lstm_single_stock

September 21, 2023

```
[52]: import numpy as np
  import pandas as pd
  from lstm_functions import *
  from lost_functions import *
  from sklearn.preprocessing import MinMaxScaler
  import matplotlib.pyplot as plt
  from sklearn.metrics import mean_absolute_error, mean_squared_error
  import yfinance as yf
```

1 This to try to tune and try to get a good prediction for Apple Stock

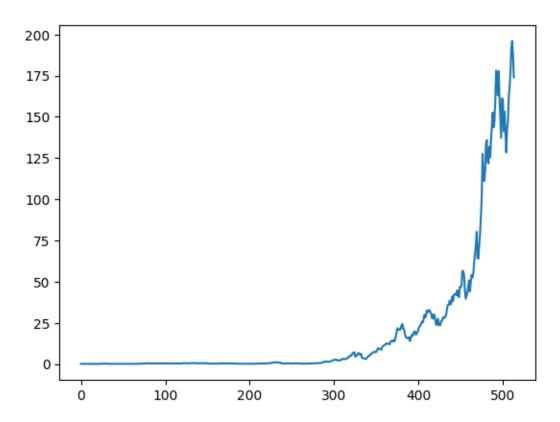
If i can get a good prediction for Apple Stock, then i can use the same model for other stocks. This notebook is mainly to tune the model and get a good prediction for Apple Stock

2 Reading and storing the Data

```
[53]: xls = pd.ExcelFile('data/data_for_testing.xlsx')
all_data = {}
# This is too much data to load into memory at once
# for sheet in xls.sheet_names:
# all_data[sheet] = pd.read_excel(xls, sheet_name=sheet)
for sheet in ["AAPL"]:
    data = pd.read_excel(xls, sheet_name=sheet).set_index('Date')
    # Resample to monthly data as a simple way to reduce the number of data__
    **points
    # Daily data is too much and take too long to train
    new_data = data.resample('M').last().reset_index()
    # new_data = new_data[new_data['Date'] < '2019-12-01']
    all_data[sheet] = new_data</pre>
```

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[55]: all_data["AAPL"]["Open"].plot()
```

[55]: <Axes: >



```
[56]: final_importance_values = {}
final_predictions = {}
# 30 is not a good number of batches, but it's a start for testing
# 60 is a good number of batches, but it takes a long time to train
time_steps = 12
features = 6
```

```
return train_mae, test_mae, train_rmse, test_rmse
```

```
[58]: def plot_predictions(y_train, train_predictions, y_test, test_predictions,_
       ⇔ticker, feature):
          plt.figure(figsize=(14,7))
          plt.plot(y_train, label="Actual Train Values", color='blue')
          plt.plot(train_predictions, label="Predicted Train Values", color='blue', u
       →linestyle='dashed')
          plt.plot(np.arange(len(y_train), len(y_train) + len(y_test)), y_test,__
       ⇔label="Actual Test Values", color='red')
          plt.plot(np.arange(len(y_train), len(y_train) + len(y_test)),__
       otest_predictions, label="Predicted Test Values", color='red',
       ⇔linestyle='dashed')
          plt.title(f"{ticker} {feature} - Actual vs Predicted Values")
          plt.legend()
          plt.show()
[64]: ticker = "AAPL"
      data = all_data[ticker]
      # Drop non-numeric columns
      data = data.drop(columns=['Sector', 'Ticker', 'Date']) # Assuming 'Date' is_
       ⇒the index
      lstm_model = LstmBuilder(time_step=time_steps, loss=huber_loss, neutrons=50)
      model = lstm_model.create_model(features=features)
      scaler = MinMaxScaler()
      normalized_data = scaler.fit_transform(data)
      X, y = lstm_model.create_sequences(normalized_data)
      X_train, X_test, y_train, y_test = lstm_model.split_data(X,y, size=0.9)
      print(len(X_train), len(X_test))
      print()
      print("Working on: " + ticker)
      model.fit(X_train, y_train, epochs=200, batch_size=16, validation_split=0.2,_
       yerbose=0)
      # Predict the next day value
      last_days = normalized_data[-time_steps:].reshape(1, time_steps, features)
      prediction_next_day = model.predict(last_days)
      prediction_next_day_actual = scaler.inverse_transform(prediction_next_day)
      final_predictions[ticker] = prediction_next_day_actual.flatten()
      print(f"Predicted value for {ticker}: {prediction_next_day_actual.flatten()}")
      # Extracting importance
```

dense_weights = model.layers[-1].get_weights()[0]

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# Think about to use sum or mean and to use abs() or not
feature_weights = dense_weights.sum(axis=0)
weighted importance = prediction next_day.flatten() * feature_weights
final_importance_value = np.sum(weighted_importance) # Final importance as a__
 ⇔single value
print(f"Importance value for {ticker}: {final_importance_value}")
# Store the importance value in the dictionary
final_importance_values[ticker] = final_importance_value
# Predict for both training and testing data
train_predictions = scaler.inverse_transform(model.predict(X_train))
test_predictions = scaler.inverse_transform(model.predict(X_test))
y_train = scaler.inverse_transform(y_train)
y_test = scaler.inverse_transform(y_test)
features_list = ['Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume']
for feature_index, feature_name in enumerate(features_list):
    # Extracting data for the specific feature
    y_train_feature = y_train[:, feature_index]
    y test feature = y test[:, feature index]
    train_predictions_feature = train_predictions[:, feature_index]
    test_predictions_feature = test_predictions[:, feature_index]
    # Evaluating the model for this feature
    evaluate model(y_train_feature, train_predictions_feature, y_test_feature,_u
 stest_predictions_feature, ticker, feature_name)
    # Plotting the results for this feature
    plot_predictions(y_train_feature, train_predictions_feature,_

y_test_feature, test_predictions_feature, ticker, feature_name)

WARNING:tensorflow:Layer 1stm 12 will not use cuDNN kernels since it doesn't
meet the criteria. It will use a generic GPU kernel as fallback when running on
GPU.
451 51
Working on: AAPL
2023-09-21 11:14:53.505289: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.
2023-09-21 11:14:57.994807: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.
1/1 [======] - 0s 128ms/step
Predicted value for AAPL: [ 1.2163395e+02 1.3229443e+02 1.6007982e+02
```

1.7978258e+02

1.6037697e+02 -2.1153059e+09]

Importance value for AAPL: -0.3126019835472107

1/15 [=>...] - ETA: Os

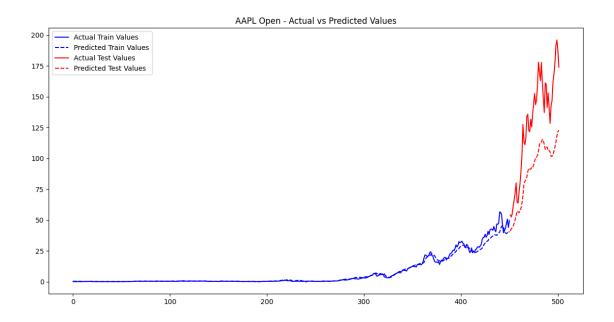
2023-09-21 11:25:45.162736: I

tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

```
15/15 [======] - Os 24ms/step 2/2 [========] - Os 55ms/step
```

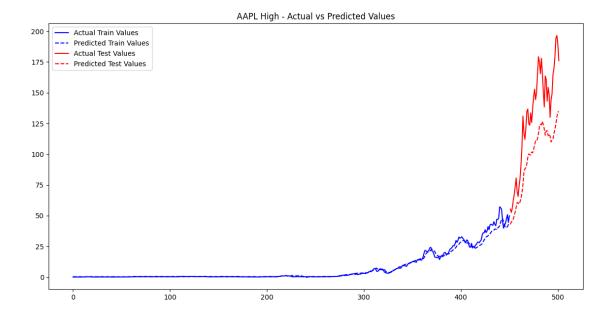
Evaluation for AAPL on Open:

Training MAE: 0.9271098523093034, Testing MAE: 40.5348565344717 Training RMSE: 2.139178396505041, Testing RMSE: 44.49680306562039



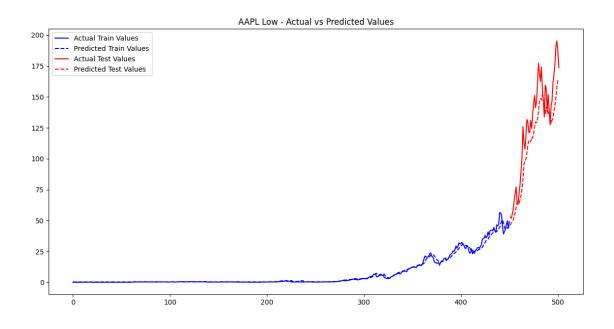
Evaluation for AAPL on High:

Training MAE: 0.9260569844898786, Testing MAE: 34.636538262460746 Training RMSE: 2.034001775209022, Testing RMSE: 38.18017706098558



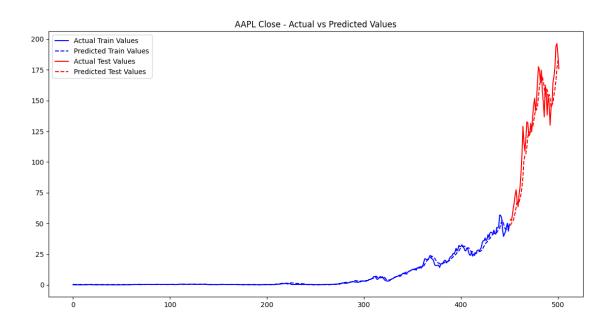
Evaluation for AAPL on Low:

Training MAE: 0.7814142409290813, Testing MAE: 16.868437673531325 Training RMSE: 1.599263907231037, Testing RMSE: 19.97828568039068



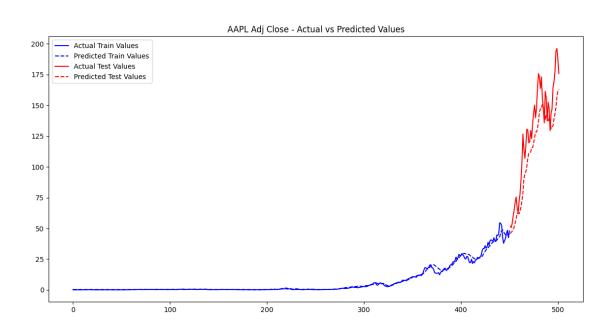
Evaluation for AAPL on Close:

Training MAE: 0.7391139996421839, Testing MAE: 11.447251338584753 Training RMSE: 1.5406203461779269, Testing RMSE: 14.316703308676688



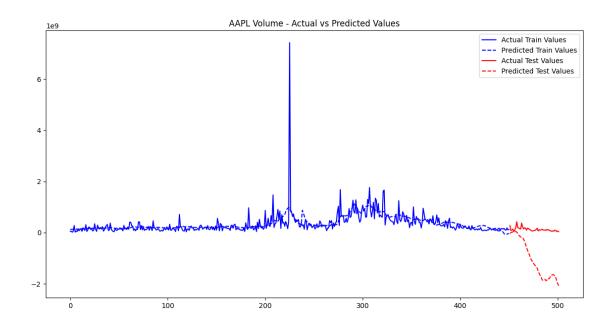
Evaluation for AAPL on Adj Close:

Training MAE: 0.7332923506983366, Testing MAE: 18.391362882127943 Training RMSE: 1.5633733303764892, Testing RMSE: 21.636413639021843



Evaluation for AAPL on Volume:

Training MAE: 150939940.54101995, Testing MAE: 1168166504.4117646 Training RMSE: 364157704.5740528, Testing RMSE: 1364662996.656598



[60]: final_importance_values

[60]: {'AAPL': -1.2869408}