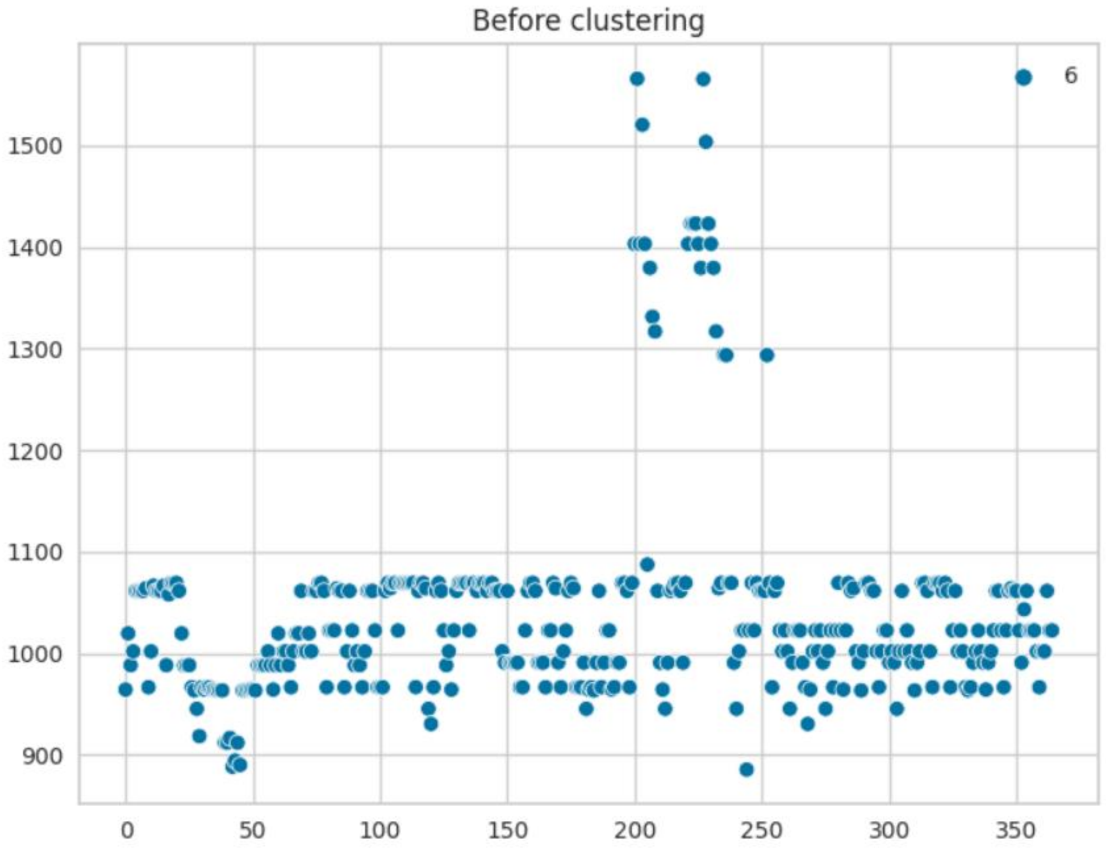
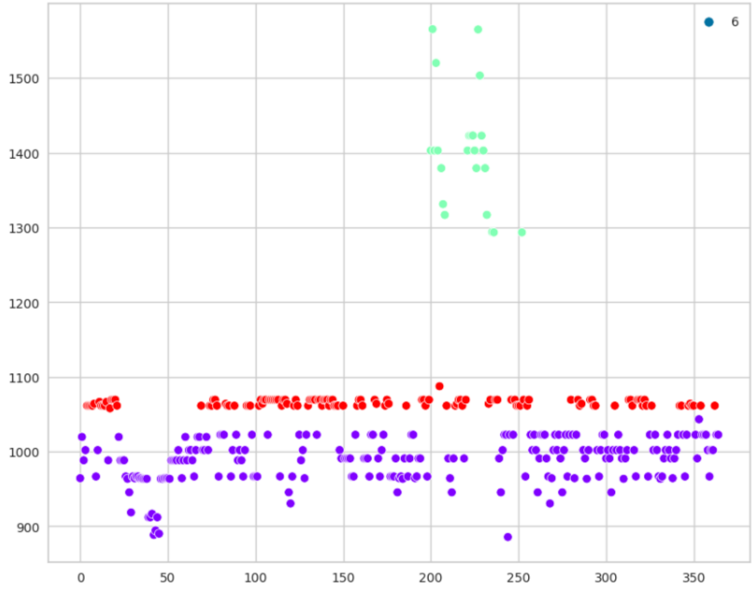
```
#ricopue's notebook's code snippet
from sklearn.model_selection import StratifiedKFold
X_new=df_new.loc[train_index][feats]
y=df_new.loc[train_index]['preds']

params_lgb = {'learning_rate': 0.06,'objective': 'multiclass','boosting': 'gbdt','n_jobs': -1,'verbosity'

model_list=[]

gkf = StratifiedKFold(11)
for fold, (train_idx, valid_idx) in enumerate(gkf.split(X_new,y)):

    tr_dataset = lgb.Dataset(X_new.iloc[train_idx],y.iloc[train_idx],feature_name = feats)
    vl_dataset = lgb.Dataset(X_new.iloc[valid_idx],y.iloc[valid_idx],feature_name = feats)

    model = lgb.train(params = params_lgb,
                train_set = tr_dataset,
                valid_sets =  vl_dataset,
                num_boost_round = 5000,
                callbacks=[ lgb.early_stopping(stopping_rounds=300, verbose=False), lgb.log_evaluation(pe

    model_list.append(model)
```

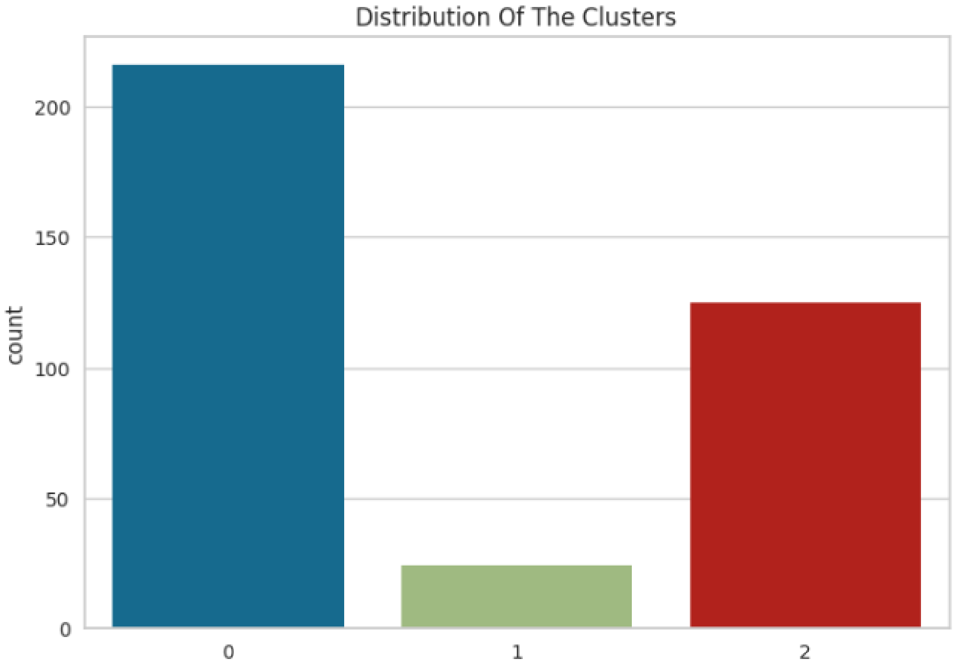
```
fig = plt.figure(figsize=(8,6))
ax = plt.subplot(label="bla")
sns.scatterplot(df[feats], marker='o');
ax.set_title("Before clustering");
```



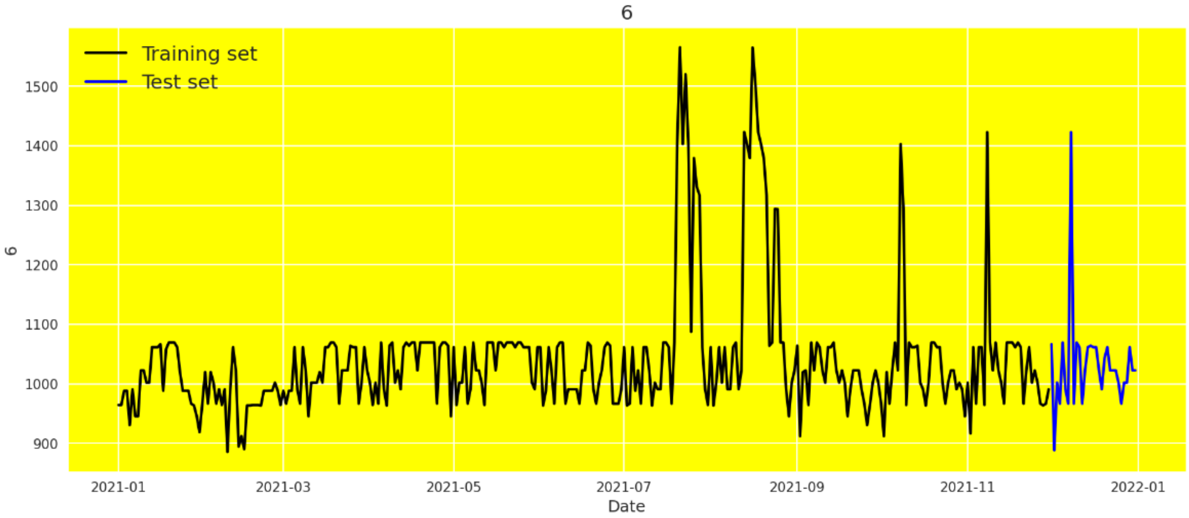
```
fig = plt.figure(figsize=(10,8))
sns.scatterplot(df[feats], c=df["Clusters"], marker='o',cmap="rainbow");
ax.set_title("After Clustering");
```



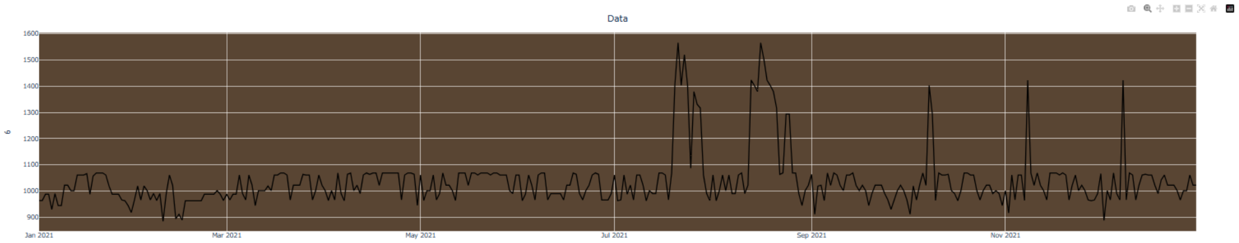
```
pl = sns.countplot(x=np.argmax(lgb_preds,axis=1))
pl.set_title("Distribution Of The Clusters")
plt.show()
```



```
plt.figure(figsize=(15, 6), dpi=150)
plt.rcParams['axes.facecolor'] = 'yellow'
plt.rc('axes',edgecolor='white')
plt.plot(df['Ngay'][:-test_size], df['6'][:-test_size], color='black', lw=2)
plt.plot(df['Ngay'][-test_size:], df['6'][-test_size:], color='blue', lw=2)
plt.title('6', fontsize=15)
plt.xlabel('Date', fontsize=12)
plt.ylabel('6', fontsize=12)
plt.legend(['Training set', 'Test set'], loc='upper left', prop={'size': 15})
plt.grid(color='white')
plt.show()
```

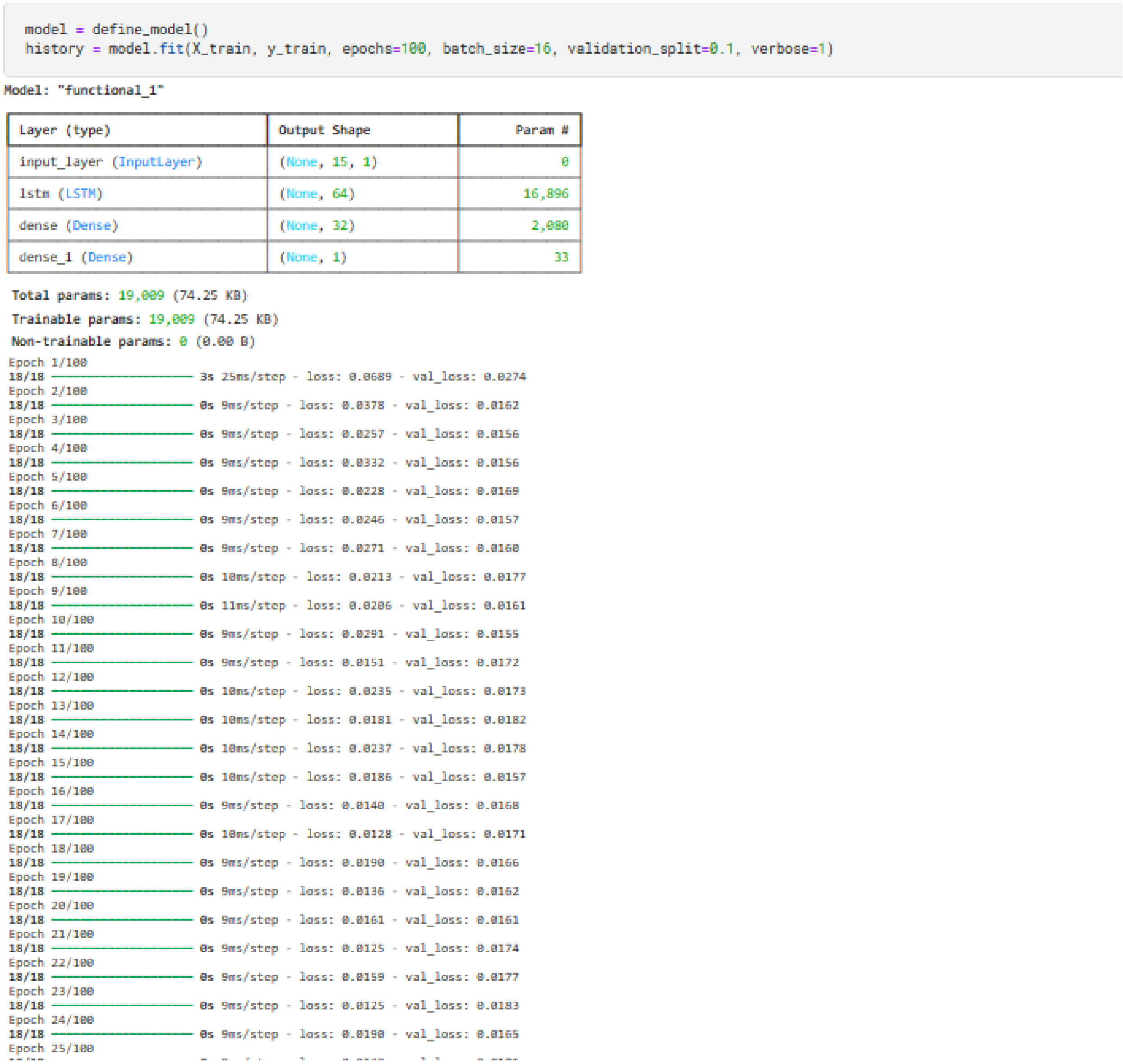


```
import plotly.express as px
fig = px.line(y=df['6'], x=df['Ngay'])
fig.update_traces(line_color='black')
fig.update_layout(xaxis_title="Ngay",
                  yaxis_title="6",
                  title={'text': "Data", 'y':0.95, 'x':0.5, 'xanchor':'center', 'yanchor':'top'},
                  plot_bgcolor='rgba(47,23,0,0.8)')
```



```
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))
X_test  = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
y_train = np.reshape(y_train, (-1,1))
y_test  = np.reshape(y_test, (-1,1))
```

```
def define_model():
    input1 = Input(shape=(window_size,1))
    x = LSTM(units = 64)(input1)
    x = Dense(32, activation='softmax')(x)
    dnn_output = Dense(1)(x)

    model = Model(inputs=input1, outputs=[dnn_output])
    model.compile(loss='mean_squared_error', optimizer='Nadam')
    model.summary()

    return model
```

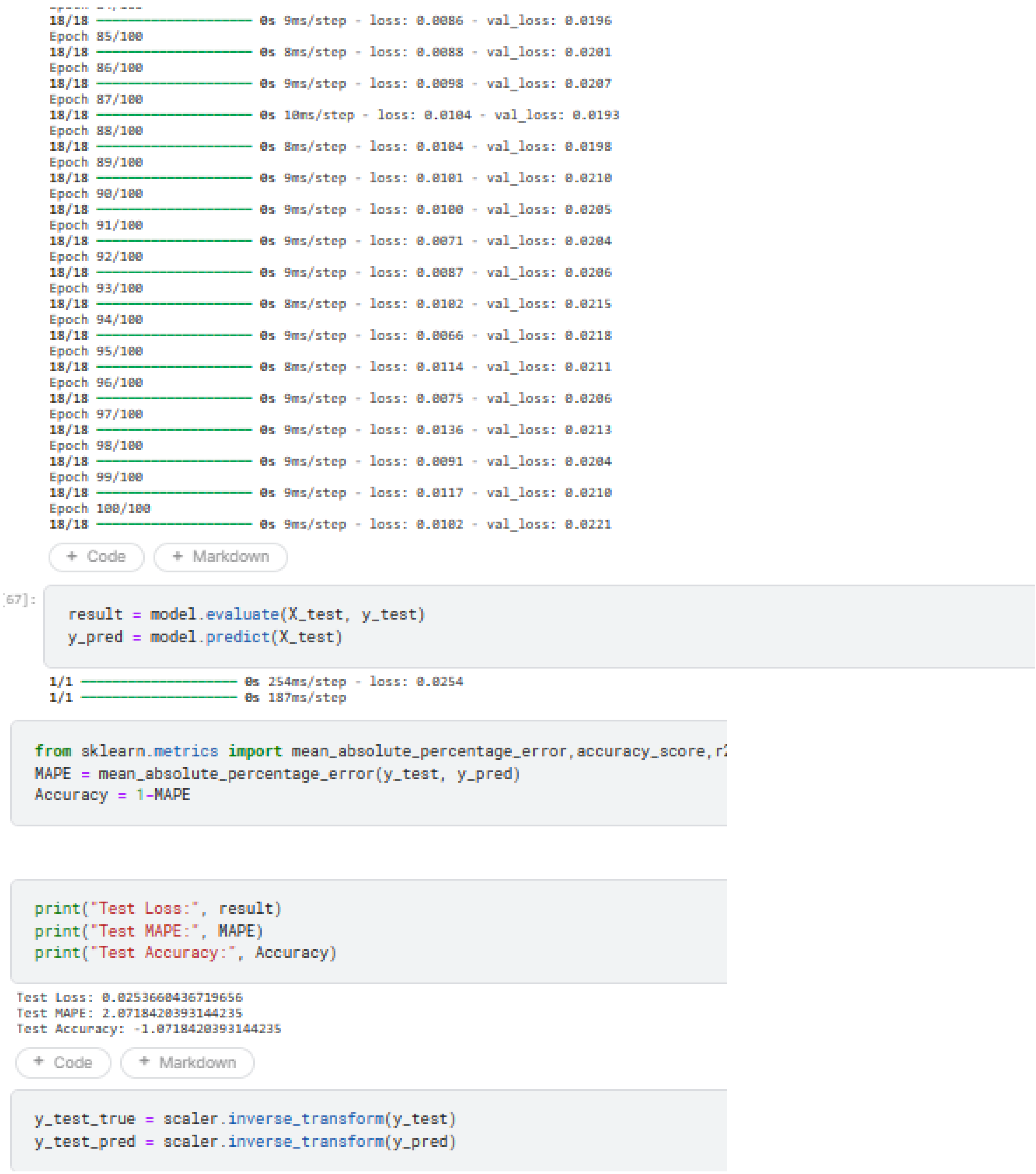


```python
model = define_model()
history = model.fit(X_train, y_train, epochs=100, batch_size=16, validation_split=0.1, verbose=1)
```

```
Model: "functional_1"
```

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 15, 1)	0
lstm (LSTM)	(None, 64)	16,896
dense (Dense)	(None, 32)	2,080
dense_1 (Dense)	(None, 1)	33

```
Total params: 19,009 (74.25 KB)
Trainable params: 19,009 (74.25 KB)
Non-trainable params: 0 (0.00 B)
Epoch 1/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 3s 25ms/step - loss: 0.0689 - val_loss: 0.0274
Epoch 2/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0378 - val_loss: 0.0162
Epoch 3/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0257 - val_loss: 0.0156
Epoch 4/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0332 - val_loss: 0.0156
Epoch 5/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0228 - val_loss: 0.0169
Epoch 6/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0246 - val_loss: 0.0157
Epoch 7/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0271 - val_loss: 0.0160
Epoch 8/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - loss: 0.0213 - val_loss: 0.0177
Epoch 9/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0206 - val_loss: 0.0161
Epoch 10/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0291 - val_loss: 0.0155
Epoch 11/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0151 - val_loss: 0.0172
Epoch 12/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - loss: 0.0235 - val_loss: 0.0173
Epoch 13/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - loss: 0.0181 - val_loss: 0.0182
Epoch 14/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - loss: 0.0237 - val_loss: 0.0178
Epoch 15/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - loss: 0.0186 - val_loss: 0.0157
Epoch 16/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0140 - val_loss: 0.0168
Epoch 17/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - loss: 0.0128 - val_loss: 0.0171
Epoch 18/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0190 - val_loss: 0.0166
Epoch 19/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0136 - val_loss: 0.0162
Epoch 20/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0161 - val_loss: 0.0161
Epoch 21/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0125 - val_loss: 0.0174
Epoch 22/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0159 - val_loss: 0.0177
Epoch 23/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0125 - val_loss: 0.0183
Epoch 24/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0190 - val_loss: 0.0165
Epoch 25/100
```



```
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0086 - val_loss: 0.0196
Epoch 85/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - loss: 0.0088 - val_loss: 0.0201
Epoch 86/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0098 - val_loss: 0.0207
Epoch 87/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - loss: 0.0104 - val_loss: 0.0193
Epoch 88/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - loss: 0.0104 - val_loss: 0.0198
Epoch 89/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0101 - val_loss: 0.0210
Epoch 90/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0100 - val_loss: 0.0205
Epoch 91/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0071 - val_loss: 0.0204
Epoch 92/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0087 - val_loss: 0.0206
Epoch 93/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - loss: 0.0102 - val_loss: 0.0215
Epoch 94/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0066 - val_loss: 0.0218
Epoch 95/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - loss: 0.0114 - val_loss: 0.0211
Epoch 96/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0075 - val_loss: 0.0206
Epoch 97/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0136 - val_loss: 0.0213
Epoch 98/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0091 - val_loss: 0.0204
Epoch 99/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0117 - val_loss: 0.0210
Epoch 100/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0102 - val_loss: 0.0221
```

```
result = model.evaluate(X_test, y_test)
y_pred = model.predict(X_test)
```

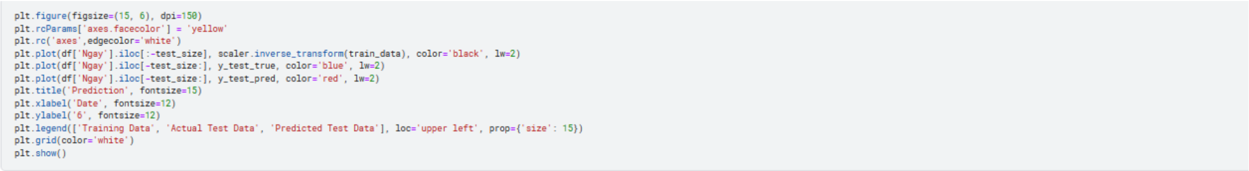
```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 254ms/step - loss: 0.0254
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 187ms/step
```

```
from sklearn.metrics import mean_absolute_percentage_error,accuracy_score,r2
MAPE = mean_absolute_percentage_error(y_test, y_pred)
Accuracy = 1-MAPE
```

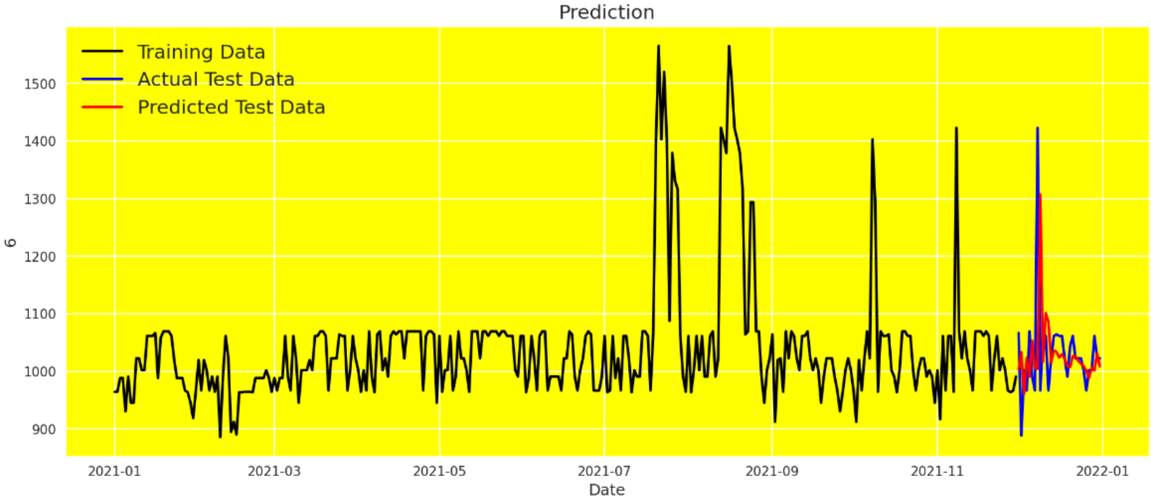
```
print("Test Loss:", result)
print("Test MAPE:", MAPE)
print("Test Accuracy:", Accuracy)
```

```
Test Loss: 0.02536608436719656
Test MAPE: 2.0718420393144235
Test Accuracy: -1.0718420393144235
```

```
y_test_true = scaler.inverse_transform(y_test)
y_test_pred = scaler.inverse_transform(y_pred)
```



```
plt.figure(figsize=(15, 6), dpi=150)
plt.rcParams['axes.facecolor'] = 'yellow'
plt.rc('axes',edgecolor='white')
plt.plot(df['Ngay'].iloc[:-test_size], scaler.inverse_transform(train_data), color='black', lw=2)
plt.plot(df['Ngay'].iloc[-test_size:], y_test_true, color='blue', lw=2)
plt.plot(df['Ngay'].iloc[-test_size:], y_test_pred, color='red', lw=2)
plt.title('Prediction', fontsize=15)
plt.xlabel('Date', fontsize=12)
plt.ylabel('6', fontsize=12)
plt.legend(['Training Data', 'Actual Test Data', 'Predicted Test Data'], loc='upper left', prop={'size': 15})
plt.grid(color='white')
plt.show()
```


Prediction
Training Data
Actual Test Data
Predicted Test Data
Date