Descripcion:Este programa utiliza una Recurrent NN llamada Long Short Term Memory (LSTM).

Se busca predecir el valor de la acciones de la empresa "Apple Inc", utilizando los datos de los ultimos 60 dias de las acciones.

```
#Importaemos las librerias a utilizar
import math
import pandas_datareader as web
import numpy as np
import pandas as pd
import tensorflow as tf

from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from tensorflow.keras.layers import Input, Dense, BatchNormalization, Dropout
from keras.layers import Dense, LSTM

import matplotlib.pyplot as plt
plt.style.use('dark_background')
```

```
%%capture
#Por alguna razon no funcionaba el API de yahoo en datareader
!pip install fix-yahoo-finance;
import fix_yahoo_finance as yf;
```

```
#Obtenenemos el dataframe de las acciones
df=yf.download('AAPL',start='2012-01-01', end='2023-09-08')
#Mostremos los datos
df
```

```
[*********************100%%**********************]  1 of 1 completed
```

Date	Open	High	Low	Close	Adj Close	Volume
2012-01-03	14.621429	14.732143	14.607143	14.686786	12.466090	302220800
2012-01-04	14.642857	14.810000	14.617143	14.765714	12.533086	260022000
2012-01-05	14.819643	14.948214	14.738214	14.929643	12.672228	271269600
2012-01-06	14.991786	15.098214	14.972143	15.085714	12.804705	318292800
2012-01-09	15.196429	15.276786	15.048214	15.061786	12.784393	394024400
...	...	...	...	...	...	...
2023-08-31	187.839996	189.119995	187.479996	187.869995	187.869995	60794500
2023-09-01	189.490005	189.919998	188.279999	189.460007	189.460007	45732600
2023-09-05	188.279999	189.979996	187.610001	189.699997	189.699997	45280000
2023-09-06	188.399994	188.850006	181.470001	182.910004	182.910004	81755800
2023-09-07	175.179993	178.210007	173.539993	177.559998	177.559998	112488800

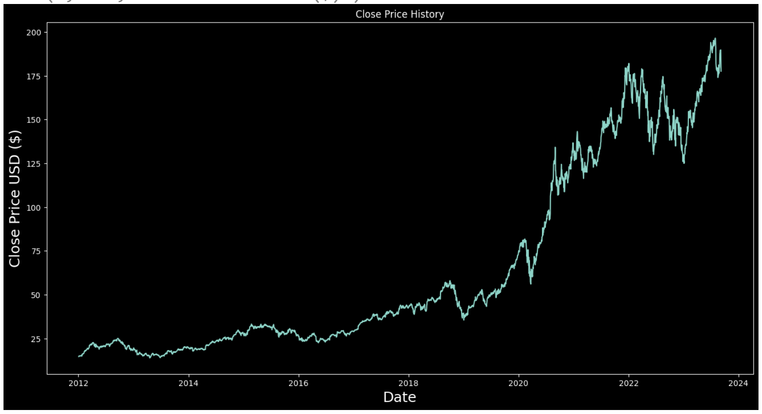
2939 rows × 6 columns

```
#Obtenenemos el numero de filas y columnas del dataset
df.shape
```

```
(2939, 6)
```

```
#Visualizemos el precio de cierre
plt.figure(figsize=(16,8))
plt.title('Close Price History')
plt.plot((df['Close']))
plt.xlabel('Date',fontsize=18)
plt.ylabel('Close Price USD ($)', fontsize=18)
```

```
Text(0, 0.5, 'Close Price USD ($)')
```




```
#Creemos un nuevo dataframe solo con la columna 'Close'
data=df.filter(['Close'])
#Convertimos el dataframe a un numpy array
dataset=data.values
#Obtenemos el numero de filas para el train
training_data_len=math.ceil(len(dataset)*.8)
training_data_len
```

```
2352
```

```
#Escalemos los datos

scaler=MinMaxScaler(feature_range=(0,1))
scaled_data=scaler.fit_transform(dataset)

scaled_data
```

```
array([[0.00405082],
       [0.0044833 ],
       [0.00538153],
       ...,
       [0.9630142 ],
       [0.92580927],
       [0.89649457]])
```

```
#Creamos la data set de entrenamiento
#Creamos la data escalada de entrenamiento
train_data=scaled_data[0:training_data_len,:]
#Separmos el entremaiento en x_train y_train
x_train=[]
y_train=[]

for i in range(60,len(train_data)):
  x_train.append(train_data[i-60:i,0])
  y_train.append(train_data[i,0])
  if i<=61:
    print("x_train=",x_train)
    print()
    print("y_train=",y_train)
    print()
```

```
x_train= [array([0.00405082, 0.0044833 , 0.00538153, 0.0062367 , 0.00610559,
       0.00640108, 0.00626606, 0.00603905, 0.00572986, 0.0066868 ,
       0.0075498 , 0.00728366, 0.00582575, 0.00721712, 0.00584728,
       0.01098419, 0.01058694, 0.01110552, 0.01222684, 0.01290588,
       0.01284914, 0.01263975, 0.0135321 , 0.01437162, 0.01532269,
       0.01685887, 0.02008583, 0.02013475, 0.02193121, 0.02327365,
       0.02096645, 0.02185489, 0.02183728, 0.02432844, 0.02397423,
       0.02462979, 0.02580786, 0.02646344, 0.02835186, 0.02972757,
       0.03012483, 0.03026377, 0.02791156, 0.02734404, 0.0274282 ,
       0.02963952, 0.03026182, 0.0315984 , 0.03474903, 0.0389525 ,
       0.03816582, 0.03816777, 0.04120687, 0.04215794, 0.04148084,
       0.04086246, 0.04021863, 0.04235754, 0.04382523, 0.04443971])]
```

```
y_train= [0.04292113229660477]

x_train= [array([0.00405082, 0.0044833 , 0.00538153, 0.0062367 , 0.00610559,
       0.00640108, 0.00626606, 0.00603905, 0.00572986, 0.0066868 ,
       0.0075498 , 0.00728366, 0.00582575, 0.00721712, 0.00584728,
       0.01098419, 0.01058694, 0.01110552, 0.01222684, 0.01290588,
       0.01284914, 0.01263975, 0.0135321 , 0.01437162, 0.01532269,
       0.01685887, 0.02008583, 0.02013475, 0.02193121, 0.02327365,
       0.02096645, 0.02185489, 0.02183728, 0.02432844, 0.02397423,
       0.02462979, 0.02580786, 0.02646344, 0.02835186, 0.02972757,
       0.03012483, 0.03026377, 0.02791156, 0.02734404, 0.0274282 ,
       0.02963952, 0.03026182, 0.0315984 , 0.03474903, 0.0389525 ,
       0.03816582, 0.03816777, 0.04120687, 0.04215794, 0.04148084,
       0.04086246, 0.04021863, 0.04235754, 0.04382523, 0.04443971]), array([0.0044833 , 0.00538153, 0.0062367 , 0.00610559, 0.00640108,
       0.00626606, 0.00603905, 0.00572986, 0.0066868 , 0.0075498 ,
       0.00728366, 0.00582575, 0.00721712, 0.00584728, 0.01098419,
       0.01058694, 0.01110552, 0.01222684, 0.01290588, 0.01284914,
       0.01263975, 0.0135321 , 0.01437162, 0.01532269, 0.01685887,
       0.02008583, 0.02013475, 0.02193121, 0.02327365, 0.02096645,
       0.02185489, 0.02183728, 0.02432844, 0.02397423, 0.02462979,
       0.02580786, 0.02646344, 0.02835186, 0.02972757, 0.03012483,
       0.03026377, 0.02791156, 0.02734404, 0.0274282 , 0.02963952,
       0.03026182, 0.0315984 , 0.03474903, 0.0389525 , 0.03816582,
       0.03816777, 0.04120687, 0.04215794, 0.04148084, 0.04086246,
       0.04021863, 0.04235754, 0.04382523, 0.04443971, 0.04292113])]

y_train= [0.04292113229660477, 0.04090355083781154]
```

```
#Convertimos x_train & y_train a numpy arrays
x_train, y_train=np.array(x_train),np.array(y_train)
```

```
#Reshape a los datos
x_train=np.reshape(x_train,(x_train.shape[0],x_train.shape[1],1))
x_train.shape
```

```
(2292, 60, 1)
```

```
#Construimos el modelo LSTM
model1=Sequential()
model1.add(LSTM(10,return_sequences=True,input_shape=(x_train.shape[1],1) ))
model1.add(LSTM(10,return_sequences=False))
model1.add(Dense(5))
model1.add(Dense(5))
model1.add(Dense(5))
model1.add(Dense(1))
```

```
model1.summary()
```

```
Model: "sequential_20"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_40 (LSTM)              (None, 60, 10)            480

 lstm_41 (LSTM)              (None, 10)                840

 dense_62 (Dense)            (None, 5)                 55

 dense_63 (Dense)            (None, 5)                 30

 dense_64 (Dense)            (None, 5)                 30

 dense_65 (Dense)            (None, 1)                 6

=================================================================
Total params: 1441 (5.63 KB)
Trainable params: 1441 (5.63 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
#Definamos el optimizer
adam = tf.keras.optimizers.Adam(learning_rate=0.0001)

#Definamos la metrica
RMSE=tf.keras.metrics.RootMeanSquaredError()
```

```
#Compilamos el modelo
model1.compile(optimizer=adam,loss='mean_squared_error',metrics=[RMSE])


#Entrenamos al modelo
#model.fit(x_train,y_train,batch_size=1,epochs=1)


e=200
#Entrenamos al modelo
training_history1 = model1.fit(x_train, y_train, epochs=e, validation_split=0.15, batch_size=80, verbose=0)
```

Learning Curve

```
def plot_acc_loss(training_history):
  plt.plot(training_history.history['root_mean_squared_error'])
  plt.plot(training_history.history['val_root_mean_squared_error'])
  # plt.ylim([0, 1])
  plt.title('RMSE vs. Epochs')
  plt.ylabel('RMSE')
  plt.xlabel('Epoch')
  plt.legend(['Training', 'Validation'], loc='lower right')
  plt.show()
  plt.plot(training_history.history['loss'])
  plt.plot(training_history.history['val_loss'])
  plt.title('Loss vs. Epochs')
  plt.ylabel('Loss')
  plt.xlabel('Epoch')
  plt.legend(['Training', 'Validation'], loc='upper right')
  plt.show()

plot_acc_loss(training_history1)
```

Introducing Dropout and Batch Normalization to reduce Overfitting

```
#Construimos el modelo LSTM numero 2
def set_nn_model_architecture_2():
  model=Sequential()
  model.add(LSTM(50,return_sequences=True,input_shape=(x_train.shape[1],1) ))
  model.add(LSTM(50,return_sequences=False))
  model.add(Dropout(rate=0.3, seed=44, name='dropout1'))
  model.add(BatchNormalization(name='batch_normalization'))
  model.add(Dense(25))
  model.add(Dense(1))
  return model

model_2 = set_nn_model_architecture_2()
```

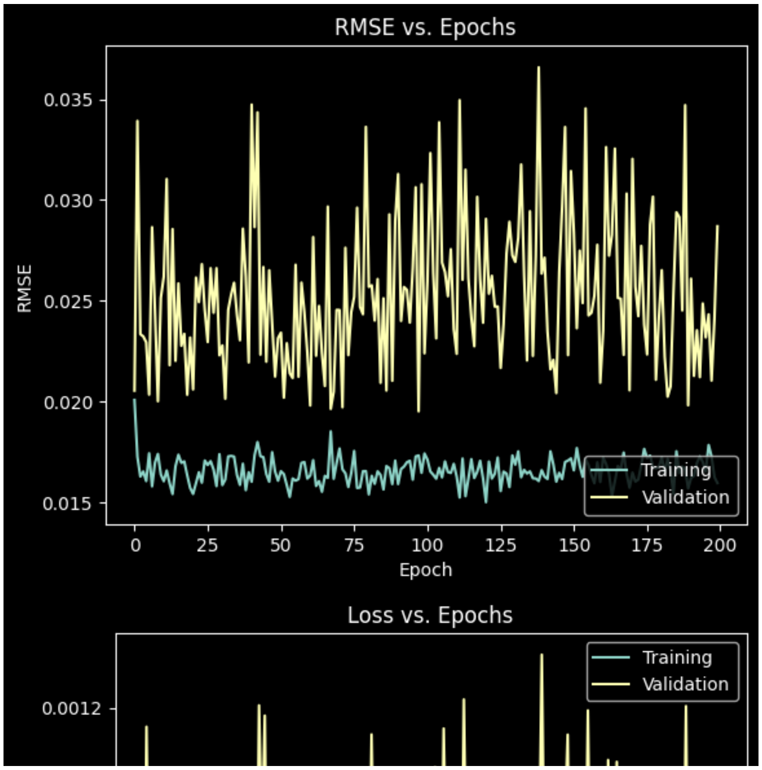
Loss vs. Epochs

```
model2.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_2 (LSTM)               (None, 60, 10)            480

 lstm_3 (LSTM)               (None, 10)                840

 dropout1 (Dropout)          (None, 10)                0

 batch_normalization (Batch  (None, 10)                40
 Normalization)

 dense_4 (Dense)             (None, 5)                 55

 dense_5 (Dense)             (None, 5)                 30

 dense_6 (Dense)             (None, 5)                 30

 dense_7 (Dense)             (None, 1)                 6

=================================================================
Total params: 1481 (5.79 KB)
Trainable params: 1461 (5.71 KB)
Non-trainable params: 20 (80.00 Byte)
_________________________________________________________________
```

```
model2.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.0001),loss='mean_squared_error',metrics=[RMSE])
training_history2 = model2.fit(x_train, y_train, epochs=e, validation_split=0.15, batch_size=80, verbose=0)
```

```
plot_acc_loss(training_history2)
```



Regularization using Callbacks: Earlystopping & learning rate reduction

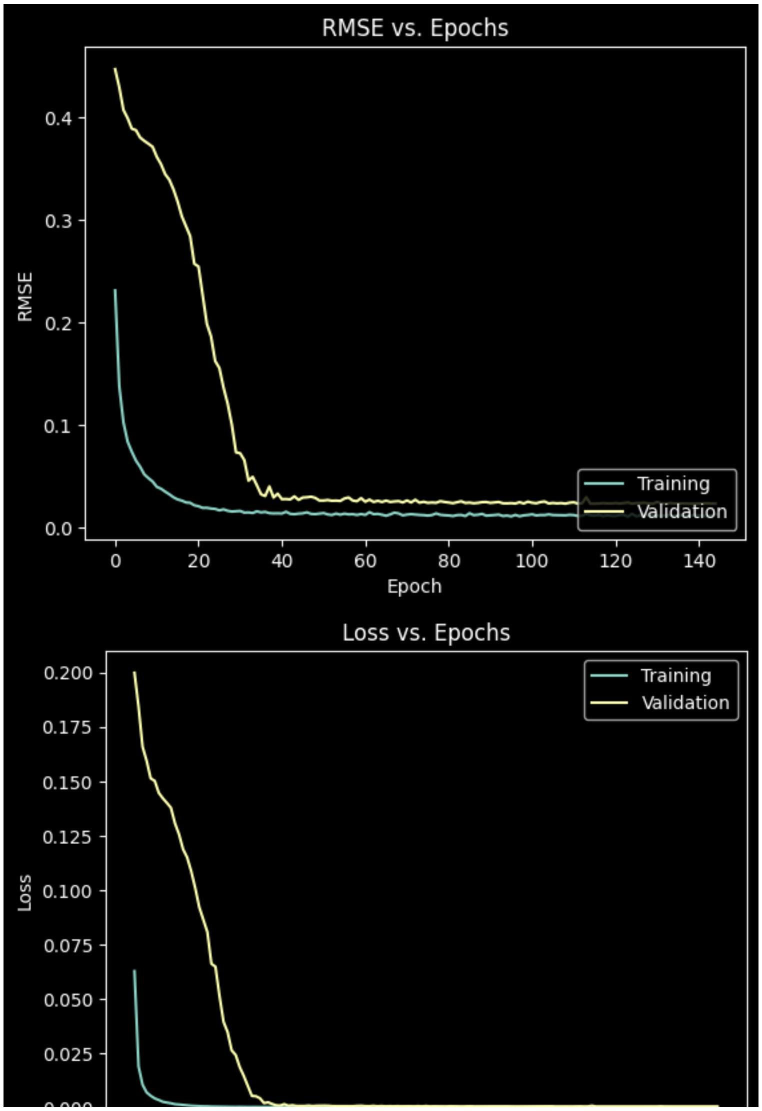
```
#Si nuestro modelo no ve mejoras despues de 3 epoch, se detien
early_stopping = tf.keras.callbacks.EarlyStopping(patience = 30, mode =  "min")
#Reduce el learning rate un 20% si no ve mejors en 2 epochs
lr_reduction = tf.keras.callbacks.ReduceLROnPlateau(patience = 20, factor = 0.2)
```

```
model3 = set_nn_model_architecture_2()
model3.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.0001), loss='mean_squared_error',metrics=[RMSE])
training_history3 = model3.fit(x_train, y_train, epochs=e, validation_split=0.15, batch_size=80,
                                 callbacks=[early_stopping, lr_reduction], verbose=0)
```

```
model3.summary()
```

```
Model: "sequential_22"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 lstm_44 (LSTM)              (None, 60, 50)            10400     
                                                                 
 lstm_45 (LSTM)              (None, 50)                20200     
                                                                 
 dropout1 (Dropout)          (None, 50)                0         
                                                                 
 batch_normalization (Batch  (None, 50)                200       
 Normalization)                                                  
                                                                 
 dense_68 (Dense)            (None, 25)                1275      
                                                                 
 dense_69 (Dense)            (None, 1)                 26        
                                                                 
=================================================================
Total params: 32101 (125.39 KB)
Trainable params: 32001 (125.00 KB)
Non-trainable params: 100 (400.00 Byte)
_________________________________________________________________
```

```
plot_acc_loss(training_history3)
```




```
#Creamos el testing data set
#Creamos un nuevo array que contenga los valores escalados del 2292 al 2352
test_data=scaled_data[training_data_len-60:,:]

#Creamos los data sets x_test & y_test
x_test=[]
y_test=dataset[training_data_len:,:]

for i in range(60,len(test_data)):
  x_test.append(test_data[i-60:i,0])


#Convertimos los datos a numpy array
x_test=np.array(x_test)
```

```
x_test.shape
```

    (587, 60)

```
#Reshape a los datop
x_test=np.reshape(x_test,(x_test.shape[0],x_test.shape[1],1))
x_test.shape
```

    (587, 60, 1)

```
#Obtener los valores predichos por el modelo
predictions=model3.predict(x_test)
predictions=scaler.inverse_transform(predictions)
```

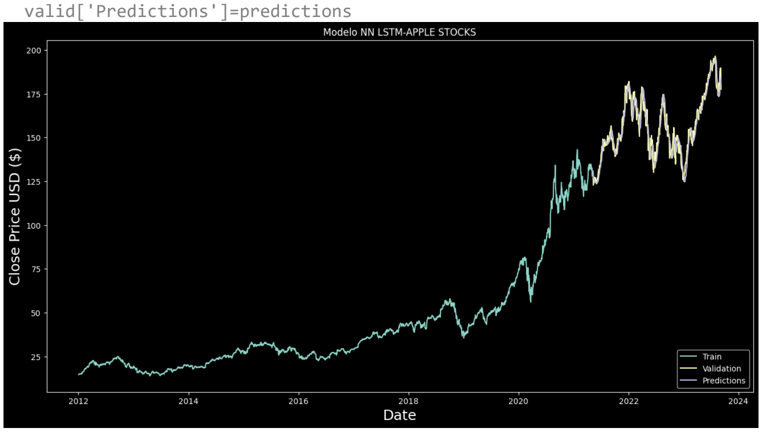
    19/19 [==============================] - 1s 22ms/step

```
#Obtenemos el (RMSE)
rmse=np.sqrt(np.mean(predictions-y_test)**2)
rmse
```

```
0.5796637851903548
```

```
#Grafiquemos los datos
train=data[:training_data_len]
valid=data[training_data_len:]
valid['Predictions']=predictions
#Visualizamos el modelo
plt.figure(figsize=(16,8))
plt.title('Modelo NN LSTM-APPLE STOCKS')
plt.xlabel('Date',fontsize=18)
plt.ylabel('Close Price USD ($)',fontsize=18)
plt.plot(train['Close'])
plt.plot(valid[['Close','Predictions']])
plt.legend(['Train','Validation','Predictions'],loc='lower right')
plt.show()
```

```
<ipython-input-236-e0f7c91c15f3>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
  valid['Predictions']=predictions
```




```
#Mostremos los valores reales y los que predice nuestro modelo
valid
```

	Close	Predictions
Date		

```
#Obtengamos el valor predicho para el viernes 8 de septiembre
value=yf.download('AAPL',start='2012-01-01', end='2023-09-09')
#Hacemos un nuevo dataframe
new_df=value.filter(['Close'])
#Obtener los ultimos 60 valores y hacer el dataframe en array
last_60_days=new_df[-60:].values
#Escalamos los dato para valores entre 0 y 1
last_60_days_scaled=scaler.transform(last_60_days)
#Creamos una lista vacia
X_test=[]
#Adjuntar los ultimos 60 dias
X_test.append(last_60_days_scaled)
#Convertimos X_test a un numpy array
X_test=np.array(X_test)
#Reshape a los datos
X_test=np.reshape(X_test,(X_test.shape[0],X_test.shape[1],1))
#Obtener el valor predicho
pred_price=model3.predict(X_test)
pred_price=scaler.inverse_transform(pred_price)
print()
print("Valor predicho el 8 de septiembre:",pred_price[0][0],"$")
```

```
[*********************100%%**********************]  1 of 1 completed
1/1 [==============================] - 0s 80ms/step

Valor predicho el 8 de septiembre: 184.38437 $
```

Reporte

En este cuaderno, se desarrolló una Red Neuronal Recurrente (RNN), específicamente una Long Short Term Memory (LSTM), con el propósito de predecir los valores de las acciones de "Apple". La elección de esta arquitectura se basó en el conocimiento adquirido en clase, donde se destacó su eficacia para abordar problemas relacionados con series temporales.

Inicialmente, se configuró una red que consistía en dos capas LSTM, cada una con 10 neuronas, seguidas de tres capas densas, cada una con cinco neuronas. Dado que el objetivo era predecir un único valor de salida, se empleó una sola neurona en la capa de salida.

Para mejorar la precisión del modelo, se implementaron estrategias clave. Se introdujo la técnica de Dropout, que mitiga el sobreajuste al desconectar de forma aleatoria ciertas conexiones neuronales durante el entrenamiento. Asimismo, se incorporó Batch Normalization para estabilizar el proceso de entrenamiento y acelerar la convergencia del modelo. Adicionalmente, se utilizaron callbacks, como Early Stopping y la reducción de la tasa de aprendizaje, con el fin de prevenir el sobreajuste y optimizar el rendimiento del modelo a lo largo de múltiples épocas.

La métrica de Error Cuadrático Medio de Raíz (RMSE) se empleó para evaluar la precisión del modelo en la tarea de predicción de los precios de las acciones de Apple. Estas mejoras y enfoques se aplicaron en busca de obtener resultados más precisos y confiables en la predicción de series temporales.