In [ ]:
```
import pandas as pd
import numpy as np
import statsmodels.api as sm
import statsmodels.formula.api as smf
import sklearn.metrics as metrics
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

In [ ]:
```
FIGURE_SIZE = (20, 10)
plt.rcParams['axes.grid'] = True

%matplotlib inline
```

In [ ]:
```
import tensorflow as tf
```

In [ ]:
```
tf.random.set_seed(1234)
```

In [ ]:
```
df11 = pd.read_csv("/content/stock.csv")
df11.head()
```

Out [42]:

	Date	Adj Close	differenced_trasnformation_demand	differenced_demand_filled	differenced_inv_transformation_demand	date	year	month	week	do
0	2010-01-04	6.562589	NaN	6.562589	6.562589	2010-01-04	2010	1	1	4
1	2010-01-05	6.573936	0.011347	0.011347	6.573936	2010-01-05	2010	1	1	5
2	2010-01-06	6.469368	-0.104568	-0.104568	6.469368	2010-01-06	2010	1	1	6
3	2010-01-07	6.457407	-0.011961	-0.011961	6.457407	2010-01-07	2010	1	1	7
4	2010-01-08	6.500340	0.042933	0.042933	6.500340	2010-01-08	2010	1	1	8

In [ ]:
```
df11
```

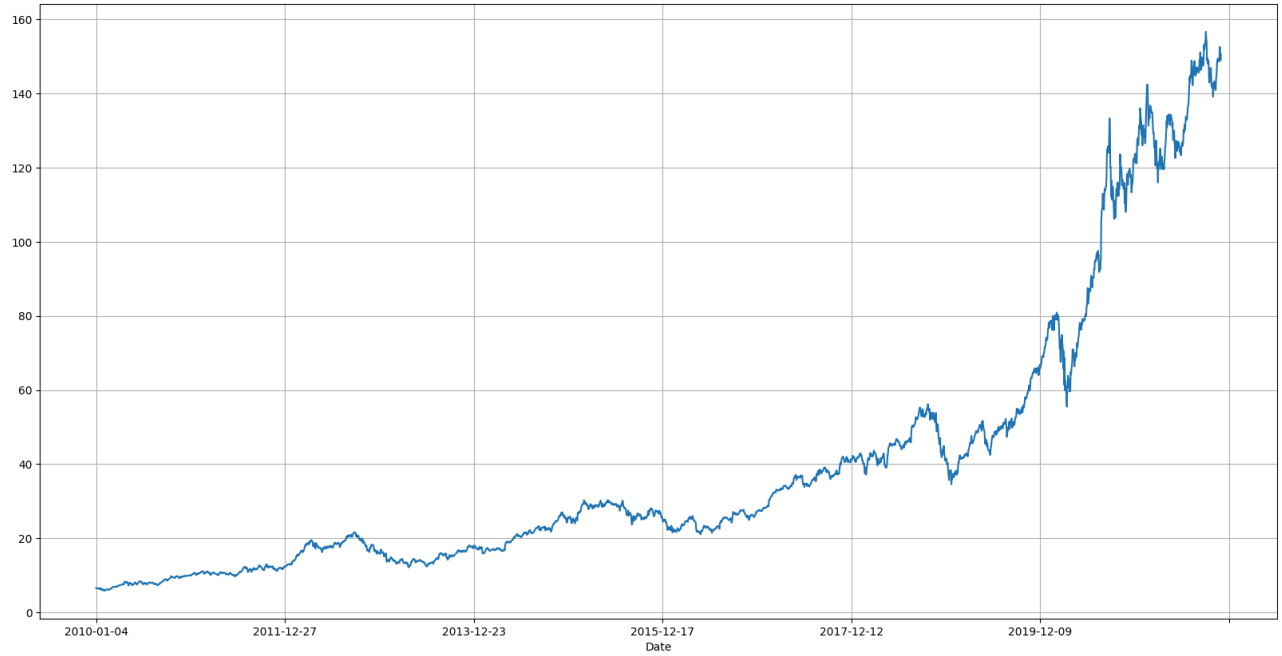
Out [43]:

	Date	Adj Close	differenced_trasnformation_demand	differenced_demand_filled	differenced_inv_transformation_demand	date	year	month	wee
0	2010-01-04	6.562589	NaN	6.562589	6.562589	2010-01-04	2010	1	1
1	2010-01-05	6.573936	0.011347	0.011347	6.573936	2010-01-05	2010	1	1
2	2010-01-06	6.469368	-0.104568	-0.104568	6.469368	2010-01-06	2010	1	1
3	2010-01-07	6.457407	-0.011961	-0.011961	6.457407	2010-01-07	2010	1	1
4	2010-01-08	6.500340	0.042933	0.042933	6.500340	2010-01-08	2010	1	1
...	...	...	...	...	...	...	...	...	...
2975	2021-10-27	148.850006	-0.470001	-0.470001	148.850006	2021-10-27	2021	10	43
2976	2021-10-28	152.570007	3.720001	3.720001	152.570007	2021-10-28	2021	10	43
2977	2021-10-29	149.800003	-2.770004	-2.770004	149.800003	2021-10-29	2021	10	43
2978	2021-11-01	148.960007	-0.839996	-0.839996	148.960007	2021-11-01	2021	11	44
2979	2021-11-02	150.580002	1.619995	1.619995	150.580002	2021-11-02	2021	11	44

2980 rows × 13 columns

In [ ]:
```
df11.set_index('Date')['Adj Close'].plot(figsize=FIGURE_SIZE)
```

Out [44]:
```
<Axes: xlabel='Date'>
```



In [ ]:
```
mask = (df11['date'] > '2010-01-01') & (df11['date'] <= '2019-12-31')
print(df11.loc[mask])
```

```
            Date  Adj Close  differenced_trasnformation_demand  \
0     2010-01-04   6.562589                                NaN
1     2010-01-05   6.573936                           0.011347
2     2010-01-06   6.469368                          -0.104568
3     2010-01-07   6.457407                          -0.011961
4     2010-01-08   6.500340                           0.042933
...          ...        ...                                ...
2511  2019-12-24  70.129509                           0.066605
2512  2019-12-26  71.520905                           1.391396
2513  2019-12-27  71.493767                          -0.027138
2514  2019-12-30  71.918076                           0.424309
2515  2019-12-31  72.443565                           0.525489

      differenced_demand_filled  differenced_inv_transformation_demand  \
0                      6.562589                               6.562589
1                      0.011347                               6.573936
2                     -0.104568                               6.469368
3                     -0.011961                               6.457407
4                      0.042933                               6.500340
...                         ...                                    ...
2511                   0.066605                              70.129509
2512                   1.391396                              71.520905
2513                  -0.027138                              71.493767
2514                   0.424309                              71.918076
2515                   0.525489                              72.443565

            date  year  month  week  day  dayofweek  week_of_month  is_weekend
0     2010-01-04  2010      1     1    4          0              1           0
1     2010-01-05  2010      1     1    5          1              1           0
2     2010-01-06  2010      1     1    6          2              1           0
3     2010-01-07  2010      1     1    7          3              1           0
4     2010-01-08  2010      1     1    8          4              2           0
...          ...   ...    ...   ...  ...        ...            ...         ...
2511  2019-12-24  2019     12    52   24          1              4           0
2512  2019-12-26  2019     12    52   26          3              4           0
2513  2019-12-27  2019     12    52   27          4              4           0
2514  2019-12-30  2019     12     1   30          0              5           0
2515  2019-12-31  2019     12     1   31          1              5           0

[2516 rows x 13 columns]
```

In [ ]:
```
df12=df11.loc[mask]
```

In [ ]:
```
#X=  df11[['Date']]
y= df11['Adj Close']
```

In [ ]:
```

from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler(feature_range=(0,1))
y=scaler.fit_transform(np.array(y).reshape(-1,1))
```

In [ ]:
```
##splitting dataset into train and test split
##splitting dataset into train and test split
training_size=int(len(y)*0.65)
test_size=len(y)-training_size
train_data,test_data=y[0:training_size],y[training_size:len(y)]
```

In [ ]:
```
training_size,test_size
```

Out [50]:
```
(1937, 1043)
```

In [ ]:
```
train_data[2]
```

Out [51]: array([0.00384731])

In [ ]:
```
def create_dataset(dataset, time_step=1):
 dataX, dataY = [], []
 for i in range(len(dataset)-time_step-1):
  a = dataset[i:(i+time_step), 0]  #0-100
  dataX.append(a)
  dataY.append(dataset[i + time_step, 0])
 return numpy.array(dataX), numpy.array(dataY)
```

In [ ]:
```
import numpy
```

In [ ]:
```
time_step = 100
X_train, y_train = create_dataset(train_data, time_step)
X_test, ytest = create_dataset(test_data, time_step)
```

In [ ]:
```

print(X_train.shape), print(y_train.shape)
```

```
(1836, 100)
(1836,)
```

Out [55]: (None, None)

In [ ]:
```
print(X_test.shape), print(ytest.shape)
```

```
(942, 100)
(942,)
```

Out [56]: (None, None)

In [ ]:
```
X_train =X_train.reshape(X_train.shape[0],X_train.shape[1] , 1)
X_test = X_test.reshape(X_test.shape[0],X_test.shape[1] , 1)
```

In [ ]:
```
### Create the Stacked LSTM model
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense,Dropout ,BatchNormalization
from tensorflow.keras.layers import LSTM
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.initializers import RandomNormal, Constant
```

In [ ]:
```
# model=Sequential()
# model.add(LSTM(150,return_sequences=True,input_shape=(100,1)))
# model.add(Dropout(0.2))
# model.add(LSTM(150,return_sequences=True))
# model.add(LSTM(150, return_sequences=True))
# model.add(Dropout(0.2))
# model.add(LSTM(100))
# model.add(Dropout(0.2))
# model.add(Dense(1))
# model.compile(loss='mean_squared_error',optimizer='adam')


model=Sequential()
# Adding first LSTM layer
model.add(LSTM(units=100, return_sequences=True, input_shape=(100,1)))
model.add(Dropout(0.2))
# second LSTM layer
model.add(LSTM(units=100, return_sequences=True))
model.add(Dropout(0.2))
# Adding third LSTM layer
model.add(LSTM(units=100, return_sequences=True))
model.add(Dropout(0.2))
# Adding fourth LSTM layer
model.add(LSTM(units=100, return_sequences=True))
model.add(Dropout(0.2))
# Adding fifth LSTM layer a
model.add(LSTM(units=100))
model.add(Dropout(0.2))
# Adding the Output Layer
model.add(Dense(units=1))

model.compile(optimizer = 'adam', loss = 'mean_squared_error')
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(**kwargs)
```

In [ ]:
```
model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
lstm_5 (LSTM)	(None, 100, 100)	40,800
dropout_5 (Dropout)	(None, 100, 100)	0
lstm_6 (LSTM)	(None, 100, 100)	80,400
dropout_6 (Dropout)	(None, 100, 100)	0
lstm_7 (LSTM)	(None, 100, 100)	80,400
dropout_7 (Dropout)	(None, 100, 100)	0
lstm_8 (LSTM)	(None, 100, 100)	80,400
dropout_8 (Dropout)	(None, 100, 100)	0
lstm_9 (LSTM)	(None, 100)	80,400
dropout_9 (Dropout)	(None, 100)	0
dense_1 (Dense)	(None, 1)	101

Total params: 362,501 (1.38 MB)

Trainable params: 362,501 (1.38 MB)

Non-trainable params: 0 (0.00 B)

In [ ]:
```
history= model.fit(X_train,y_train,validation_data=(X_test,ytest),epochs=54,batch_size=84,verbose=1)
```

```
Epoch 1/54
[1m22/22[0m [32m[0m[37m[0m [1m40s[0m 1s/step - loss: 0.0031 - val_loss: 0.0129
Epoch 2/54
[1m22/22[0m [32m[0m[37m[0m [1m28s[0m 1s/step - loss: 2.6321e-04 - val_loss: 0.0072
Epoch 3/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 1.4188e-04 - val_loss: 0.0071
Epoch 4/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 1.1015e-04 - val_loss: 0.0049
Epoch 5/54
[1m22/22[0m [32m[0m[37m[0m [1m28s[0m 1s/step - loss: 1.1249e-04 - val_loss: 0.0021
Epoch 6/54
[1m22/22[0m [32m[0m[37m[0m [1m28s[0m 1s/step - loss: 1.0997e-04 - val_loss: 0.0029
Epoch 7/54
[1m22/22[0m [32m[0m[37m[0m [1m28s[0m 1s/step - loss: 1.0238e-04 - val_loss: 0.0035
Epoch 8/54
[1m22/22[0m [32m[0m[37m[0m [1m28s[0m 1s/step - loss: 1.0415e-04 - val_loss: 0.0035
Epoch 9/54
[1m22/22[0m [32m[0m[37m[0m [1m28s[0m 1s/step - loss: 8.4367e-05 - val_loss: 0.0024
Epoch 10/54
[1m22/22[0m [32m[0m[37m[0m [1m28s[0m 1s/step - loss: 9.6758e-05 - val_loss: 0.0019
Epoch 11/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 8.1482e-05 - val_loss: 0.0024
Epoch 12/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 1.0200e-04 - val_loss: 0.0018
Epoch 13/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 9.0130e-05 - val_loss: 0.0022
Epoch 14/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 1.1286e-04 - val_loss: 0.0023
Epoch 15/54
[1m22/22[0m [32m[0m[37m[0m [1m27s[0m 1s/step - loss: 8.9666e-05 - val_loss: 0.0012
Epoch 16/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 7.5273e-05 - val_loss: 0.0021
Epoch 17/54
[1m22/22[0m [32m[0m[37m[0m [1m28s[0m 1s/step - loss: 7.8671e-05 - val_loss: 0.0015
Epoch 18/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 7.6980e-05 - val_loss: 0.0019
Epoch 19/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 8.0058e-05 - val_loss: 9.0734e-04
Epoch 20/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 6.8539e-05 - val_loss: 0.0016
Epoch 21/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 6.4114e-05 - val_loss: 0.0018
Epoch 22/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 7.0074e-05 - val_loss: 0.0013
Epoch 23/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 6.9356e-05 - val_loss: 0.0014
Epoch 24/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 6.0413e-05 - val_loss: 0.0015
Epoch 25/54
[1m22/22[0m [32m[0m[37m[0m [1m28s[0m 1s/step - loss: 6.7956e-05 - val_loss: 9.2141e-04
Epoch 26/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 7.0859e-05 - val_loss: 0.0011
Epoch 27/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 6.5086e-05 - val_loss: 0.0013
Epoch 28/54
[1m22/22[0m [32m[0m[37m[0m [1m28s[0m 1s/step - loss: 6.9632e-05 - val_loss: 0.0013
Epoch 29/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 6.3742e-05 - val_loss: 7.3908e-04
Epoch 30/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 7.1048e-05 - val_loss: 0.0011
Epoch 31/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 5.7715e-05 - val_loss: 8.4844e-04
Epoch 32/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 6.1453e-05 - val_loss: 8.0602e-04
Epoch 33/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 6.2500e-05 - val_loss: 7.2109e-04
Epoch 34/54
```

```
[1m22/22[0m [32m[0m[37m[0m [1m28s[0m 1s/step - loss: 6.7047e-05 - val_loss: 6.9042e-04
Epoch 35/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 6.4456e-05 - val_loss: 0.0010
Epoch 36/54
[1m22/22[0m [32m[0m[37m[0m [1m28s[0m 1s/step - loss: 5.7577e-05 - val_loss: 0.0015
Epoch 37/54
[1m22/22[0m [32m[0m[37m[0m [1m28s[0m 1s/step - loss: 5.7091e-05 - val_loss: 0.0017
Epoch 38/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 6.8253e-05 - val_loss: 7.0713e-04
Epoch 39/54
[1m22/22[0m [32m[0m[37m[0m [1m28s[0m 1s/step - loss: 5.4861e-05 - val_loss: 9.8485e-04
Epoch 40/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 5.7716e-05 - val_loss: 0.0011
Epoch 41/54
[1m22/22[0m [32m[0m[37m[0m [1m28s[0m 1s/step - loss: 5.5418e-05 - val_loss: 0.0012
Epoch 42/54
[1m22/22[0m [32m[0m[37m[0m [1m42s[0m 1s/step - loss: 5.5514e-05 - val_loss: 7.9161e-04
Epoch 43/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 4.9925e-05 - val_loss: 6.3920e-04
Epoch 44/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 6.4440e-05 - val_loss: 6.4325e-04
Epoch 45/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 6.3553e-05 - val_loss: 6.7204e-04
Epoch 46/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 5.4100e-05 - val_loss: 8.1958e-04
Epoch 47/54
[1m22/22[0m [32m[0m[37m[0m [1m29s[0m 1s/step - loss: 4.8503e-05 - val_loss: 6.1019e-04
Epoch 48/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 5.3706e-05 - val_loss: 6.8528e-04
Epoch 49/54
[1m22/22[0m [32m[0m[37m[0m [1m40s[0m 1s/step - loss: 4.9619e-05 - val_loss: 6.0612e-04
Epoch 50/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 5.0407e-05 - val_loss: 6.2809e-04
Epoch 51/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 4.5109e-05 - val_loss: 6.0091e-04
Epoch 52/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 4.5303e-05 - val_loss: 0.0014
Epoch 53/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 5.1183e-05 - val_loss: 6.5330e-04
Epoch 54/54
[1m22/22[0m [32m[0m[37m[0m [1m41s[0m 1s/step - loss: 4.7880e-05 - val_loss: 5.4366e-04
```

In [ ]:
```
from tensorflow.keras.callbacks import EarlyStopping
```

In [ ]:
```
monitor = EarlyStopping(monitor='val_loss', min_delta=1e-3, patience=10,
        verbose=1, mode='auto', restore_best_weights=True)

history=model.fit(X_train,y_train,validation_data=(X_test,ytest),
        callbacks=[monitor],verbose=1,epochs=1000)
```

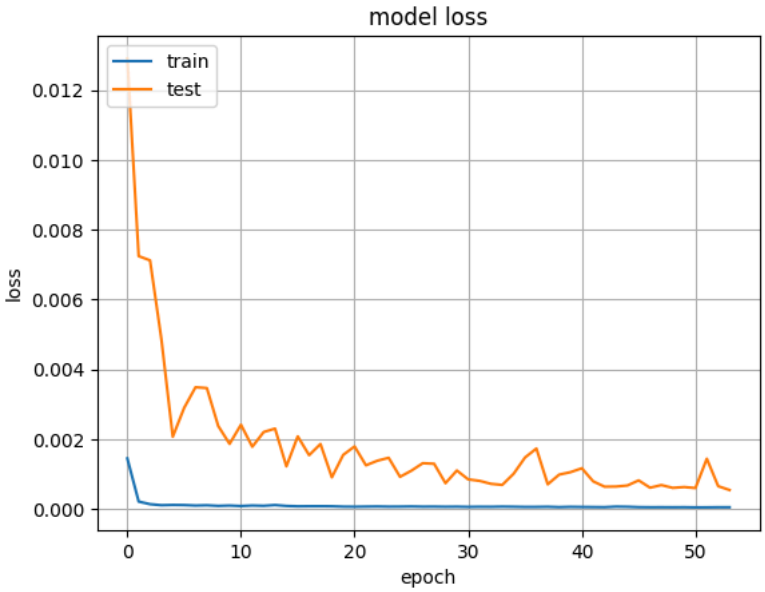
```
Epoch 1/1000
[1m58/58[0m [32m[0m[37m[0m [1m30s[0m 515ms/step - loss: 4.5824e-05 - val_loss: 0.0011
Epoch 2/1000
[1m58/58[0m [32m[0m[37m[0m [1m30s[0m 512ms/step - loss: 5.8404e-05 - val_loss: 6.4865e-04
Epoch 3/1000
[1m58/58[0m [32m[0m[37m[0m [1m41s[0m 510ms/step - loss: 4.6847e-05 - val_loss: 0.0036
Epoch 4/1000
[1m58/58[0m [32m[0m[37m[0m [1m30s[0m 510ms/step - loss: 4.2078e-05 - val_loss: 4.5071e-04
Epoch 5/1000
[1m58/58[0m [32m[0m[37m[0m [1m30s[0m 517ms/step - loss: 5.1238e-05 - val_loss: 0.0012
Epoch 6/1000
[1m58/58[0m [32m[0m[37m[0m [1m41s[0m 521ms/step - loss: 4.4823e-05 - val_loss: 0.0013
Epoch 7/1000
[1m58/58[0m [32m[0m[37m[0m [1m41s[0m 520ms/step - loss: 3.7618e-05 - val_loss: 0.0014
Epoch 8/1000
[1m58/58[0m [32m[0m[37m[0m [1m41s[0m 523ms/step - loss: 4.7397e-05 - val_loss: 0.0015
Epoch 9/1000
[1m58/58[0m [32m[0m[37m[0m [1m41s[0m 525ms/step - loss: 3.7037e-05 - val_loss: 3.0727e-04
Epoch 10/1000
[1m58/58[0m [32m[0m[37m[0m [1m30s[0m 520ms/step - loss: 3.8037e-05 - val_loss: 0.0017
Epoch 11/1000
[1m58/58[0m [32m[0m[37m[0m [1m41s[0m 518ms/step - loss: 3.3931e-05 - val_loss: 8.4130e-04
Epoch 11: early stopping
Restoring model weights from the end of the best epoch: 1.
```

In [ ]:
```
import tensorflow as tf
```

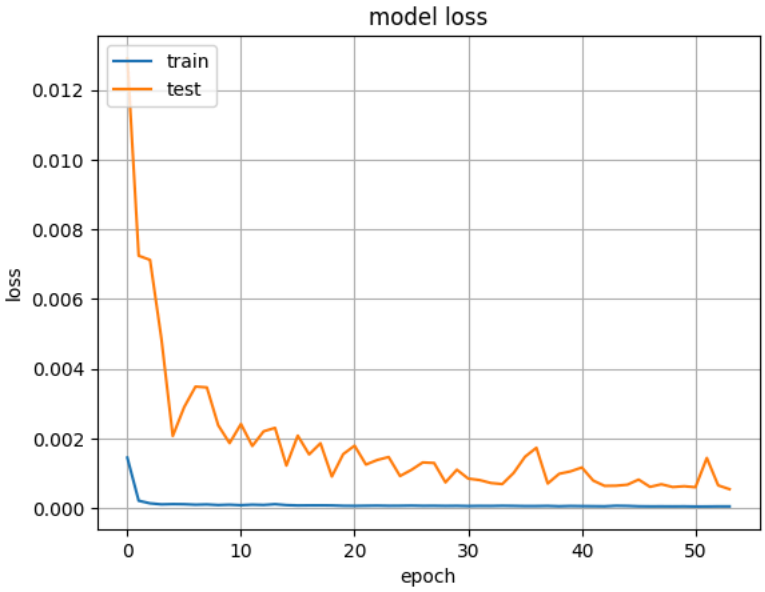
In [ ]:
```
tf.__version__
```

Out [64]:
```
'2.17.0'
```

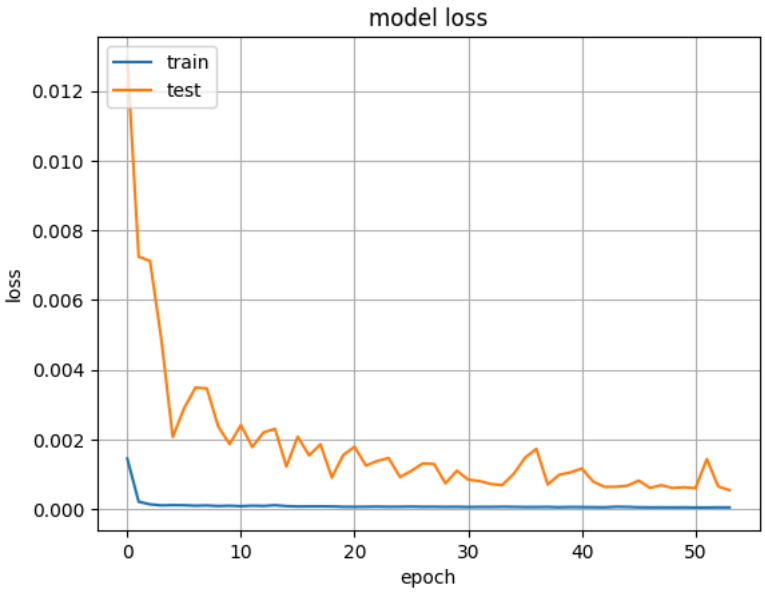
In [ ]:
```
plt.plot(history.history['loss']) #r
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```



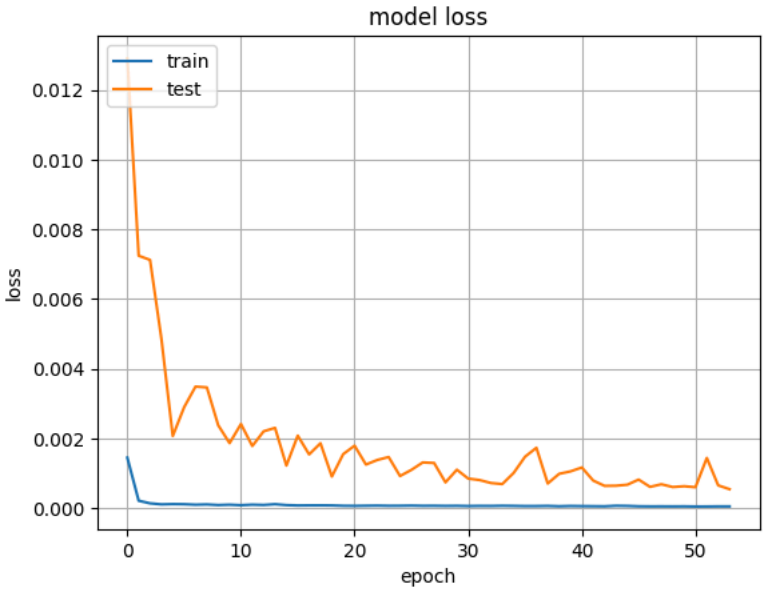
In [ ]:
```
plt.plot(history.history['loss']) # vn
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```



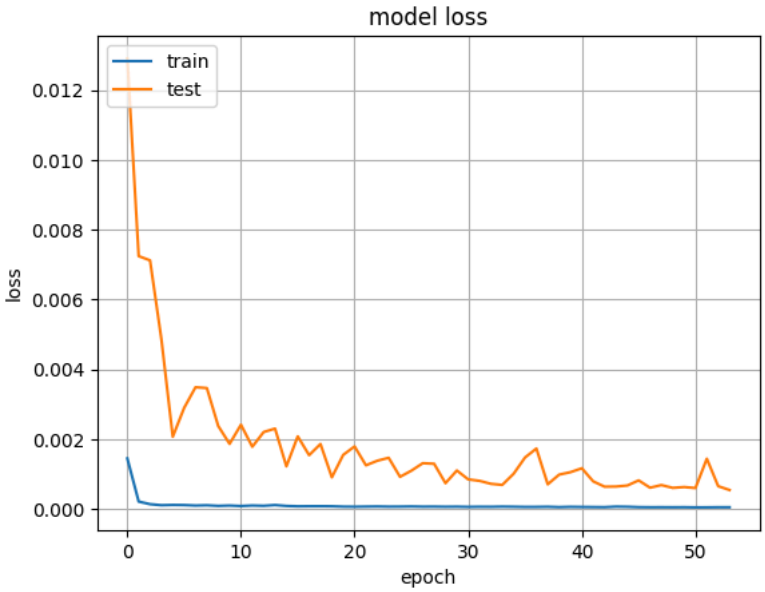
In [ ]:
```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```



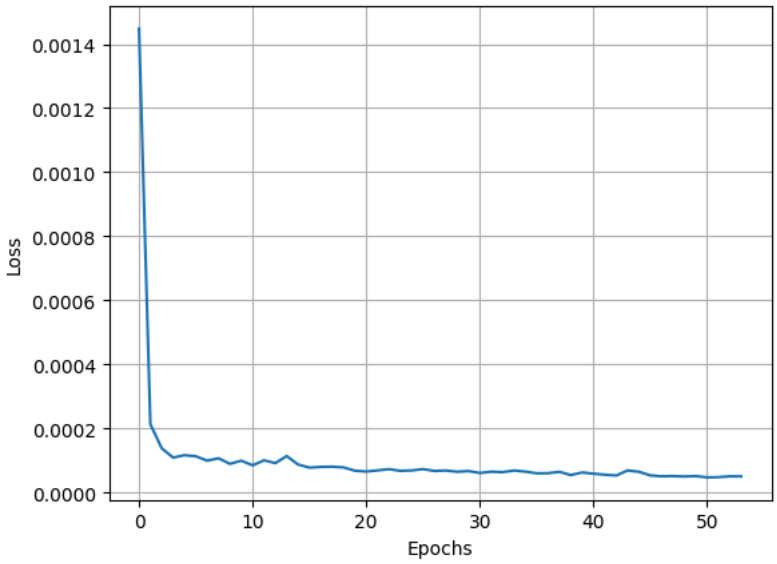
In [ ]:
```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```



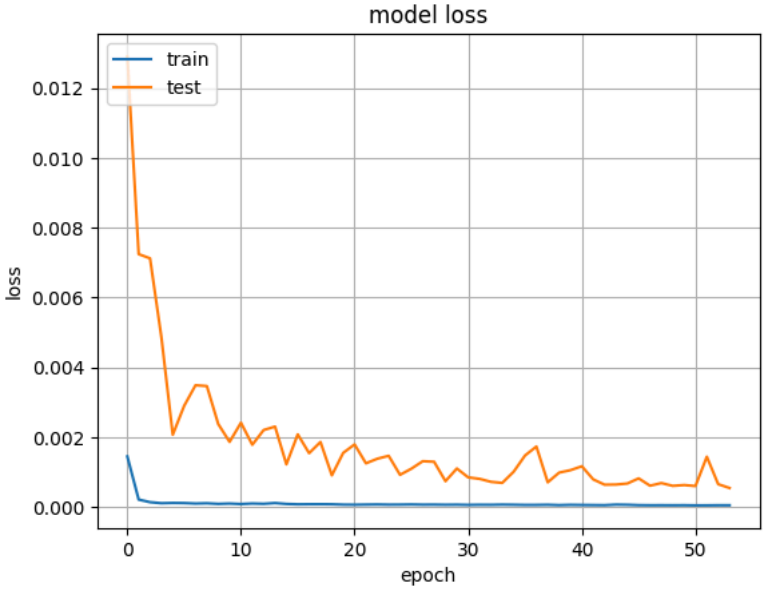
In [ ]:
```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```



In [ ]:
```
plt.plot(history.history['loss'])
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.show()
```



In [ ]:
```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```



In [ ]:
```
### Lets Do the prediction and check performance metrics
train_predict=model.predict(X_train)
test_predict=model.predict(X_test)
```

```
[1m58/58[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m10s[0m 153ms/step
[1m30/30[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m4s[0m 116ms/step
```

In [ ]:
```
##Transformback to original form
train_predict=scaler.inverse_transform(train_predict)
test_predict=scaler.inverse_transform(test_predict)
```

In [ ]:
```
### Calculate RMSE performance metrics
import math
from sklearn.metrics import mean_squared_error
math.sqrt(mean_squared_error(y_train,train_predict))
```

Out [78]: 21.398138293579052

In [ ]:
```
math.sqrt(mean_squared_error(ytest,test_predict))
```

Out [79]: 88.26001396112548

In [ ]:
```
### Calculate RMSE performance metrics
import math
from sklearn.metrics import mean_squared_error
math.sqrt(mean_squared_error(y_train,train_predict))
```

Out [80]: 21.398138293579052

In [ ]:
```
### Test Data RMSE
math.sqrt(mean_squared_error(ytest,test_predict))
```

Out [81]: 88.26001396112548

In [ ]:
```

### Calculate RMSE performance metrics
import math
from sklearn.metrics import mean_squared_error
math.sqrt(mean_squared_error(y_train,train_predict))
```

Out [83]: 21.398138293579052

In [ ]:
```
math.sqrt(mean_squared_error(ytest,test_predict))
```

Out [82]: 88.26001396112548

In [ ]:
```
## Calculate RMSE performance metrics
import math
from sklearn.metrics import mean_squared_error
math.sqrt(mean_squared_error(y_train,train_predict))
```

Out [85]: 21.398138293579052

In [ ]:
```
#Test Data RMSE
math.sqrt(mean_squared_error(ytest,test_predict))
```

Out [84]: 88.26001396112548

In [ ]:
```
## Calculate RMSE performance metrics
import math
from sklearn.metrics import mean_squared_error
math.sqrt(mean_squared_error(y_train,train_predict))
```

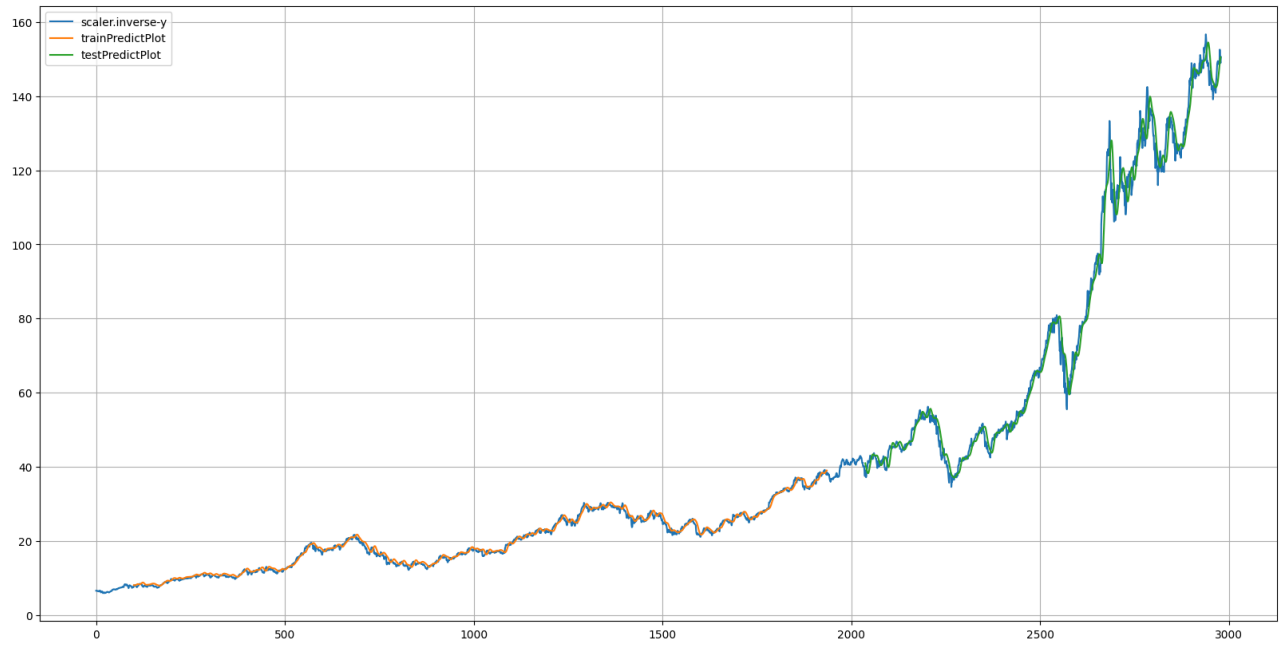
Out [86]: 21.398138293579052

In [ ]:
```
### Test Data RMSE
math.sqrt(mean_squared_error(ytest,test_predict))
```

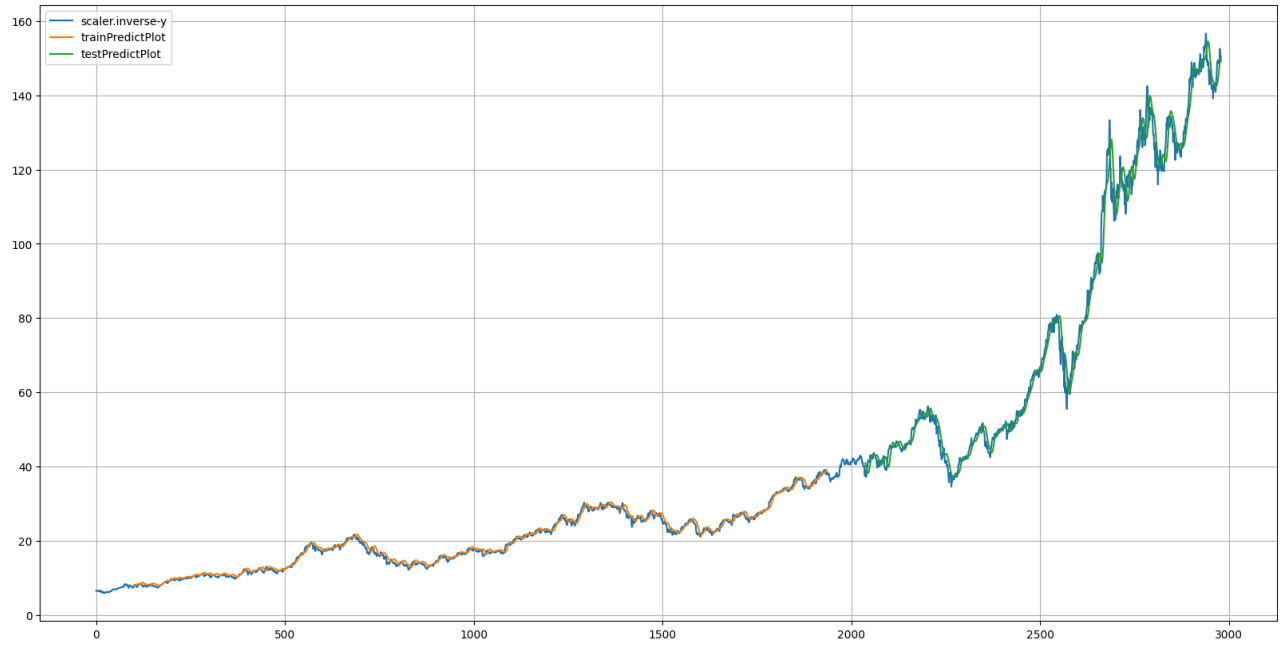
Out [87]: 88.26001396112548

In [ ]:
```
### Plotting
# shift train predictions for plotting
look_back=100
fig, ax = plt.subplots(figsize=(20,10))
trainPredictPlot = numpy.empty_like(y)
trainPredictPlot[:, :] = np.nan
trainPredictPlot[look_back:len(train_predict)+look_back, :] = train_predict
# shift test predictions for plotting
testPredictPlot = numpy.empty_like(y)
testPredictPlot[:, :] = numpy.nan
testPredictPlot[len(train_predict)+(look_back*2)+1:len(y)-1, :] = test_predict
```

```
# plot baseline and predictions
plt.plot(scaler.inverse_transform(y))
plt.plot(trainPredictPlot)
plt.plot(testPredictPlot)
plt.legend(['scaler.inverse-y','trainPredictPlot','testPredictPlot'])
plt.show()
```

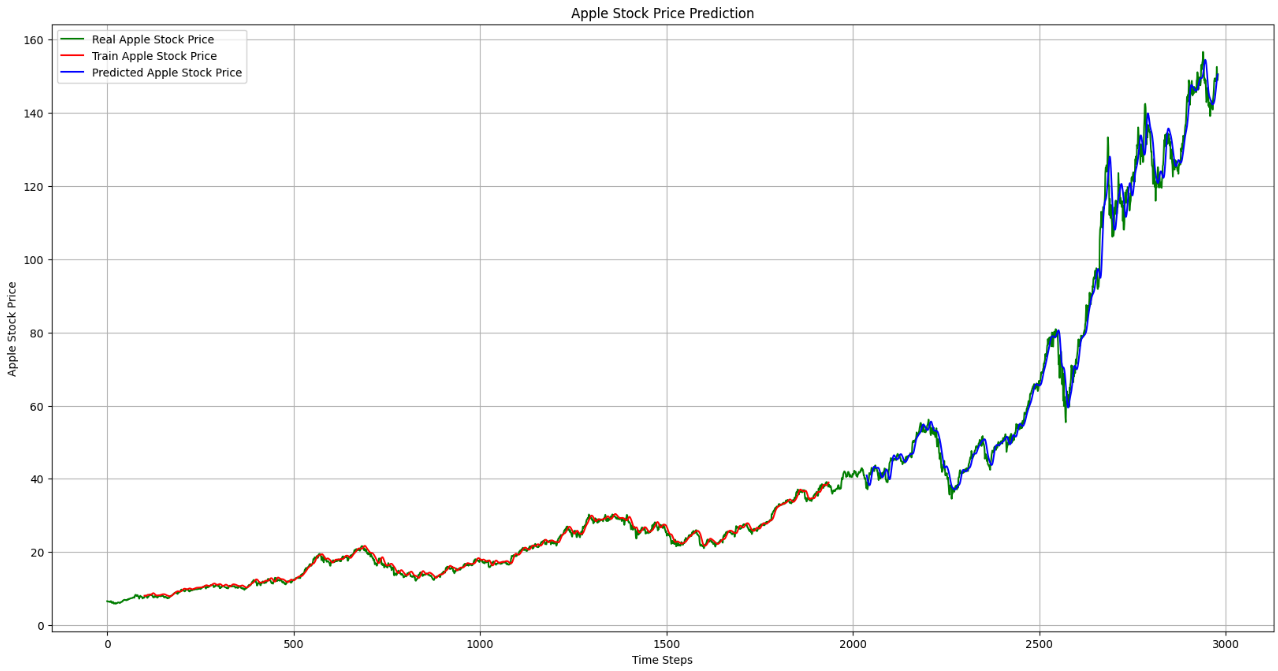


In [ ]:
```
# shift train predictions for plotting
look_back=100
fig, ax = plt.subplots(figsize=(20,10))
trainPredictPlot = numpy.empty_like(y)
trainPredictPlot[:, :] = np.nan
trainPredictPlot[look_back:len(train_predict)+look_back, :] = train_predict
# shift test predictions for plotting
testPredictPlot = numpy.empty_like(y)
testPredictPlot[:, :] = numpy.nan
testPredictPlot[len(train_predict)+(look_back*2)+1:len(y)-1, :] = test_predict
# plot baseline and predictions
plt.plot(scaler.inverse_transform(y))
plt.plot(trainPredictPlot)
plt.plot(testPredictPlot)
plt.legend(['scaler.inverse-y','trainPredictPlot','testPredictPlot'])
plt.show()
```



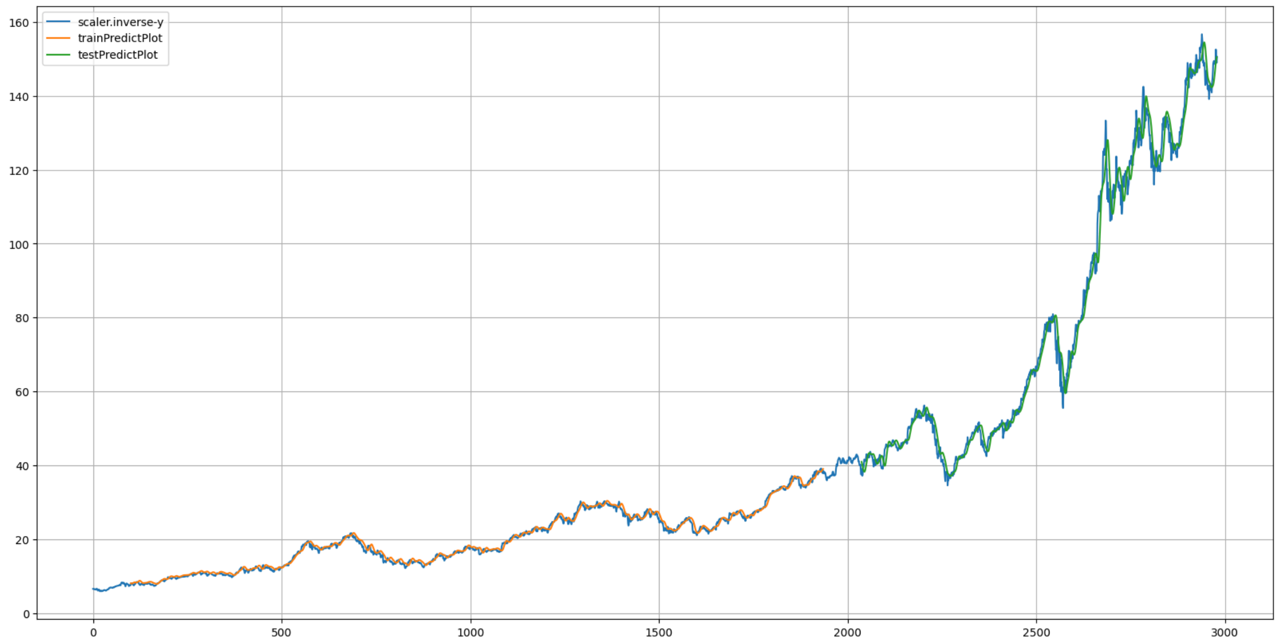
In [ ]:
```
fig, ax = plt.subplots(figsize=(20,10))
plt.plot(scaler.inverse_transform(y), color='Green', label='Real Apple Stock Price')
plt.plot(trainPredictPlot, color='Red', label='Train Apple Stock Price')
plt.plot(testPredictPlot, color='Blue', label='Predicted Apple Stock Price')

plt.title('Apple Stock Price Prediction')
plt.xlabel('Time Steps')
```

```
plt.ylabel('Apple Stock Price')
plt.legend()
plt.show()
```



In [ ]:

```
## Plotting
# shift train predictions for plotting
look_back=100
fig, ax = plt.subplots(figsize=(20,10))
trainPredictPlot = numpy.empty_like(y)
trainPredictPlot[:, :] = np.nan
trainPredictPlot[look_back:len(train_predict)+look_back, :] = train_predict
# shift test predictions for plotting
testPredictPlot = numpy.empty_like(y)
testPredictPlot[:, :] = numpy.nan
testPredictPlot[len(train_predict)+(look_back*2)+1:len(y)-1, :] = test_predict
# plot baseline and predictions
plt.plot(scaler.inverse_transform(y))
plt.plot(trainPredictPlot)
plt.plot(testPredictPlot)
plt.legend(['scaler.inverse-y','trainPredictPlot','testPredictPlot'])
plt.show()
```



In [ ]:

```
# evaluate the model
train_mse = model.evaluate(X_train, y_train, verbose=1)
test_mse = model.evaluate(X_test, ytest, verbose=1)
```

```
□[1m58/58□[0m □[32m□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□[0m□[37m□[0m □[1m8s□[0m 132ms/step - loss: 1.7484e-05
□[1m30/30□[0m □[32m□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□[0m□[37m□[0m □[1m4s□[0m 137ms/step - loss: 2.9463e-04
```

In [ ]:

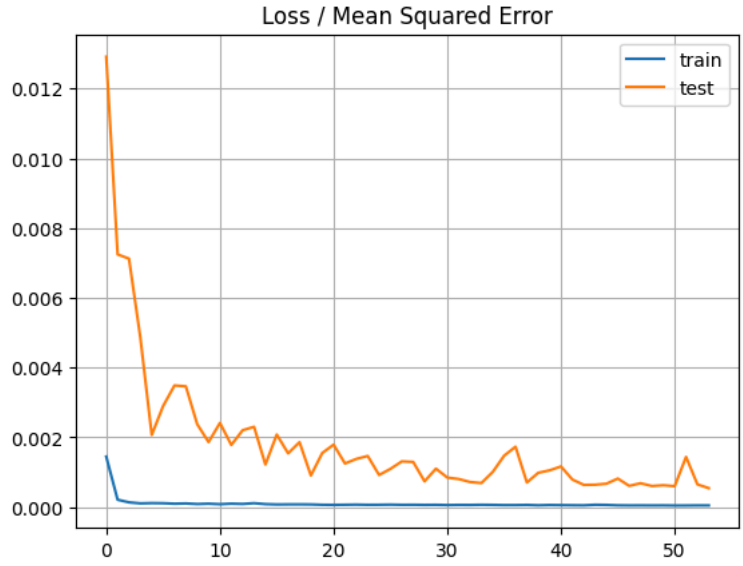
```
train_mse > test_mse
```

Out [93]: False

In [ ]:
```
print('Train: %.3f, Test: %.3f' % (train_mse, test_mse))
```

```
Train: 0.000, Test: 0.001
```

In [ ]:
```
# plot loss during training
plt.title('Loss / Mean Squared Error')
plt.plot(history.history['loss'], label='train')
plt.plot(history.history['val_loss'], label='test')
plt.legend()
plt.show()
```



In [ ]:
```
import numpy as np
import pandas as pd
from sklearn.linear_model import LinearRegression

import warnings
warnings.filterwarnings("ignore")

import yfinance as yf
# The pdr_override function is no longer necessary in recent versions of yfinance.
# yf.pdr_override() # Remove or comment out this line

# You can directly use yfinance to download data.
# For example, to download data for Apple (AAPL) for the past year:
# data = yf.download("AAPL", period="1y")
```

In [ ]:
```
symbol = 'AAPL'
start = '2020-01-01'
end = '2021-01-01'
df = yf.download(symbol, start, end)
df = df.reset_index()
```

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

In [ ]:
```
df.head()
```

Out [99]:

Price	Date	Adj Close	Close	High	Low	Open	Volume
Ticker		AAPL	AAPL	AAPL	AAPL	AAPL	AAPL
0	2020-01-02 00:00:00+00:00	72.876122	75.087502	75.150002	73.797501	74.059998	135480400
1	2020-01-03 00:00:00+00:00	72.167603	74.357498	75.144997	74.125000	74.287498	146322800
2	2020-01-06 00:00:00+00:00	72.742653	74.949997	74.989998	73.187500	73.447502	118387200
3	2020-01-07 00:00:00+00:00	72.400528	74.597504	75.224998	74.370003	74.959999	108872000
4	2020-01-08 00:00:00+00:00	73.565193	75.797501	76.110001	74.290001	74.290001	132079200

In [ ]:
```
df.tail()
```

Out [100]:

Price	Date	Adj Close	Close	High	Low	Open	Volume
Ticker		AAPL	AAPL	AAPL	AAPL	AAPL	AAPL
248	2020-12-24 00:00:00+00:00	129.189514	131.970001	133.460007	131.100006	131.320007	54930100
249	2020-12-28 00:00:00+00:00	133.810059	136.690002	137.339996	133.509995	133.990005	124486200
250	2020-12-29 00:00:00+00:00	132.028427	134.869995	138.789993	134.339996	138.050003	121047300

Price	Date	Adj Close	Close	High	Low	Open	Volume
Ticker		AAPL	AAPL	AAPL	AAPL	AAPL	AAPL
251	2020-12-30 00:00:00+00:00	130.902618	133.720001	135.990005	133.399994	135.580002	96452100
252	2020-12-31 00:00:00+00:00	129.894348	132.690002	134.740005	131.720001	134.080002	99116600

In [ ]:
```
X_train = df[df.columns[1:5]] # data_aal[['open', 'high', 'low', 'close']]
Y_train = df['Adj Close']
```

In [ ]:
```
X_train = X_train.values[:-1]
Y_train = Y_train.values[1:]
```

In [ ]:
```
lr = LinearRegression()
```

In [ ]:
```
lr.fit(X_train, Y_train)
```

Out [105]:
```
LinearRegression
LinearRegression()
```

In [ ]:
```
X_test = df[df.columns[1:5]].values[:-1]
Y_test = df['Adj Close'].values[1:]
```

In [ ]:
```
lr.score(X_test, Y_test)
```

Out [107]:
```
0.986882023892524
```

In [ ]:
```
opening_price = float(input('Open: '))
high = float(input('High: '))
low = float(input('Low: '))
close = float(input('Close: '))
print('My Prediction the opening price will be:', lr.predict([[opening_price, high, low, close]])[0])
```

```
Open: 131.320007
High: 133.460007
Low: 131.100006
Close: 131.970001
My Prediction the opening price will be: [133.41927907]
```