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# Phase 1: Stock Price Prediction using LSTM and GRU
# --- 0. Import Required Libraries ---
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error, mean_absolute_error
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, GRU, Dense
# --- 1. Load Dataset ---
df = pd.read_csv("/content/drive/MyDrive/stock_data(1) .csv", parse_dates=['trading_date'], index_col='trading_date')
print("Dataset Preview:")
print(df.head())
# --- 2. Data Preprocessing ---
def preprocess_data(df):
    if 'closing_price' not in df.columns:
        raise ValueError("Dataset must contain 'closing_price' column")
    df = df.dropna()
    scaler = MinMaxScaler()
    df['scaled_price'] = scaler.fit_transform(df[['closing_price']])
    return df, scaler
# Create sequential data for time series
def create_sequences(data, seq_len):
    X, y = [], []
    for i in range(len(data) - seq_len):
        X.append(data[i:i+seq_len])
        y.append(data[i+seq_len])
    return np.array(X), np.array(y)
# --- 3. Build Model (LSTM or GRU) ---
def build_model(model_type='LSTM', seq_len=30, features=1):
    model = Sequential()
    if model_type == 'LSTM':
        model.add(LSTM(64, return_sequences=True, input_shape=(seq_len, features)))
        model.add(LSTM(32))
    elif model_type == 'GRU':
        model.add(GRU(64, return_sequences=True, input_shape=(seq_len, features)))
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model.add(GRU(32))
    else:
        raise ValueError("Invalid model_type. Choose 'LSTM' or 'GRU'.")
    model.add(Dense(1))
    model.compile(optimizer='adam', loss='mean_squared_error')
    model.summary()
    return model
# --- 4. Evaluation ---
def evaluate(y_true, y_pred):
    mse = mean_squared_error(y_true, y_pred)
    mae = mean_absolute_error(y_true, y_pred)
    print(f"MSE: {mse:.4f}, MAE: {mae:.4f}")
    return mse, mae
# --- 5. Plot Results ---
def plot_results(actual, predicted, dates):
    plt.figure(figsize=(12,6))
    plt.plot(dates, actual, label='Actual Price', color='blue')
    plt.plot(dates, predicted, label='Predicted Price', color='red')
    plt.title("Stock Price Prediction")
    plt.xlabel("Date")
    plt.ylabel("Price")
   plt.legend()
   plt.grid(True)
    plt.show()
# --- 6. Main Execution ---
sequence_length = 30
df, scaler = preprocess_data(df)
data = df['scaled_price'].values
X, y = create_sequences(data, sequence_length)
# Train/test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, shuffle=False)
# Reshape for LSTM/GRU input
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))
# Choose model type: 'LSTM' or 'GRU'
model = build_model(model_type='LSTM', seq_len=sequence_length)
# Train model
```

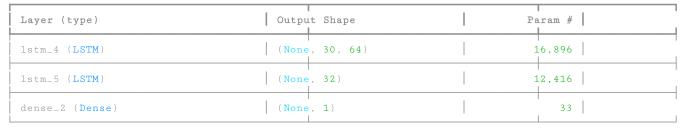
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history = model.fit(X_train, y_train, epochs=50, batch_size=32, validation_split=0.1, verbose=1)
# Predict
predictions = model.predict(X_test)
predicted_prices = scaler.inverse_transform(predictions)
actual_prices = scaler.inverse_transform(y_test.reshape(-1, 1))
# Evaluation and Visualization
evaluate(actual_prices, predicted_prices)
plot_results(actual_prices, predicted_prices, df.index[-len(predicted_prices):])
```

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→ Dataset Preview:
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closing\_price symbol trading\_date 2023-01-02 1504.967142 INFY 2023-01-03 1503.584499 INFY 2023-01-04 1510.061384 INFY 2023-01-05 1525.291682 INFY 2023-01-06 1522.950149 INFY

/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200: UserWarning: Do not pass an `input\_s super().\_\_init\_\_(\*\*kwargs)

Model: "sequential\_2"



Total params: 29,345 (114.63 KB) **Trainable params: 29,345** (114.63 KB) Non-trainable params: 0 (0.00 B) Epoch 1/50 12/12 -— 8s 155ms/step - loss: 0.0610 - val loss: 0.0078 Epoch 2/50 12/12 -**- 1s** 99ms/step - loss: 0.0095 - val\_loss: 0.0131 Epoch 3/50 12/12 -**- 1s** 108ms/step - loss: 0.0069 - val\_loss: 0.0058 Epoch 4/50 **- 3s** 114ms/step - loss: 0.0065 - val\_loss: 0.0041 12/12 -Epoch 5/50 12/12 -**- 1s** 82ms/step - loss: 0.0052 - val\_loss: 0.0035 Epoch 6/50 12/12 -- 1s 58ms/step - loss: 0.0050 - val\_loss: 0.0043 Epoch 7/50 - Os 33ms/step - loss: 0.0047 - val\_loss: 0.0039 12/12 -Epoch 8/50 12/12 -— 1s 33ms/step - loss: 0.0040 - val\_loss: 0.0038 Epoch 9/50 12/12 -- 1s 36ms/step - loss: 0.0042 - val loss: 0.0063 Epoch 10/50

	— <b>Os</b> 33ms/step - loss: 0.0038 - val_loss: 0.0045
Epoch 11/50 12/12 —	— <b>Os</b> 37ms/step - loss: 0.0042 - val_loss: 0.0043
Epoch 12/50 12/12 ——————————————————————————————————	— <b>1s</b> 34ms/step - loss: 0.0038 - val_loss: 0.0104
Epoch 13/50 12/12	— 1s 35ms/step - loss: 0.0050 - val loss: 0.0042
Epoch 14/50	- 1s 36ms/step - loss: 0.0043 - val_loss: 0.0057
Epoch 15/50	
12/12 — Epoch 16/50	— <b>Os</b> 35ms/step - loss: 0.0038 - val_loss: 0.0052
12/12 — Epoch 17/50	— <b>Os</b> 34ms/step - loss: 0.0034 - val_loss: 0.0040
12/12 ——————————————————————————————————	— <b>1s</b> 35ms/step - loss: 0.0029 - val_loss: 0.0043
12/12 ——————————————————————————————————	— <b>1s</b> 33ms/step - loss: 0.0029 - val_loss: 0.0056
12/12 ——————————————————————————————————	<b>— Os</b> 35ms/step - loss: 0.0033 - val_loss: 0.0049
12/12 —	— <b>Os</b> 33ms/step - loss: 0.0031 - val_loss: 0.0091
Epoch 21/50 12/12 ——————————————————————————————————	— <b>1s</b> 35ms/step - loss: 0.0030 - val_loss: 0.0041
Epoch 22/50 12/12 ——————————————————————————————————	— <b>Os</b> 37ms/step - loss: 0.0026 - val_loss: 0.0041
Epoch 23/50 12/12	— <b>1s</b> 52ms/step - loss: 0.0028 - val_loss: 0.0046
Epoch 24/50 12/12 ——————————————————————————————————	— 1s 50ms/step - loss: 0.0026 - val loss: 0.0046
Epoch 25/50	_
Epoch 26/50	- 1s 54ms/step - loss: 0.0025 - val_loss: 0.0045
12/12 — Epoch 27/50	— 1s 40ms/step - loss: 0.0025 - val_loss: 0.0039
12/12 ——————————————————————————————————	— 1s 33ms/step - loss: 0.0027 - val_loss: 0.0038
12/12 — Epoch 29/50	— <b>Os</b> 36ms/step - loss: 0.0025 - val_loss: 0.0042
12/12 — Epoch 30/50	— <b>1s</b> 33ms/step - loss: 0.0027 - val_loss: 0.0039
12/12 —	— <b>Os</b> 38ms/step - loss: 0.0027 - val_loss: 0.0040
Epoch 31/50	0e 26me/stop   loss: 0 002E   val loss: 0 00E4

	32/50	- <b>us</b> 201112/21eh - 1022. U.UUZ3 - Val_1025. U.UU34
12/12		<b>- Os</b> 36ms/step - loss: 0.0028 - val_loss: 0.0037
12/12 Epoch 12/12 Epoch		- <b>Os</b> 32ms/step - loss: 0.0025 - val_loss: 0.0037
	34/50	- <b>Os</b> 34ms/step - loss: 0.0026 - val_loss: 0.0032
	35/50	- 1s 33ms/step - loss: 0.0022 - val loss: 0.0036
Epoch	36/50	· –
	37/50	- <b>Os</b> 35ms/step - loss: 0.0025 - val_loss: 0.0061
	38/50	<b>— Os</b> 36ms/step - loss: 0.0025 - val_loss: 0.0032
12/12		<b>- 1s</b> 35ms/step - loss: 0.0024 - val_loss: 0.0032
12/12		<b>- Os</b> 35ms/step - loss: 0.0023 - val_loss: 0.0034
Epoch		- <b>Os</b> 34ms/step - loss: 0.0020 - val_loss: 0.0045
	41/50	- 1s 36ms/step - loss: 0.0028 - val loss: 0.0035
Epoch	42/50	- <b>Os</b> 35ms/step - loss: 0.0023 - val_loss: 0.0030
Epoch	43/50	
Epoch <b>12/12</b>	44/50	- 1s 34ms/step - loss: 0.0021 - val_loss: 0.0029
	45/50	<b>- 1s</b> 38ms/step - loss: 0.0022 - val_loss: 0.0029
12/12		<b>- Os</b> 34ms/step - loss: 0.0021 - val_loss: 0.0033
Epoch <b>12/12</b>		- 1s 54ms/step - loss: 0.0023 - val_loss: 0.0031
	47/50	- 1s 52ms/step - loss: 0.0023 - val_loss: 0.0031
	48/50	- <b>1s</b> 58ms/step - loss: 0.0022 - val loss: 0.0047
Epoch	49/50	· –
Epoch	50/50	- 1s 37ms/step - loss: 0.0020 - val_loss: 0.0039
		<pre>- Os 33ms/step - loss: 0.0021 - val_loss: 0.0025 1s 115ms/step</pre>
	298.8003, MAE: 13.9100	

Stock Price Prediction

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