CSC660 DEEP LEARNING

CONTINUOUS ASSESSMENT 2

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M.Sc. DEGREE(AI)-TERM 4

1. Implement as transfer learning on the chosen dataset using Xception architecture

SOURCE CODE:

```
import numpy as np
import tensorflow as tf
from tensorflow.keras.datasets import cifar10
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.applications import ResNet50
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense, GlobalAveragePooling2D
from tensorflow.keras.preprocessing.image import img_to_array, array_to_img
# Load the CIFAR-10 dataset
(train_images, train_labels), (test_images, test_labels) = cifar10.load_data()
# Normalize pixel values to be between 0 and 1
train_images = train_images.astype('float32') / 255.0
test_images = test_images.astype('float32') / 255.0
# Convert labels to one-hot encoded
train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)
# Resize images to (71, 71, 3) for ResNet50 input
def resize_image(img):
    img = array_to_img(img)
    img = img.resize((71, 71))
    return img_to_array(img)
train_images = np.array([resize_image(img) for img in train_images])
test_images = np.array([resize_image(img) for img in test_images])
```

```
# Load the pre-trained ResNet50 model
base_model = ResNet50(weights='imagenet', include_top=False, input_shape=(71, 71, 3))
# Freeze the base model layers
for layer in base_model.layers:
    layer.trainable = False
# Add custom layers for the CIFAR-10 task
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(128, activation='relu')(x)
predictions = Dense(10, activation='softmax')(x)
# Create the full model
model = Model(inputs=base_model.input, outputs=predictions)

# Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
# Train the model
model.fit(train_images, train_labels, epochs=10, batch_size=32, validation_split=0.2)
```

```
# Train the model
model.fit(train_images, train_labels, epochs=10, batch_size=32, validation_split=0.2)

Epoch 1/10
1250/1250 [==============================] - 1198s 952ms/step - loss: 0.9240 - accuracy: 0.6783 - val_loss: 0.8135 - val_accuracy: 0.7171
Epoch 2/10
1250/1250 [==============================] - 1176s 941ms/step - loss: 0.6927 - accuracy: 0.7559 - val_loss: 0.7691 - val_accuracy: 0.7278
Epoch 3/10
1250/1250 [==============================] - 1171s 937ms/step - loss: 0.6044 - accuracy: 0.7858 - val_loss: 0.7459 - val_accuracy: 0.7402
Epoch 4/10
1250/1250 [==============================] - 1174s 939ms/step - loss: 0.5272 - accuracy: 0.8130 - val_loss: 0.7975 - val_accuracy: 0.7343
Epoch 5/10
1250/1250 [==============================] - 1174s 939ms/step - loss: 0.4651 - accuracy: 0.8350 - val_loss: 0.7953 - val_accuracy: 0.7384
Epoch 6/10
1250/1250 [==============================] - 1177s 942ms/step - loss: 0.4017 - accuracy: 0.8572 - val_loss: 0.8598 - val_accuracy: 0.7346
Epoch 7/10
1250/1250 [==============================] - 1189s 951ms/step - loss: 0.3495 - accuracy: 0.8766 - val_loss: 0.8523 - val_accuracy: 0.7373
Epoch 8/10
1250/1250 [==============================] - 1175s 940ms/step - loss: 0.3005 - accuracy: 0.8937 - val_loss: 0.9358 - val_accuracy: 0.7354
Epoch 9/10
1250/1250 [==============================] - 1147s 917ms/step - loss: 0.2570 - accuracy: 0.9094 - val_loss: 1.0445 - val_accuracy: 0.7283
Epoch 10/10
1250/1250 [==============================] - 1182s 946ms/step - loss: 0.2251 - accuracy: 0.9206 - val_loss: 1.0712 - val_accuracy: 0.7298
<keras.src.callbacks.History at 0x7808b8c01ba0>
```

```
# Evaluate the model on test data
loss, accuracy = model.evaluate(test_images, test_labels)
print(f'Test accuracy: {accuracy * 100:.2f}%')
```

```
# Evaluate the model on test data
loss, accuracy = model.evaluate(test_images, test_labels)
print(f'Test accuracy: {accuracy * 100:.2f}%')
```

```
313/313 [==============================] - 233s 745ms/step - loss: 1.0812 - accuracy: 0.7336
Test accuracy: 73.36%
```

2.On the chosen dataset , using RNN for image classification

SOURCE CODE:

```
import numpy as np
import tensorflow as tf
from tensorflow.keras.datasets import cifar10
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
# Load the CIFAR-10 dataset
(train_images, train_labels), (test_images, test_labels) = cifar10.load_data()
# Normalize pixel values to be between 0 and 1
train_images = train_images.astype('float32') / 255.0
test_images = test_images.astype('float32') / 255.0
# Convert labels to one-hot encoded
train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)
# Flatten images into sequences
train_sequences = train_images.reshape(-1, 32, 32 * 3)
test_sequences = test_images.reshape(-1, 32, 32 * 3)
# Build RNN model
model = Sequential([
    LSTM(128, input_shape=(32, 32 * 3), return_sequences=True),
    Dropout(0.5),
```

```
    LSTM(128),
    Dropout(0.5),
    Dense(10, activation='softmax')
])
# Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# Train the model
model.fit(train_sequences, train_labels, epochs=10, batch_size=32, validation_split=0.2)
```

```
Epoch 1/10
1250/1250 [==============================] - 152s 117ms/step - loss: 1.8447 - accuracy: 0.3227 - val_loss: 1.6518 - val_accuracy: 0.3997
Epoch 2/10
1250/1250 [==============================] - 147s 118ms/step - loss: 1.6158 - accuracy: 0.4117 - val_loss: 1.4793 - val_accuracy: 0.4643
Epoch 3/10
1250/1250 [==============================] - 159s 127ms/step - loss: 1.4973 - accuracy: 0.4584 - val_loss: 1.4184 - val_accuracy: 0.4824
Epoch 4/10
1250/1250 [==============================] - 158s 126ms/step - loss: 1.4198 - accuracy: 0.4904 - val_loss: 1.3688 - val_accuracy: 0.5058
Epoch 5/10
1250/1250 [==============================] - 158s 126ms/step - loss: 1.3612 - accuracy: 0.5105 - val_loss: 1.3093 - val_accuracy: 0.5306
Epoch 6/10
1250/1250 [==============================] - 154s 123ms/step - loss: 1.3000 - accuracy: 0.5331 - val_loss: 1.3115 - val_accuracy: 0.5264
Epoch 7/10
1250/1250 [==============================] - 145s 116ms/step - loss: 1.2553 - accuracy: 0.5521 - val_loss: 1.2650 - val_accuracy: 0.5456
Epoch 8/10
1250/1250 [==============================] - 146s 117ms/step - loss: 1.2134 - accuracy: 0.5665 - val_loss: 1.2081 - val_accuracy: 0.5644
Epoch 9/10
1250/1250 [==============================] - 147s 117ms/step - loss: 1.1807 - accuracy: 0.5792 - val_loss: 1.1880 - val_accuracy: 0.5788
Epoch 10/10
1250/1250 [==============================] - 144s 115ms/step - loss: 1.1448 - accuracy: 0.5916 - val_loss: 1.1886 - val_accuracy: 0.5777
<keras.src.callbacks.History at 0x7808b5fc5ae0>
```

```
# Evaluate the model on test data
loss, accuracy = model.evaluate(test_sequences, test_labels)
print(f'Test accuracy: {accuracy * 100:.2f}%')
```

```
# Evaluate the model on test data
loss, accuracy = model.evaluate(test_sequences, test_labels)
print(f'Test accuracy: {accuracy * 100:.2f}%')

313/313 [==============================] - 13s 43ms/step - loss: 1.1892 - accuracy: 0.5732
Test accuracy: 57.32%
```

3. On a chosen time-series dataset, forecast the trend using LSTM and GRU. Compare the performance of these two models

SOURCE CODE:

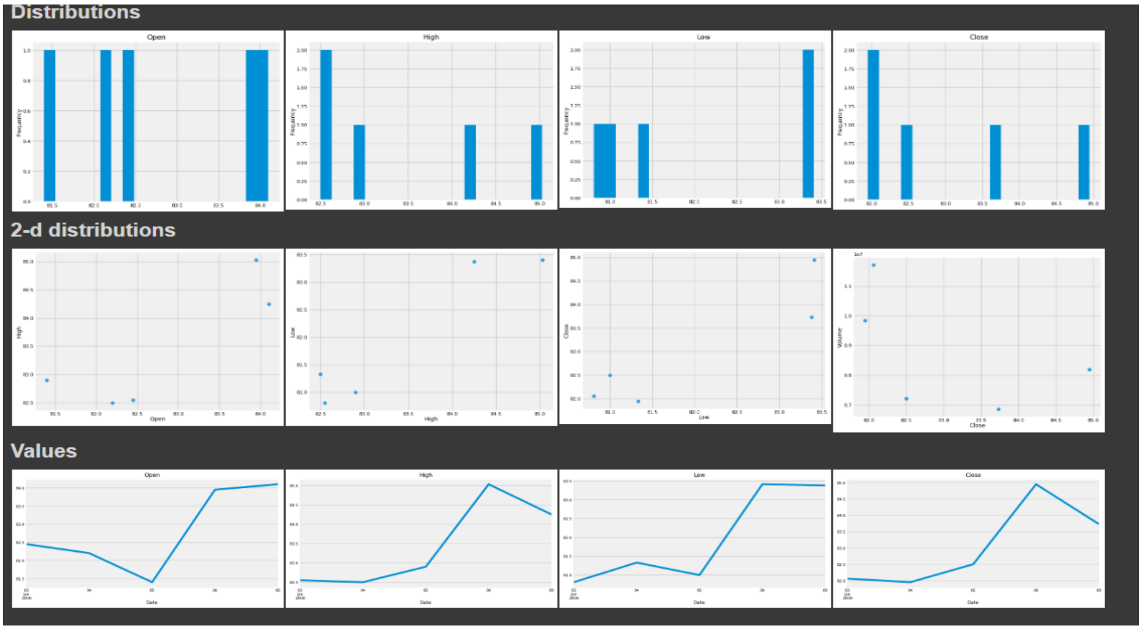
 # Importing the libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import math
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
from tensorflow.keras.optimizers import SGD
from tensorflow.keras.models import Sequential
from keras.layers import Dense, LSTM, Dropout, GRU, Bidirectional
plt.style.use('fivethirtyeight')
```

 # Load the dataset

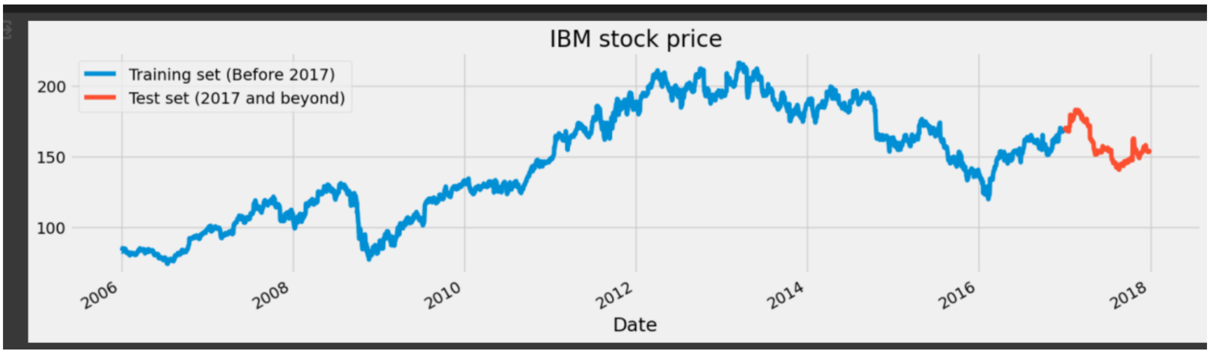
```
dataset = pd.read_csv('/content/IBM_2006-01-01_to_2018-01-01.csv', index_col='Date', parse_dates=['Date'])
dataset.head()
```

Date	Open	High	Low	Close	Volume	Name
2006-01-03	82.45	82.55	80.81	82.06	11715200	IBM
2006-01-04	82.20	82.50	81.33	81.95	9840600	IBM
2006-01-05	81.40	82.90	81.00	82.50	7213500	IBM
2006-01-06	83.95	85.03	83.41	84.95	8197400	IBM
2006-01-09	84.10	84.25	83.38	83.73	6858200	IBM




```
# Some functions to help out with
def plot_predictions(test,predicted):
    plt.plot(test, color='red',label='Real IBM Stock Price')
    plt.plot(predicted, color='blue',label='Predicted IBM Stock Price')
    plt.title('IBM Stock Price Prediction')
    plt.xlabel('Time')
    plt.ylabel('IBM Stock Price')
    plt.legend()
    plt.show()

def return_rmse(test,predicted):
    rmse = math.sqrt(mean_squared_error(test, predicted))
    print("The root mean squared error is {}.".format(rmse))
# Checking for missing values
training_set = dataset[:'2016'].iloc[:,1:2].values
test_set = dataset['2017':].iloc[:,1:2].values
# We have chosen 'High' attribute for prices. Let's see what it looks like
dataset["High"][:'2016'].plot(figsize=(16,4),legend=True)
dataset["High"]['2017':].plot(figsize=(16,4),legend=True)
plt.legend(['Training set (Before 2017)','Test set (2017 and beyond)'])
plt.title('IBM stock price')
```

```
plt.show()
```




```
# Scaling the training set
sc = MinMaxScaler(feature_range=(0,1))
training_set_scaled = sc.fit_transform(training_set)
# Since LSTMs store long term memory state, we create a data structure with 60 timesteps and 1 output
# So for each element of training set, we have 60 previous training set elements
X_train = []
y_train = []
for i in range(60,2769):
    X_train.append(training_set_scaled[i-60:i,0])
    y_train.append(training_set_scaled[i,0])
X_train, y_train = np.array(X_train), np.array(y_train)
# Reshaping X_train for efficient modelling
X_train = np.reshape(X_train, (X_train.shape[0],X_train.shape[1],1))
# The LSTM architecture
regressor = Sequential()
# First LSTM layer with Dropout regularisation
regressor.add(LSTM(units=50, return_sequences=True, input_shape=(X_train.shape[1],1)))
regressor.add(Dropout(0.2))
# Second LSTM layer
regressor.add(LSTM(units=50, return_sequences=True))
regressor.add(Dropout(0.2))
# Third LSTM layer
regressor.add(LSTM(units=50, return_sequences=True))
regressor.add(Dropout(0.2))
```

Fourth LSTM layer

regressor.add(LSTM(units=50))

regressor.add(Dropout(0.2))

The output layer

regressor.add(Dense(units=1))

Compiling the RNN

regressor.compile(optimizer='rmsprop',loss='mean_squared_error')

Fitting to the training set

regressor.fit(X_train,y_train,epochs=50,batch_size=32)

```
85/85 [==============================] - 9s 109ms/step - loss: 0.0018
Epoch 41/50
85/85 [==============================] - 11s 133ms/step - loss: 0.0019
Epoch 42/50
85/85 [==============================] - 10s 119ms/step - loss: 0.0017
Epoch 43/50
85/85 [==============================] - 10s 117ms/step - loss: 0.0018
Epoch 44/50
85/85 [==============================] - 11s 134ms/step - loss: 0.0017
Epoch 45/50
85/85 [==============================] - 10s 115ms/step - loss: 0.0017
Epoch 46/50
85/85 [==============================] - 10s 123ms/step - loss: 0.0017
Epoch 47/50
85/85 [==============================] - 11s 133ms/step - loss: 0.0016
Epoch 48/50
85/85 [==============================] - 9s 109ms/step - loss: 0.0017
Epoch 49/50
85/85 [==============================] - 11s 127ms/step - loss: 0.0016
Epoch 50/50
85/85 [==============================] - 11s 134ms/step - loss: 0.0016
<keras.src.callbacks.History at 0x7fdb717f7880>
```

Now to get the test set ready in a similar way as the training set.

The following has been done so forst 60 entires of test set have 60 previous values which is impossible to get unless we take the whole 'High' attribute data for processing

dataset_total = pd.concat((dataset["High"][:'2016'],dataset["High"]['2017':]),axis=0)

inputs = dataset_total[len(dataset_total)-len(test_set) - 60:].values

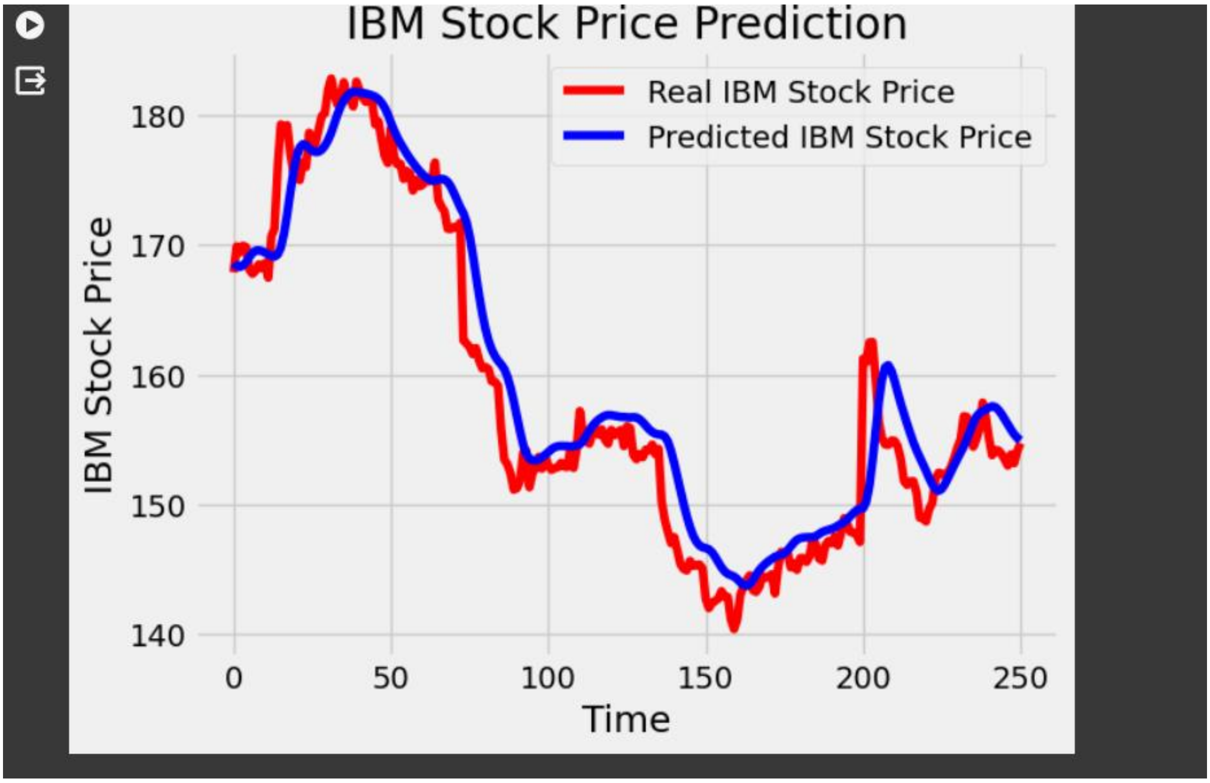
inputs = inputs.reshape(-1,1)

inputs = sc.transform(inputs)

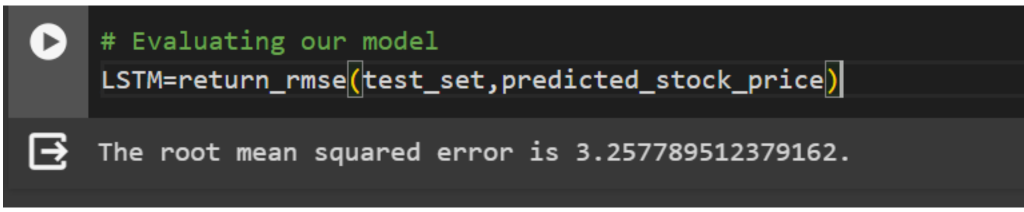
Preparing X_test and predicting the prices

X_test = []

```
for i in range(60,311):
    X_test.append(inputs[i-60:i,0])
X_test = np.array(X_test)
X_test = np.reshape(X_test, (X_test.shape[0],X_test.shape[1],1))
predicted_stock_price = regressor.predict(X_test)
predicted_stock_price = sc.inverse_transform(predicted_stock_price)
# Visualizing the results for LSTM
plot_predictions(test_set,predicted_stock_price)
```




```
# Evaluating our model
LSTM=return_rmse(test_set,predicted_stock_price)
```




```
# Make predictions using GRU model
regressorGRU = Sequential()
# First GRU layer with Dropout regularisation
regressorGRU.add(GRU(units=50, return_sequences=True,
input_shape=(X_train.shape[1],1), activation='tanh'))
```

regressorGRU.add(Dropout(0.2))

Second GRU layer

regressorGRU.add(GRU(units=50, return_sequences=True, input_shape=(X_train.shape[1],1), activation='tanh'))

regressorGRU.add(Dropout(0.2))

Third GRU layer

regressorGRU.add(GRU(units=50, return_sequences=True, input_shape=(X_train.shape[1],1), activation='tanh'))

regressorGRU.add(Dropout(0.2))

Fourth GRU layer

regressorGRU.add(GRU(units=50, activation='tanh'))

regressorGRU.add(Dropout(0.2))

The output layer

regressorGRU.add(Dense(units=1))

Compiling the RNN

regressorGRU.compile(tf.keras.optimizers.legacy.SGD(lr=0.01, decay=1e-7, momentum=0.9, nesterov=False),loss='mean_squared_error')

Fitting to the training set

regressorGRU.fit(X_train,y_train,epochs=50,batch_size=150)

```
Epoch 41/50
19/19 [==============================] - 4s 217ms/step - loss: 0.0023
Epoch 42/50
19/19 [==============================] - 7s 341ms/step - loss: 0.0023
Epoch 43/50
19/19 [==============================] - 4s 213ms/step - loss: 0.0024
Epoch 44/50
19/19 [==============================] - 4s 216ms/step - loss: 0.0021
Epoch 45/50
19/19 [==============================] - 6s 319ms/step - loss: 0.0021
Epoch 46/50
19/19 [==============================] - 5s 235ms/step - loss: 0.0022
Epoch 47/50
19/19 [==============================] - 4s 212ms/step - loss: 0.0023
Epoch 48/50
19/19 [==============================] - 5s 260ms/step - loss: 0.0024
Epoch 49/50
19/19 [==============================] - 6s 286ms/step - loss: 0.0021
Epoch 50/50
19/19 [==============================] - 4s 209ms/step - loss: 0.0021
<keras.src.callbacks.History at 0x7fdb709590c0>
```

Preparing X_test and predicting the prices

X_test = []

for i in range(60,311):

    X_test.append(inputs[i-60:i,0])

X_test = np.array(X_test)

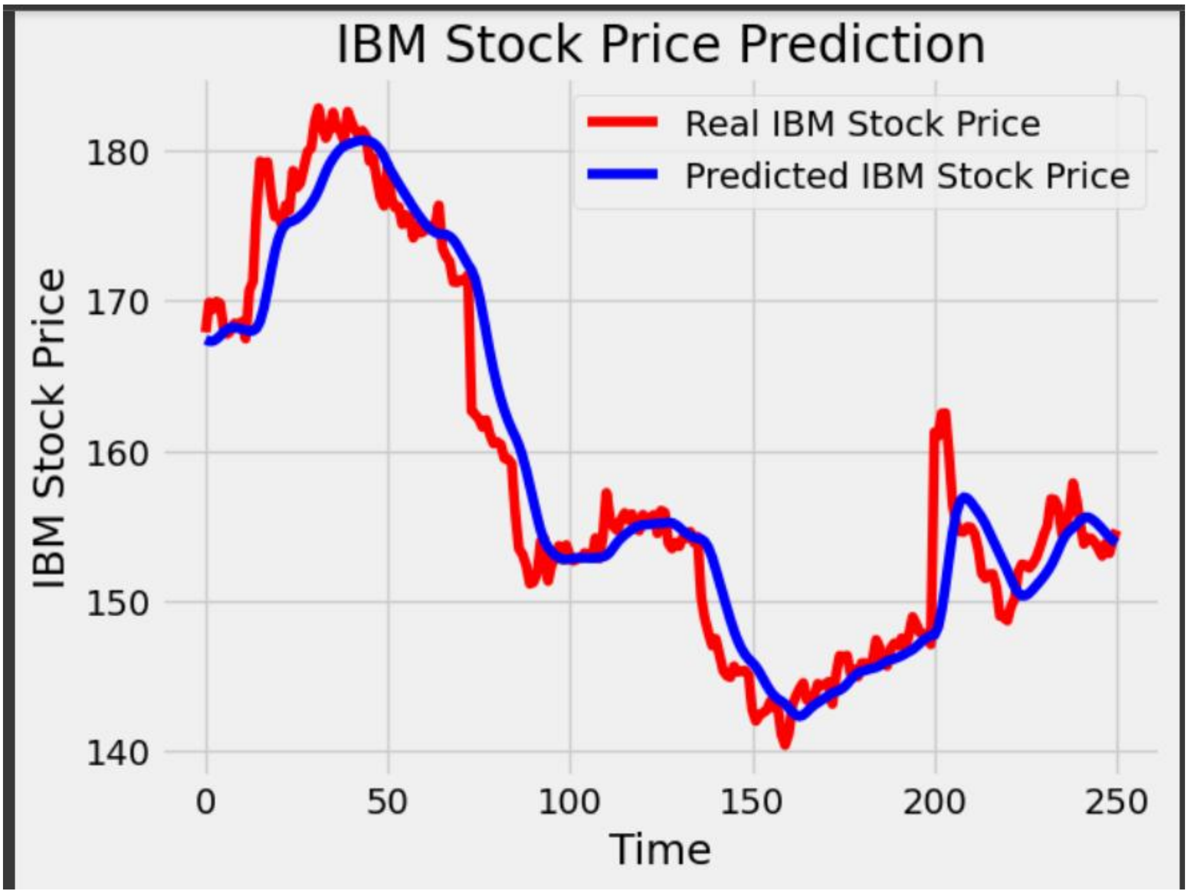
X_test = np.reshape(X_test, (X_test.shape[0],X_test.shape[1],1))

GRU_predicted_stock_price = regressorGRU.predict(X_test)

GRU_predicted_stock_price = sc.inverse_transform(GRU_predicted_stock_price)

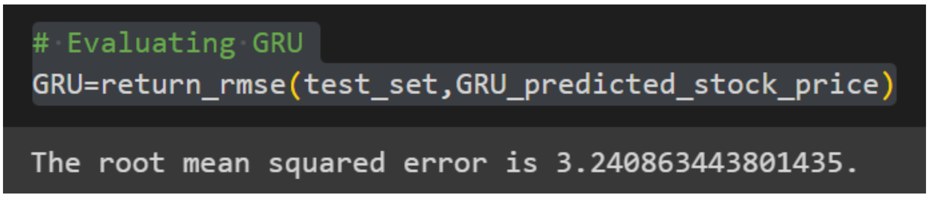
Visualizing the results for GRU

plot_predictions(test_set,GRU_predicted_stock_price)



Evaluating GRU

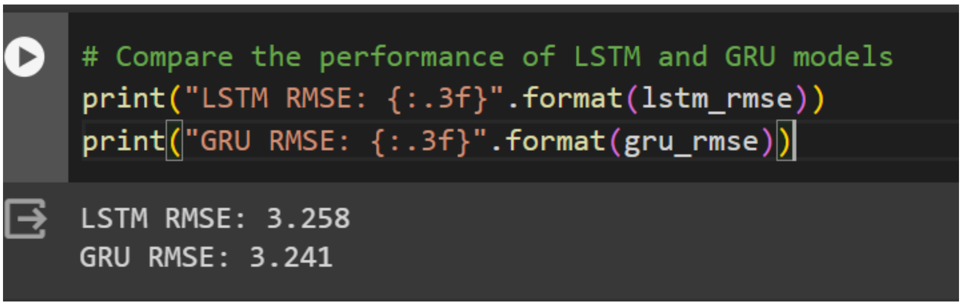
GRU=return_rmse(test_set,GRU_predicted_stock_price)



Calculate RMSE for LSTM and GRU models

lstm_rmse = np.sqrt(mean_squared_error(test_set,predicted_stock_price))

```
gru_rmse = np.sqrt(mean_squared_error(test_set,GRU_predicted_stock_price))

# Compare the performance of LSTM and GRU models

print("LSTM RMSE: {:.3f}".format(lstm_rmse))

print("GRU RMSE: {:.3f}".format(gru_rmse))
```



INTERPRETATION:

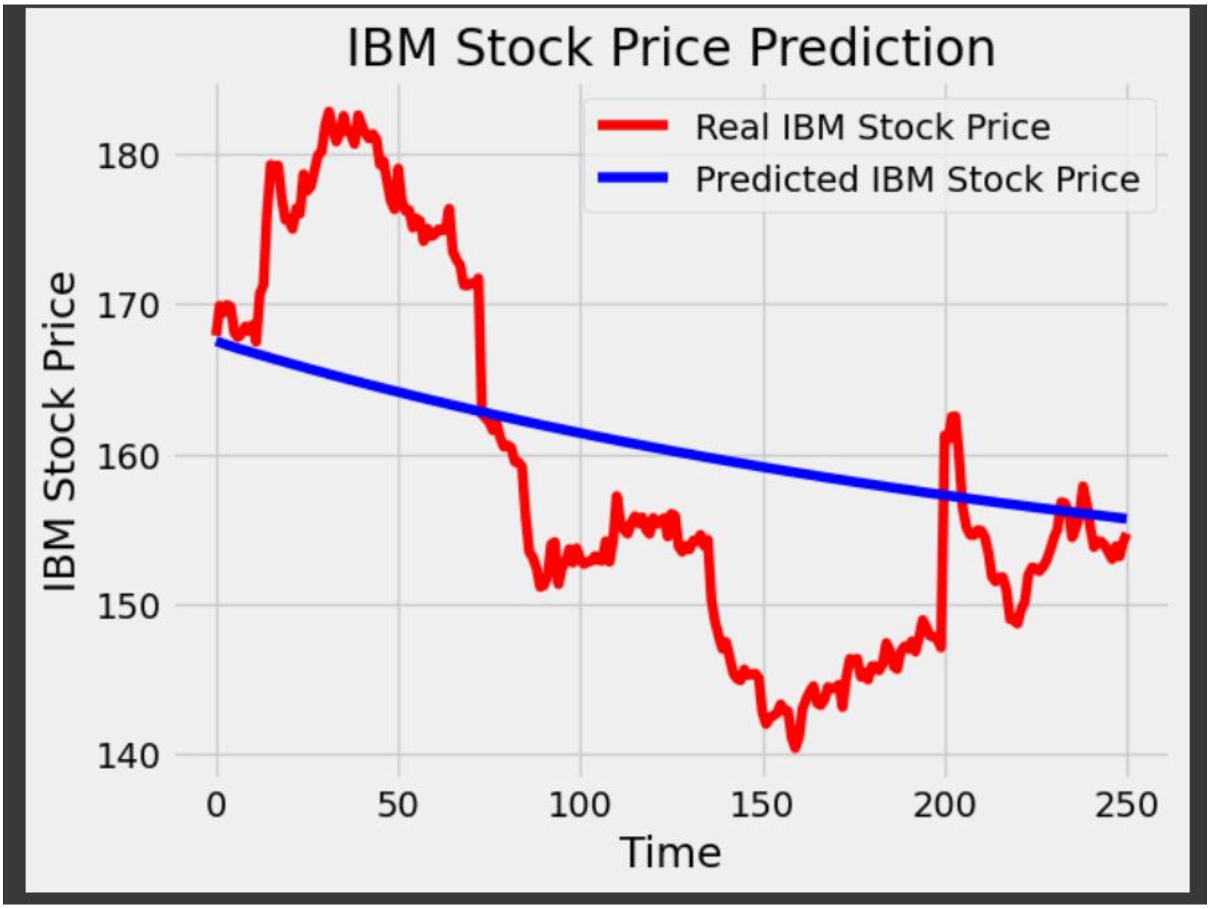
- Based on the provided RMSE values, the GRU model demonstrates slightly better prediction accuracy than the LSTM model for the given time series dataset.
- However, the difference in performance is minor.

```
# Preparing sequence data

initial_sequence = X_train[2708,:]

sequence = []

for i in range(251):

    new_prediction = regressorGRU.predict(initial_sequence.reshape(initial_sequence.shape[1],initial_sequence.shape[0],1))

    initial_sequence = initial_sequence[1:]

    initial_sequence = np.append(initial_sequence,new_prediction,axis=0)

    sequence.append(new_prediction)

sequence = sc.inverse_transform(np.array(sequence).reshape(251,1))
```

```
1/1 [==============================] - 0s 48ms/step
1/1 [==============================] - 0s 50ms/step
1/1 [==============================] - 0s 60ms/step
1/1 [==============================] - 0s 50ms/step
1/1 [==============================] - 0s 48ms/step
1/1 [==============================] - 0s 49ms/step
1/1 [==============================] - 0s 45ms/step
1/1 [==============================] - 0s 48ms/step
1/1 [==============================] - 0s 49ms/step
1/1 [==============================] - 0s 48ms/step
1/1 [==============================] - 0s 47ms/step
1/1 [==============================] - 0s 51ms/step
1/1 [==============================] - 0s 53ms/step
1/1 [==============================] - 0s 47ms/step
1/1 [==============================] - 0s 49ms/step
1/1 [==============================] - 0s 51ms/step
1/1 [==============================] - 0s 49ms/step
1/1 [==============================] - 0s 48ms/step
1/1 [==============================] - 0s 64ms/step
```

Visualizing the sequence

plot_predictions(test_set,sequence)



Evaluating the sequence

return_rmse(test_set,sequence)

```
# Evaluating the sequence
return_rmse(test_set,sequence)
```

```
The root mean squared error is 9.958211642569788.
```

4.For the chosen dataset, implement autoencoder using (i) deep neural network (ii) CNN (iii) stacked encoder

SOURCE CODE:

Deep Neural Network Autoencoder:

```
import numpy as np

import tensorflow as tf

from tensorflow.keras.layers import Input, Dense

from tensorflow.keras.models import Model

# Load and preprocess the MNIST dataset

mnist = tf.keras.datasets.mnist

(x_train, _), (x_test, _) = mnist.load_data()

# Normalize and flatten the images

x_train = x_train.astype('float32') / 255.

x_test = x_test.astype('float32') / 255.

x_train = x_train.reshape((-1, 28 * 28))

x_test = x_test.reshape((-1, 28 * 28))

# Define the autoencoder model

input_dim = 784  # 28*28

encoding_dim = 128

input_img = Input(shape=(input_dim,))

encoded = Dense(encoding_dim, activation='relu')(input_img)

decoded = Dense(input_dim, activation='sigmoid')(encoded)

autoencoder = Model(input_img, decoded)

# Compile and train the autoencoder

autoencoder.compile(optimizer='adam', loss='binary_crossentropy')

autoencoder.fit(x_train, x_train, epochs=10, batch_size=256, shuffle=True)
```

```
235/235 [==============================] - 4s 19ms/step - loss: 0.1183
Epoch 3/10
235/235 [==============================] - 4s 17ms/step - loss: 0.0968
Epoch 4/10
235/235 [==============================] - 3s 13ms/step - loss: 0.0864
Epoch 5/10
235/235 [==============================] - 3s 13ms/step - loss: 0.0801
Epoch 6/10
235/235 [==============================] - 3s 14ms/step - loss: 0.0763
Epoch 7/10
235/235 [==============================] - 5s 21ms/step - loss: 0.0738
Epoch 8/10
235/235 [==============================] - 3s 14ms/step - loss: 0.0722
Epoch 9/10
235/235 [==============================] - 3s 13ms/step - loss: 0.0710
Epoch 10/10
235/235 [==============================] - 3s 12ms/step - loss: 0.0701
<keras.src.callbacks.History at 0x7fdb95c1bb80>
```

Perform reconstruction on test data

reconstructed_images_dnn = autoencoder.predict(x_test)

```
# Perform reconstruction on test data
reconstructed_images_dnn = autoencoder.predict(x_test)

313/313 [==============================] - 1s 2ms/step
```

ii) CNN Autoencoder

import numpy as np

import tensorflow as tf

from tensorflow.keras.layers import Input, Conv2D, MaxPooling2D, UpSampling2D

from tensorflow.keras.models import Model

Load and preprocess the MNIST dataset

mnist = tf.keras.datasets.mnist

(x_train, _), (x_test, _) = mnist.load_data()

Normalize and reshape the images

x_train = x_train.astype('float32') / 255.

x_test = x_test.astype('float32') / 255.

x_train = np.reshape(x_train, (-1, 28, 28, 1))

x_test = np.reshape(x_test, (-1, 28, 28, 1))

```
# Define the autoencoder model
input_shape = (28, 28, 1)
input_img = Input(shape=input_shape)
encoded = Conv2D(16, (3, 3), activation='relu', padding='same')(input_img)
encoded = MaxPooling2D((2, 2), padding='same')(encoded)
decoded = Conv2D(16, (3, 3), activation='relu', padding='same')(encoded)
decoded = UpSampling2D((2, 2))(decoded)
decoded = Conv2D(1, (3, 3), activation='sigmoid', padding='same')(decoded)
autoencoder = Model(input_img, decoded)
# Compile and train the autoencoder
autoencoder.compile(optimizer='adam', loss='binary_crossentropy')
autoencoder.fit(x_train, x_train, epochs=10, batch_size=128, shuffle=True)
```

```
Epoch 1/10
469/469 [==============================] - 64s 134ms/step - loss: 0.1239
Epoch 2/10
469/469 [==============================] - 68s 144ms/step - loss: 0.0675
Epoch 3/10
469/469 [==============================] - 67s 142ms/step - loss: 0.0654
Epoch 4/10
469/469 [==============================] - 68s 145ms/step - loss: 0.0645
Epoch 5/10
469/469 [==============================] - 68s 144ms/step - loss: 0.0640
Epoch 6/10
469/469 [==============================] - 68s 146ms/step - loss: 0.0636
Epoch 7/10
469/469 [==============================] - 68s 144ms/step - loss: 0.0633
Epoch 8/10
469/469 [==============================] - 67s 143ms/step - loss: 0.0630
Epoch 9/10
469/469 [==============================] - 67s 144ms/step - loss: 0.0629
Epoch 10/10
469/469 [==============================] - 67s 144ms/step - loss: 0.0627
<keras.src.callbacks.History at 0x7fdb930f1990>
```

```
# Perform reconstruction on test data
reconstructed_images_cnn = autoencoder.predict(x_test)
```

iii) Stacked Encoder Autoencoder

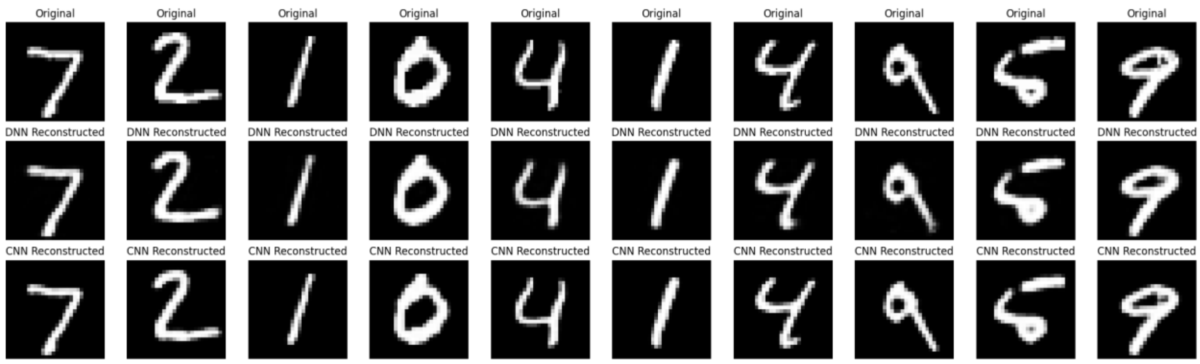
```
import numpy as np
```

```
import tensorflow as tf
from tensorflow.keras.layers import Input, Dense
from tensorflow.keras.models import Model
# Load and preprocess the MNIST dataset
mnist = tf.keras.datasets.mnist
(x_train, _), (x_test, _) = mnist.load_data()
# Normalize and flatten the images
x_train = x_train.astype('float32') / 255.
x_test = x_test.astype('float32') / 255.
x_train = x_train.reshape((-1, 28 * 28))
x_test = x_test.reshape((-1, 28 * 28))
# Define the stacked encoder model
input_dim = 784  # 28*28
encoding_dims = [256, 128, 64]
input_img = Input(shape=(input_dim,))
encoded = Dense(encoding_dims[0], activation='relu')(input_img)
encoded = Dense(encoding_dims[1], activation='relu')(encoded)
encoded = Dense(encoding_dims[2], activation='relu')(encoded)
decoded = Dense(encoding_dims[1], activation='relu')(encoded)
decoded = Dense(encoding_dims[0], activation='relu')(decoded)
decoded = Dense(input_dim, activation='sigmoid')(decoded)
autoencoder = Model(input_img, decoded)
# Compile and train the autoencoder
autoencoder.compile(optimizer='adam', loss='binary_crossentropy')
autoencoder.fit(x_train, x_train, epochs=10, batch_size=256, shuffle=True)
```

```
Epoch 1/10
235/235 [==============================] - 6s 21ms/step - loss: 0.2138
Epoch 2/10
235/235 [==============================] - 8s 32ms/step - loss: 0.1240
Epoch 3/10
235/235 [==============================] - 5s 22ms/step - loss: 0.1086
Epoch 4/10
235/235 [==============================] - 5s 22ms/step - loss: 0.1008
Epoch 5/10
235/235 [==============================] - 7s 32ms/step - loss: 0.0959
Epoch 6/10
235/235 [==============================] - 5s 22ms/step - loss: 0.0928
Epoch 7/10
235/235 [==============================] - 6s 26ms/step - loss: 0.0905
Epoch 8/10
235/235 [==============================] - 6s 27ms/step - loss: 0.0884
Epoch 9/10
235/235 [==============================] - 5s 21ms/step - loss: 0.0867
Epoch 10/10
235/235 [==============================] - 7s 30ms/step - loss: 0.0854
<keras.src.callbacks.History at 0x7fdb939b2bc0>
```

```
# Perform reconstruction on test data
reconstructed_images_stack = autoencoder.predict(x_test)
import matplotlib.pyplot as plt
# Plot original images and their reconstructions for each autoencoder
n = 10  # Number of images to display
# Deep Neural Network Autoencoder
plt.figure(figsize=(20, 6))
for i in range(n):
    # Display original images
    ax = plt.subplot(3, n, i + 1)
    plt.imshow(x_test[i].reshape(28, 28), cmap='gray')
    plt.title('Original')
    plt.axis('off')

    # Display reconstructed images
    ax = plt.subplot(3, n, i + n + 1)
    plt.imshow(reconstructed_images_dnn[i].reshape(28, 28), cmap='gray')
```

```
    plt.title('DNN Reconstructed')
    plt.axis('off')
# CNN Autoencoder
for i in range(n):
    # Display reconstructed images
    ax = plt.subplot(3, n, i + 2 * n + 1)
    plt.imshow(reconstructed_images_cnn[i].reshape(28, 28), cmap='gray')
    plt.title('CNN Reconstructed')
    plt.axis('off')
plt.tight_layout()
plt.show()
# stack Autoencoder
for i in range(n):
    # Display reconstructed images
    ax = plt.subplot(3, n, i + 2 * n + 1)
    plt.imshow(reconstructed_images_stack[i].reshape(28, 28), cmap='gray')
    plt.title('S Reconstructed')
    plt.axis('off')
plt.tight_layout()
plt.show()
```




S Reconstructed