Rename notebook

```
# IMPORTANT: RUN THIS CELL IN ORD  KAGGLE DATA SOURCES
# TO THE CORRECT LOCATION (/kaggl  NOTEBOOK,
# THEN FEEL FREE TO DELETE THIS CELL.
# NOTE: THIS NOTEBOOK ENVIRONMENT DIFFERS FROM KAGGLE'S PYTHON
# ENVIRONMENT SO THERE MAY BE MISSING LIBRARIES USED BY YOUR
# NOTEBOOK.

import os
import sys
from tempfile import NamedTemporaryFile
from urllib.request import urlopen
from urllib.parse import unquote, urlparse
from urllib.error import HTTPError
from zipfile import ZipFile
import tarfile
import shutil

CHUNK_SIZE = 40960
DATA_SOURCE_MAPPING = 'tesla-stock-price:https%3A%2F%2Fstorage.googleapis.com%2Fkaggle-data-sets%2F1007%2F1814%2Fbundle%2Farchive.zip%3F

KAGGLE_INPUT_PATH='/kaggle/input'
KAGGLE_WORKING_PATH='/kaggle/working'
KAGGLE_SYMLINK='kaggle'

!umount /kaggle/input/ 2> /dev/null
shutil.rmtree('/kaggle/input', ignore_errors=True)
os.makedirs(KAGGLE_INPUT_PATH, 0o777, exist_ok=True)
os.makedirs(KAGGLE_WORKING_PATH, 0o777, exist_ok=True)

try:
  os.symlink(KAGGLE_INPUT_PATH, os.path.join("..", 'input'), target_is_directory=True)
except FileExistsError:
  pass
try:
  os.symlink(KAGGLE_WORKING_PATH, os.path.join("..", 'working'), target_is_directory=True)
except FileExistsError:
  pass

for data_source_mapping in DATA_SOURCE_MAPPING.split(','):
    directory, download_url_encoded = data_source_mapping.split(':')
    download_url = unquote(download_url_encoded)
    filename = urlparse(download_url).path
    destination_path = os.path.join(KAGGLE_INPUT_PATH, directory)
    try:
        with urlopen(download_url) as fileres, NamedTemporaryFile() as tfile:
            total_length = fileres.headers['content-length']
            print(f'Downloading {directory}, {total_length} bytes compressed')
            dl = 0
            data = fileres.read(CHUNK_SIZE)
            while len(data) > 0:
                dl += len(data)
                tfile.write(data)
                done = int(50 * dl / int(total_length))
                sys.stdout.write(f"\r[{'=' * done}{' ' * (50-done)}] {dl} bytes downloaded")
                sys.stdout.flush()
                data = fileres.read(CHUNK_SIZE)
            if filename.endswith('.zip'):
              with ZipFile(tfile) as zfile:
                zfile.extractall(destination_path)
            else:
              with tarfile.open(tfile.name) as tarfile:
                tarfile.extractall(destination_path)
            print(f'\nDownloaded and uncompressed: {directory}')
    except HTTPError as e:
        print(f'Failed to load (likely expired) {download_url} to path {destination_path}')
        continue
    except OSError as e:
        print(f'Failed to load {download_url} to path {destination_path}')
        continue

print('Data source import complete.')
```

```
Failed to load (likely expired) https://storage.googleapis.com/kaggle-data-sets/1007/1814/bundle/archive.zip?X-Goog-Algorithm=GOOG4
Data source import complete.
```

In this notebook, i tried to predict the open price of Tesla Stock by simple RNN Model and LSTM model.
Those who want to have detailed info on simple RNN and LSTM, may refer to great post below:

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

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1.Loading Data

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
data = pd.read_csv("TSLA.csv")
```

```
data.head()
```

	Date	Open	High	Low	Close	Adj Close	Volume
0	2010-06-29	3.800	5.000	3.508	4.778	4.778	93831500
1	2010-06-30	5.158	6.084	4.660	4.766	4.766	85935500
2	2010-07-01	5.000	5.184	4.054	4.392	4.392	41094000
3	2010-07-02	4.600	4.620	3.742	3.840	3.840	25699000
4	2010-07-06	4.000	4.000	3.166	3.222	3.222	34334500

Next steps: Generate code with data   View recommended plots

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2956 entries, 0 to 2955
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Date       2956 non-null   object 
 1   Open       2956 non-null   float64
 2   High       2956 non-null   float64
 3   Low        2956 non-null   float64
 4   Close      2956 non-null   float64
 5   Adj Close  2956 non-null   float64
 6   Volume     2956 non-null   int64  
dtypes: float64(5), int64(1), object(1)
memory usage: 161.8+ KB
```

2.Spliting Data as Train and Validation

```
length_data = len(data)
split_ratio = 0.7
length_train = round(length_data
length_validation = length_data -
print("Data length :", length_data)
print("Train data length :", length_train)
print("Validation data lenth :", length_validation)
```

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```
Data length : 2956
Train data length : 2069
Validation data lenth : 887
```

```
train_data = data[:length_train].iloc[:,:2]
train_data['Date'] = pd.to_datetime(train_data['Date'])
train_data
```

	Date	Open
0	2010-06-29	3.800000
1	2010-06-30	5.158000
2	2010-07-01	5.000000
3	2010-07-02	4.600000
4	2010-07-06	4.000000
...	...	...
2064	2018-09-10	54.652000
2065	2018-09-11	55.894001
2066	2018-09-12	56.287998
2067	2018-09-13	57.604000
2068	2018-09-14	57.751999

2069 rows × 2 columns

Next steps: Generate code with `train_data` View recommended plots

```
validation_data = data[length_train:].iloc[:,:2]
validation_data['Date'] = pd.to_datetime(validation_data['Date'])
validation_data
```

	Date	Open
2069	2018-09-17	58.007999
2070	2018-09-18	59.338001
2071	2018-09-19	56.102001
2072	2018-09-20	60.712002
2073	2018-09-21	59.540001
...	...	...
2951	2022-03-18	874.489990
2952	2022-03-21	914.979980
2953	2022-03-22	930.000000
2954	2022-03-23	979.940002
2955	2022-03-24	1009.729980

887 rows × 2 columns

Next steps: Generate code with `validation_data` View recommended plots

3.Creating Train Dataset from Train split

- We will get Open column as our dataset
- Dataset to be converted to array by adding `.values`

```
dataset_train = train_data.Open.values
dataset_train.shape
```

```
(2069,)
```

```
dataset_train = np.reshape(datase
dataset_train.shape
```

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```
(2069, 1)
```

4.Normalization / Feature Scaling

- Dataset values will be in between 0 and 1 after scaling

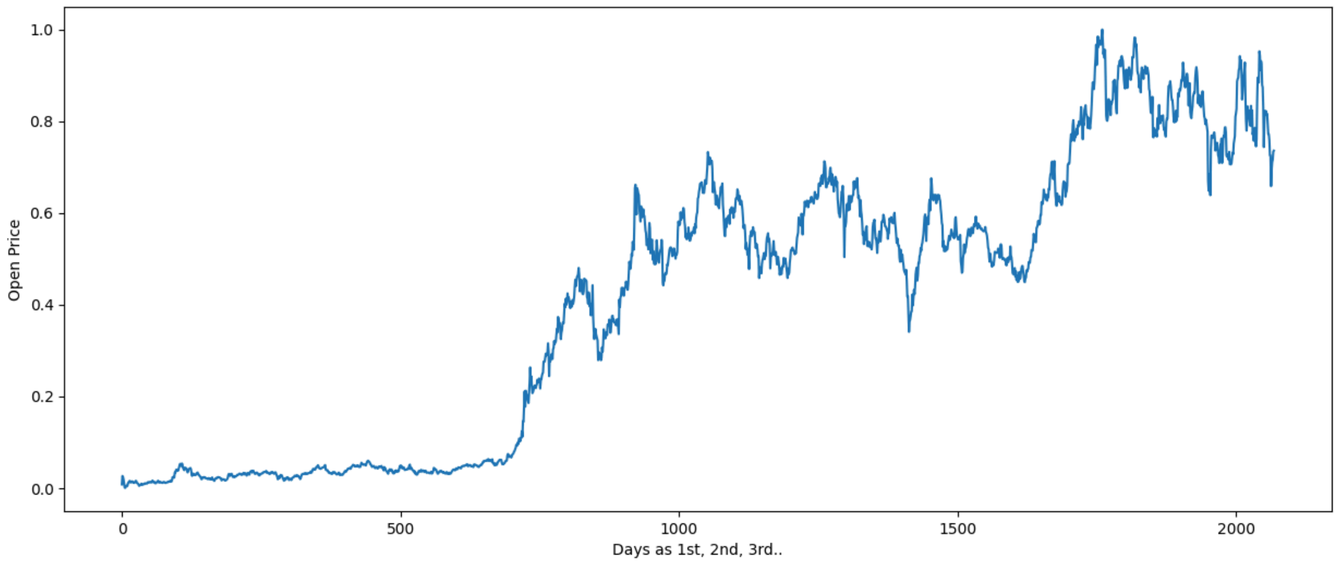
```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler(feature_range = (0,1))
```

```
# scaling dataset
dataset_train_scaled = scaler.fit_transform(dataset_train)
```

```
dataset_train_scaled.shape
```

```
(2069, 1)
```

```
plt.subplots(figsize = (15,6))
plt.plot(dataset_train_scaled)
plt.xlabel("Days as 1st, 2nd, 3rd..")
plt.ylabel("Open Price")
plt.show()
```



5.Creating X_train and y_train from Train data

image.png

- We have train data composed of stock open prices over days
- So, it has 1184 prices corresponding 1184 days
- My aim is to predict the open price of the next day.
- I can use a time step of 50 days.
- I will pick first 50 open prices (0 to 50), 1st 50 price will be in X_train data
- Then predict the price of 51th day; and 51th price will be in y_train data
- Again, i will pick prices from 1 to 51, those will be in X_train data
- Then predict the next days price, 52nd price will be in y_train data

```
X_train = []
y_train = []

time_step = 50

for i in range(time_step, length_train):
    X_train.append(dataset_train_scaled[i-time_step:i,0])
    y_train.append(dataset_train_scaled[i,0])

X_train, y_train = np.array(X_train), np.array(y_train)
```

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```
print("Shape of X_train before reshape :",X_train.shape)
print("Shape of y_train before reshape :",y_train.shape)
```

```
Shape of X_train before reshape : (2019, 50)
Shape of y_train before reshape : (2019,)
```

Reshape

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

print("Shape of X_train after reshape :",X_train.shape)
print("Shape of y_train after reshape :",y_train.shape)
```

```
Shape of X_train after reshape : (2019, 50, 1)
Shape of y_train after reshape : (2019, 1)
```

- Shape of X_train : 1134 x 50 x 1
- That means we have 1134 rows, each row has 50 rows and 1 column
- Lets check the first row: it has 50 rows (open prices of 49 days)

```
X_train[0]
```

```
array([[0.00771826],
       [0.02604237],
       [0.0239104 ],
       [0.01851302],
       [0.01041695],
       [0.00070166],
       [0.        ],
       [0.00388612],
       [0.00488463],
       [0.00337336],
       [0.00485764],
       [0.01025503],
       [0.01230603],
       [0.01411416],
       [0.01540953],
       [0.01219808],
       [0.01176629],
       [0.01362839],
       [0.01446499],
       [0.01287276],
       [0.01190123],
       [0.01249494],
       [0.01095669],
       [0.01176629],
       [0.01311564],
       [0.0156794 ],
       [0.01457293],
       [0.01068682],
       [0.01014708],
       [0.00947241],
       [0.00688166],
       [0.00447983],
       [0.00550533],
       [0.00623398],
       [0.00761031],
       [0.00931048],
       [0.00647686],
       [0.00677372],
       [0.00796114],
       [0.00839293],
       [0.00815005],
       [0.01012009],
       [0.00974228],
       [0.00960734],
       [0.00949939],
       [0.00939145],
```

```
       [0.01141546],
       [0.01276481],
       [0.01206315],
       [0.01219808]])
```

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- Check the first item in y_train
- It is the price of 50th day

```
y_train[0]
```

```
array([0.01311564])
```

6.Creating RNN model

```
# importing libraries
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import SimpleRN
from keras.layers import Dropout

# initializing the RNN
regressor = Sequential()

# adding first RNN layer and dropout regulatization
regressor.add(
    SimpleRNN(units = 50,
              activation = "tanh",
              return_sequences = True,
              input_shape = (X_train.shape[1],1))
             )

regressor.add(
    Dropout(0.2)
             )


# adding second RNN layer and dropout regulatization
regressor.add(
    SimpleRNN(units = 50,
              activation = "tanh",
              return_sequences = True)
             )

regressor.add(
    Dropout(0.2)
             )

# adding third RNN layer and dropout regulatization
regressor.add(
    SimpleRNN(units = 50,
              activation = "tanh",
              return_sequences = True)
             )

regressor.add(
    Dropout(0.2)
             )

# adding fourth RNN layer and dropout regulatization
regressor.add(
    SimpleRNN(units = 50)
             )

regressor.add(
    Dropout(0.2)
             )

# adding the output layer
regressor.add(Dense(units = 1))

# compiling RNN
regressor.compile(
    optimizer = "adam",
    loss = "mean_squared_error",
    metrics = ["accuracy"])

# fitting the RNN
history = regressor.fit(X_train, y_train, epochs = 50, batch_size = 32)
```

```
64/64 [==============================] - 4s 66ms/step - loss: 0.0042 - accuracy: 4.9529e-04
Epoch 32/50
64/64 [==============================] - 4s 62ms/step - loss: 0.0038 - accuracy: 4.9529e-04
Epoch 33/50
64/64 [====================         45ms/step - loss: 0.0038 - accuracy: 4.9529e-04
Epoch 34/50
64/64 [==============================] - 4s 58ms/step - loss: 0.0038 - accuracy: 4.9529e-04
Epoch 35/50
64/64 [==============================] - 3s 53ms/step - loss: 0.0036 - accuracy: 4.9529e-04
Epoch 36/50
64/64 [==============================] - 3s 45ms/step - loss: 0.0036 - accuracy: 4.9529e-04
Epoch 37/50
64/64 [==============================] - 3s 45ms/step - loss: 0.0037 - accuracy: 4.9529e-04
Epoch 38/50
64/64 [==============================] - 4s 56ms/step - loss: 0.0034 - accuracy: 4.9529e-04
Epoch 39/50
64/64 [==============================] - 4s 55ms/step - loss: 0.0035 - accuracy: 4.9529e-04
Epoch 40/50
64/64 [==============================] - 3s 45ms/step - loss: 0.0029 - accuracy: 4.9529e-04
Epoch 41/50
64/64 [==============================] - 3s 46ms/step - loss: 0.0028 - accuracy: 4.9529e-04
Epoch 42/50
64/64 [==============================] - 4s 56ms/step - loss: 0.0029 - accuracy: 4.9529e-04
Epoch 43/50
64/64 [==============================] - 4s 55ms/step - loss: 0.0030 - accuracy: 4.9529e-04
Epoch 44/50
64/64 [==============================] - 3s 45ms/step - loss: 0.0026 - accuracy: 4.9529e-04
Epoch 45/50
64/64 [==============================] - 3s 45ms/step - loss: 0.0027 - accuracy: 4.9529e-04
Epoch 46/50
64/64 [==============================] - 3s 54ms/step - loss: 0.0025 - accuracy: 4.9529e-04
Epoch 47/50
64/64 [==============================] - 4s 57ms/step - loss: 0.0024 - accuracy: 4.9529e-04
Epoch 48/50
64/64 [==============================] - 3s 46ms/step - loss: 0.0024 - accuracy: 4.9529e-04
Epoch 49/50
64/64 [==============================] - 3s 45ms/step - loss: 0.0025 - accuracy: 4.9529e-04
Epoch 50/50
64/64 [==============================] - 3s 53ms/step - loss: 0.0026 - accuracy: 4.9529e-04
```

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7.Evaluating Model

```
# Losses
history.history["loss"]
```

```
[0.3040654957294464,
 0.1550336331129074,
 0.09635035693645477,
 0.06635327637195587,
 0.05224841833114624,
 0.03964291140437126,
 0.03238856419920921,
 0.028899090364575386,
 0.024531910195946693,
 0.01996001787483692,
 0.018383294343948364,
 0.01560582872480154,
 0.014949054457247257,
 0.014503239654004574,
 0.011675205081701279,
 0.011309128254652023,
 0.010615644976496696,
 0.010274404659867287,
 0.008349762298166752,
 0.008240986615419388,
 0.007641125004738569,
 0.006721667945384979,
 0.006664248649030924,
 0.006143517792224884,
 0.005919544491916895,
 0.005979533772915602,
 0.005107056815177202,
 0.00500233331695199,
 0.004482133314013481,
 0.003911724779754877,
 0.004218939691781998,
 0.003762806998565793,
 0.0038017062470316887,
 0.0038106748834252357,
 0.003557385178282857,
 0.0035822088830173016,
 0.003677953267470002,
 0.003408979158848524,
 0.0035480763763189316,
 0.0029108955059200525,
 0.002758030081167817,
 0.0029070465825498104,
```

```
    0.0029619077686220407,
    0.0026210376527160406,
    0.0026545219589024782,
    0.0025382391177117825,
    0.0023643611930310726,
    0.00241807266138494,
    0.002478492446243763,
    0.0025705527514219284]
```

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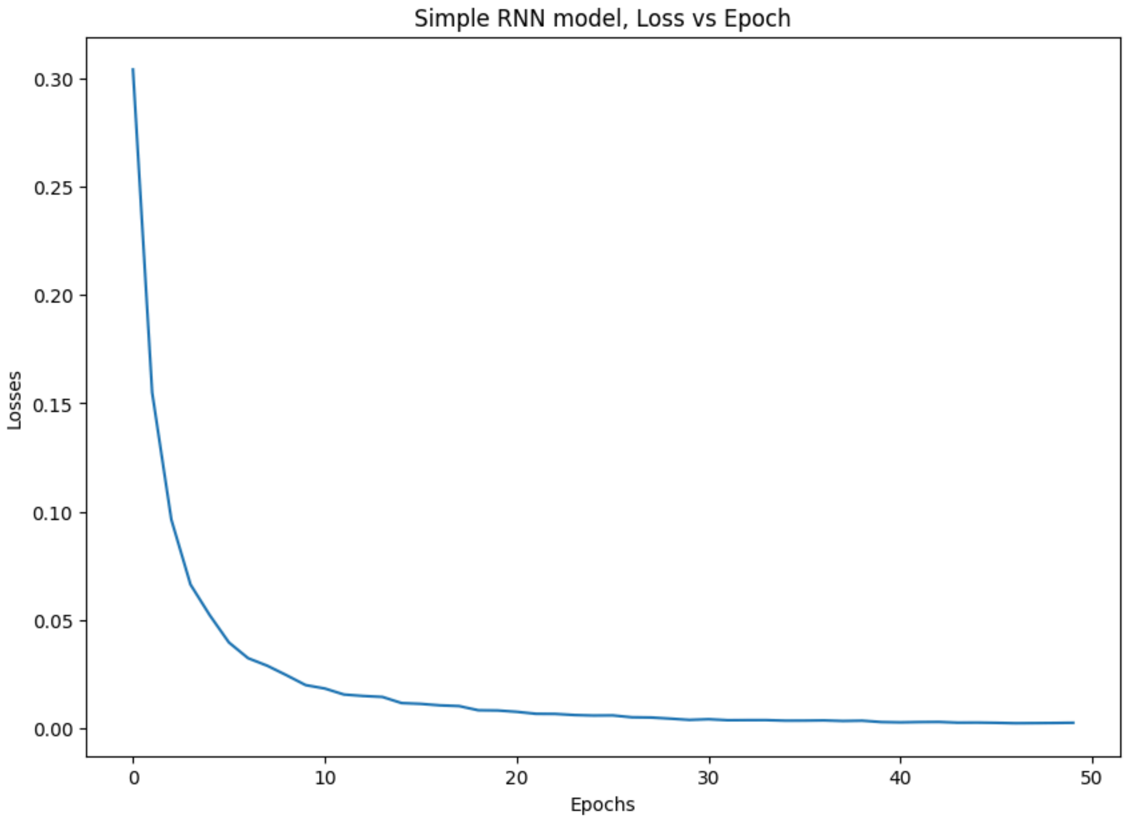
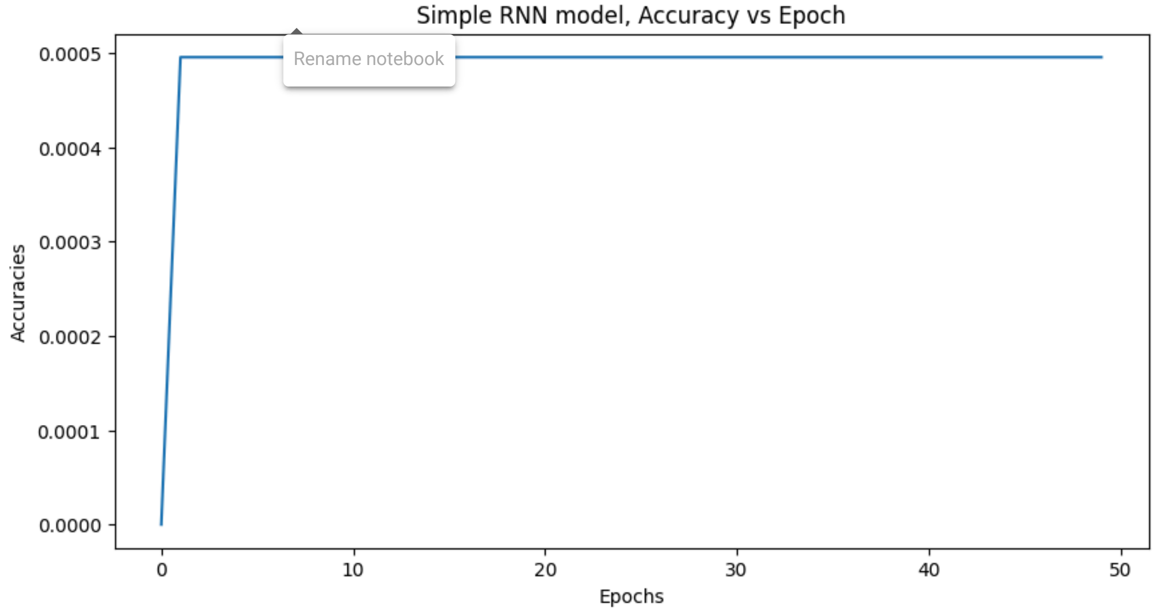
```
# Plotting Loss vs Epochs
plt.figure(figsize =(10,7))
plt.plot(history.history["loss"])
plt.xlabel("Epochs")
plt.ylabel("Losses")
plt.title("Simple RNN model, Loss vs Epoch")
plt.show()
```




```
# Plotting Accuracy vs Epochs
plt.figure(figsize =(10,5))
plt.plot(history.history["accuracy"])
plt.xlabel("Epochs")
plt.ylabel("Accuracies")
plt.title("Simple RNN model, Accuracy vs Epoch")
plt.show()
```



Model predictions for train data

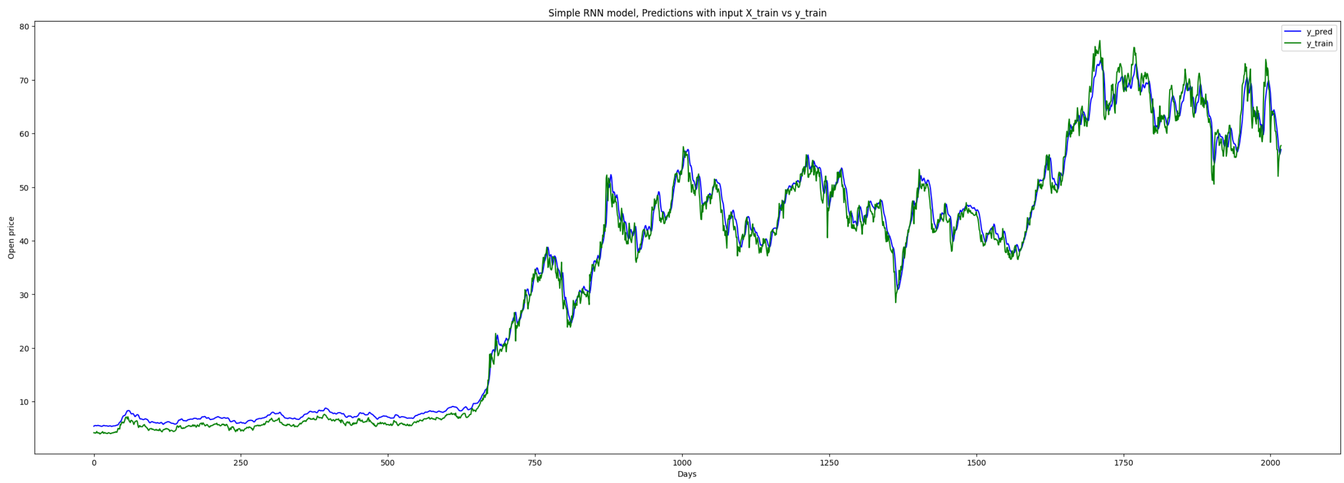
```
y_pred = regressor.predict(X_train)
y_pred = scaler.inverse_transform(y_pred)
y_pred.shape
```

```
64/64 [==============================] - 1s 13ms/step
(2019, 1)
```

```
y_train = scaler.inverse_transform(y_train)
y_train.shape
```

```
(2019, 1)
```

```
# visualisation
plt.figure(figsize = (30,10))
plt.plot(y_pred, color = "b", label = "y_pred" )
plt.plot(y_train, color = "g", label = "y_train")
plt.xlabel("Days")
plt.ylabel("Open price")
plt.title("Simple RNN model, Predictions with input X_train vs y_train")
plt.legend()
plt.show()
```



8.Creating Test Dataset from Validation Data

Converting array and scaling

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```
dataset_validation = validation_data.Open.values  # getting "open" column and converting to array
dataset_validation = np.reshape(dataset_validation, (-1,1))  # converting 1D to 2D array
scaled_dataset_validation =  scaler.fit_transform(dataset_validation)  # scaling open values to between 0 and 1
print("Shape of scaled validation dataset :",scaled_dataset_validation.shape)
```

```
Shape of scaled validation dataset : (887, 1)
```

Creating X_test and y_test

```
# Creating X_test and y_test
X_test = []
y_test = []

for i in range(time_step, length_validation):
    X_test.append(scaled_dataset_validation[i-time_step:i,0])
    y_test.append(scaled_dataset_validation[i,0])
```

Converting to array

```
# Converting to array
X_test, y_test = np.array(X_test), np.array(y_test)
```

```
print("Shape of X_test before reshape :",X_test.shape)
print("Shape of y_test before reshape :",y_test.shape)
```

```
Shape of X_test before reshape : (837, 50)
Shape of y_test before reshape : (837,)
```

Reshape

```
X_test = np.reshape(X_test, (X_test.shape[0],X_test.shape[1],1))  # reshape to 3D array
y_test = np.reshape(y_test, (-1,1))  # reshape to 2D array
```

```
print("Shape of X_test after reshape :",X_test.shape)
print("Shape of y_test after reshape :",y_test.shape)
```

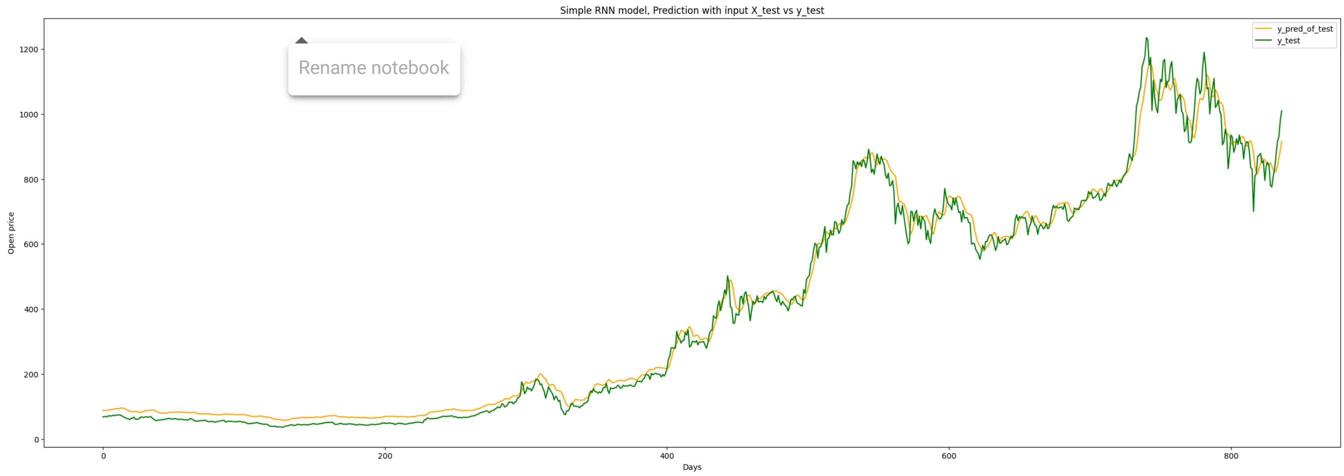
```
Shape of X_test after reshape : (837, 50, 1)
Shape of y_test after reshape : (837, 1)
```

9.Evaluating with Validation Data

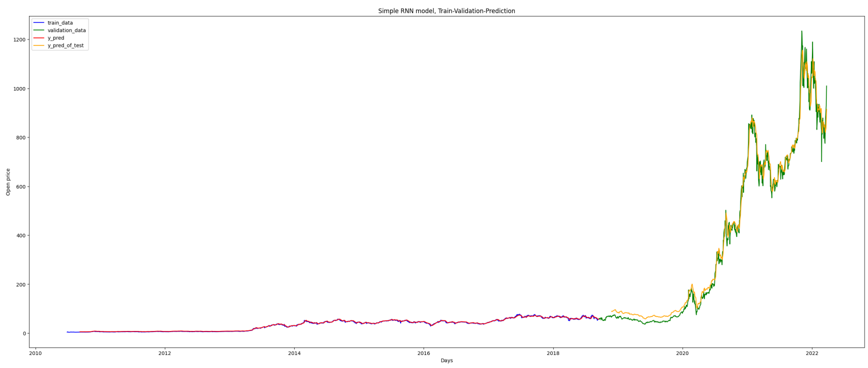
```
# predictions with X_test data
y_pred_of_test = regressor.predict(X_test)
# scaling back from 0-1 to original
y_pred_of_test = scaler.inverse_transform(y_pred_of_test)
print("Shape of y_pred_of_test :",y_pred_of_test.shape)
```

```
27/27 [==============================] - 0s 13ms/step
Shape of y_pred_of_test : (837, 1)
```

```
# visualisation
plt.figure(figsize = (30,10))
plt.plot(y_pred_of_test, label = "y_pred_of_test", c = "orange")
plt.plot(scaler.inverse_transform(y_test), label = "y_test", c = "g")
plt.xlabel("Days")
plt.ylabel("Open price")
plt.title("Simple RNN model, Prediction with input X_test vs y_test")
plt.legend()
plt.show()
```




```
# Visualisation
plt.subplots(figsize =(30,12))
plt.plot(train_data.Date, train_data.Open, label = "train_data", color = "b")
plt.plot(validation_data.Date, validation_data.Open, label = "validation_data", color = "g")
plt.plot(train_data.Date.iloc[time_step:], y_pred, label = "y_pred", color = "r")
plt.plot(validation_data.Date.iloc[time_step:], y_pred_of_test, label = "y_pred_of_test", color = "orange")
plt.xlabel("Days")
plt.ylabel("Open price")
plt.title("Simple RNN model, Train-Validation-Prediction")
plt.legend()
plt.show()
```



10.Creating LSTM Model

```
y_train = scaler.fit_transform(y_train)
```

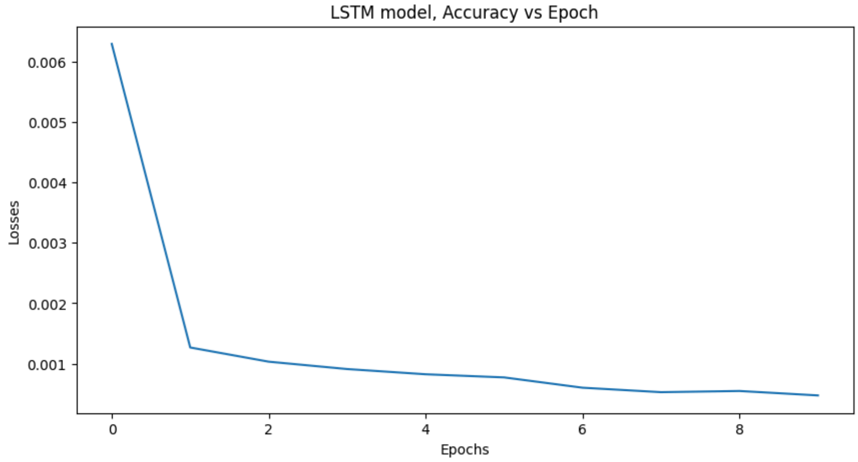
```
from keras.layers import LSTM

model_lstm = Sequential()
model_lstm.add(
    LSTM(64,return_sequences=True,input_shape = (X_train.shape[1],1))) #64 lstm neuron block
model_lstm.add(
    LSTM(64, return_sequences= False))
model_lstm.add(Dense(32))
model_lstm.add(Dense(1))
model_lstm.compile(loss = "mean_squared_error", optimizer = "adam", metrics = ["accuracy"])
history2 = model_lstm.fit(X_train, y_train, epochs = 10, batch_size = 10)
```

```
Epoch 1/10
202/202 [==============================] - 14s 44ms/step - loss: 0.0063 - accuracy: 9.9059e-04
Epoch 2/10
202/202 [==================  Rename notebook  5 45ms/step - loss: 0.0013 - accuracy: 9.9059e-04
Epoch 3/10
202/202 [==============================] - 9s 44ms/step - loss: 0.0010 - accuracy: 9.9059e-04
Epoch 4/10
202/202 [==============================] - 8s 39ms/step - loss: 9.1053e-04 - accuracy: 9.9059e-04
Epoch 5/10
202/202 [==============================] - 9s 44ms/step - loss: 8.2416e-04 - accuracy: 9.9059e-04
Epoch 6/10
202/202 [==============================] - 9s 44ms/step - loss: 7.7218e-04 - accuracy: 9.9059e-04
Epoch 7/10
202/202 [==============================] - 8s 38ms/step - loss: 6.0177e-04 - accuracy: 9.9059e-04
Epoch 8/10
202/202 [==============================] - 9s 44ms/step - loss: 5.2792e-04 - accuracy: 9.9059e-04
Epoch 9/10
202/202 [==============================] - 9s 44ms/step - loss: 5.4745e-04 - accuracy: 9.9059e-04
Epoch 10/10
202/202 [==============================] - 8s 39ms/step - loss: 4.7410e-04 - accuracy: 9.9059e-04
```

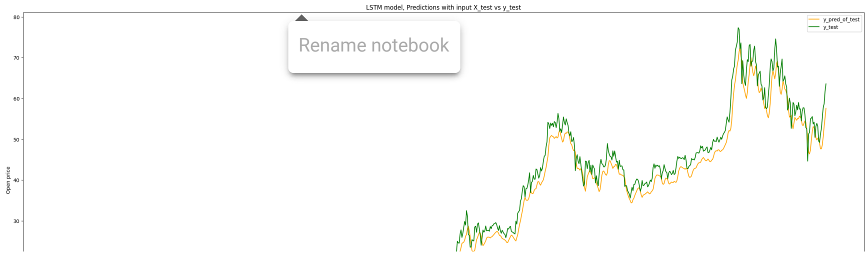
11.Evaluating LSTM Model

```
plt.figure(figsize =(10,5))
plt.plot(history2.history["loss"])
plt.xlabel("Epochs")
plt.ylabel("Losses")
plt.title("LSTM model, Accuracy vs Epoch")
plt.show()
```




```
plt.subplots(figsize =(30,12))
plt.plot(scaler.inverse_transform(model_lstm.predict(X_test)), label = "y_pred_of_test", c = "orange" )
plt.plot(scaler.inverse_transform(y_test), label = "y_test", color = "g")
plt.xlabel("Days")
plt.ylabel("Open price")
plt.title("LSTM model, Predictions with input X_test vs y_test")
plt.legend()
plt.show()
```

```
27/27 [==============================] - 1s 16ms/step
```



12.Future price prediction

- Which day is the last day in our data?

```
data.iloc[-1]
```

```
Date          2022-03-24
Open          1009.72998
High          1024.48999
Low           988.799988
Close        1013.919983
Adj Close    1013.919983
Volume          22901900
Name: 2955, dtype: object
```

- We can predict the open price for the day after 3/17/2017--> for 3/18/2017.
- We will use last 50 days Open price as input of our model for this prediction
- Let us prepare it:

```
X_input = data.iloc[-time_step:].Open.values            # getting last 50 rows and converting to array
X_input = scaler.fit_transform(X_input.reshape(-1,1))   # converting to 2D array and scaling
X_input = np.reshape(X_input, (1,50,1))                 # reshaping : converting to 3D array
print("Shape of X_input :", X_input.shape)
X_input
```

```
Shape of X_input : (1, 50, 1)
array([[[0.92605468],
        [1.        ],
        [0.7817609 ],
        [0.7982285 ],
        [0.83517668],
        [0.75692478],
        [0.72416086],
        [0.50007348],
        [0.52317225],
        [0.61671729],
        [0.57005483],
        [0.32096018],
        [0.42165028],
        [0.57458169],
        [0.5573799 ],
        [0.44438195],
        [0.48162374],
        [0.54663796],
        [0.50195764],
        [0.57406779],
        [0.50890676],
        [0.51198988],
        [0.39439175],
        [0.4884262 ],
        [0.52280515],
        [0.52087215],
        [0.45416956],
        [0.32724873],
        [0.31819516],
        [0.        ],
        [0.2663208 ],
        [0.28046397],
        [0.41423609],
        [0.42023103],
        [0.4364785 ],
        [0.3638788 ],
        [0.38149652],
        [0.23279835],
        [0.3403396 ],
        [0.3696291 ],
        [0.34210145],
        [0.19629046],
        [0.18322408],
```