Task 2: Data Processing 1

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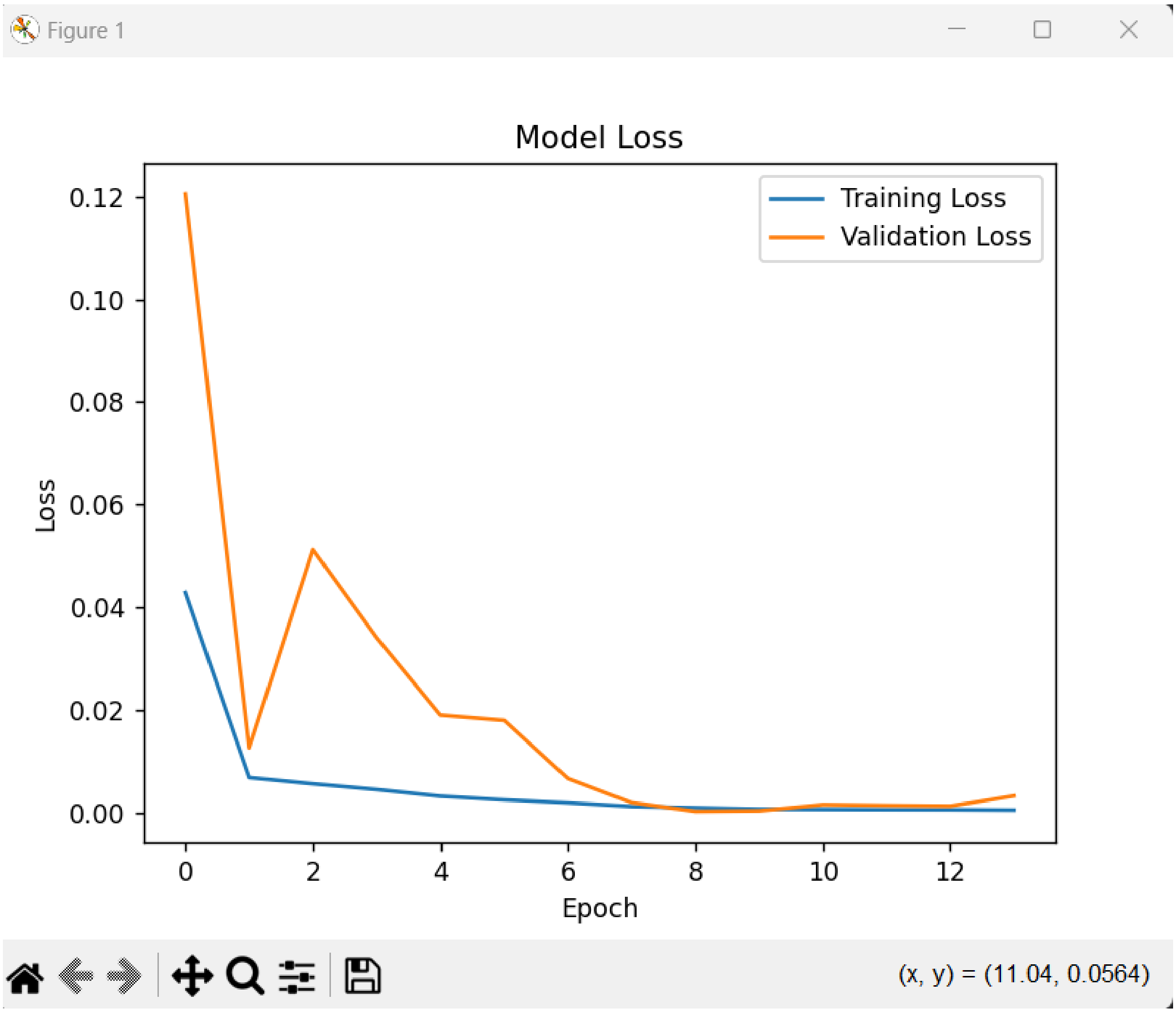
Requirements / Deliverables –

- Write a function that improves the data processing for the initial v0.1 stock prediction code.
- The function should load and process a dataset with the following requirements:
  - Allows you to specify the start date and the end date for the whole dataset as inputs.
  - Allows you to deal with the NaN issue in the data.
  - Allows you to use different methods to split the data into train/test data. E.g. You can split it according to some specified ratio of train/test and you can specify to split it by date or randomly.
  - Allows you to store the downloaded data on your local machine for future uses and to load the data locally to save time.
  - The function will also allow you to have an option to scale your feature columns and store the scalers in a data structure to allow future access to these scalers.

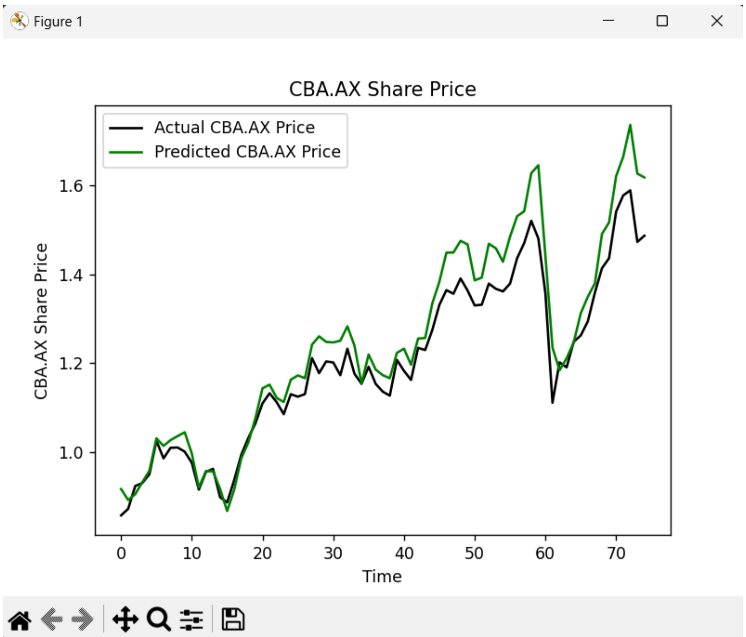
Result –

The provided function fulfils the requirements and uses an advanced data processing technique that utilizes Simple Moving Averages (SMA) and Relative Strength Index (RSI) for increased accuracy when training the model.

You must install the provided *requirements.txt in repository folder Task 2.*



The model now provides a graph that displays the model training loss and its validation loss (gradual decline is *good*).



Improve accuracy compared to the previous model. Accuracy can be further improved using more advanced techniques for architecture optimisation, data handling, and training techniques.

Load_and_process.py

```
import os
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
import yfinance as yf
from sklearn.model_selection import train_test_split

def add_technical_indicators(df):
    """
    Add technical indicators to the stock data DataFrame.
    This includes Simple Moving Average (SMA) and Relative Strength Index
(RSI).

    Parameters:
    - df (pd.DataFrame): DataFrame containing stock data with at least a
'Close' column.

    Returns:
    - df (pd.DataFrame): DataFrame with added technical indicators.
    """
    # Simple Moving Average (SMA)
    df['SMA_20'] = df['Close'].rolling(window=20).mean()
    df['SMA_50'] = df['Close'].rolling(window=50).mean()

    # Relative Strength Index (RSI)
    delta = df['Close'].diff(1)
    gain = (delta.where(delta > 0, 0)).rolling(window=14).mean()
    loss = (-delta.where(delta < 0, 0)).rolling(window=14).mean()
    rs = gain / loss
    df['RSI'] = 100 - (100 / (1 + rs))

    df.fillna(0, inplace=True)  # Fill NaNs resulting from rolling
operations

    return df

def load_and_process_data_with_gap(ticker, start_date, end_date,
handle_nan='drop',
                                   split_method='date', test_ratio=0.2,
scale_data=True,
                                   save_local=False, load_local=False,
local_dir='stock_data',
                                   feature_columns=None, gap_period='30D'):
    """
    Load and process stock market data with a gap between training and
testing periods.
    This function fetches the stock data, processes it (e.g., handling
NaNs, adding technical indicators),
    splits it into training and testing sets, and optionally scales the
data.

    Parameters:
    - ticker (str): Stock ticker symbol.
    - start_date (str): Start date for data in 'YYYY-MM-DD' format.
    - end_date (str): End date for data in 'YYYY-MM-DD' format.
    - handle_nan (str): Method to handle NaN values ('drop', 'fill',
'none').
    - split_method (str): How to split the data ('date', 'random').
    - test_ratio (float): Ratio of the test set, if split_method is
```

```
'random'.
    - scale_data (bool): Whether to scale the data.
    - save_local (bool): Whether to save the data locally.
    - load_local (bool): Whether to load data from a local file if
available.
    - local_dir (str): Directory to save/load the data.
    - feature_columns (list): List of columns to use as features.
    - gap_period (str): Gap period (e.g., '30D' for 30 days) between the
training and testing periods.

    Returns:
    - X_train, X_test (np.ndarray): Training and testing feature matrices.
    - y_train, y_test (np.ndarray): Training and testing target vectors.
    - scaler (MinMaxScaler or None): The scaler object used for data
normalization, if scaling is enabled.
    """

    # Load data from Yahoo Finance or local
    if load_local and os.path.exists(os.path.join(local_dir,
f"{ticker}.csv")):
        df = pd.read_csv(os.path.join(local_dir, f"{ticker}.csv"),
index_col=0, parse_dates=True)
    else:
        df = yf.download(ticker, start=start_date, end=end_date)
        if save_local:
            if not os.path.exists(local_dir):
                os.makedirs(local_dir)
            df.to_csv(os.path.join(local_dir, f"{ticker}.csv"))

    # Handle NaN values
    if handle_nan == 'drop':
        df.dropna(inplace=True)
    elif handle_nan == 'fill':
        df.fillna(method='ffill', inplace=True)

    # Add technical indicators to the DataFrame
    df = add_technical_indicators(df)

    # Determine features and target
    if feature_columns is None:
        feature_columns = df.columns.tolist()
        feature_columns.remove('Close')  # Assuming 'Close' is the target
by default

    X = df[feature_columns].values
    y = df['Close'].values

    # Data splitting logic
    if split_method == 'date':
        gap = pd.to_timedelta(gap_period).days
        test_start_idx = int(len(df) * (1 - test_ratio)) + gap
        X_train, X_test = X[:test_start_idx], X[test_start_idx:]
        y_train, y_test = y[:test_start_idx], y[test_start_idx:]
    else:
        X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=test_ratio, shuffle=True, random_state=42)

    # Data scaling
    scaler = None
    if scale_data:
        scaler = MinMaxScaler()
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        X_train = scaler.fit_transform(X_train)
        X_test = scaler.transform(X_test)
        y_scaler = MinMaxScaler()
        y_train = y_scaler.fit_transform(y_train.reshape(-1, 1)).flatten()
        y_test = y_scaler.transform(y_test.reshape(-1, 1)).flatten()

    return X_train, X_test, y_train, y_test, scaler
```

stock_prediction0.2

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import tensorflow as tf

from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, LSTM, GRU
from tensorflow.keras.regularizers import l2, l1_l2
from tensorflow.keras.losses import Huber
from tensorflow.keras.callbacks import EarlyStopping
from load_and_process import load_and_process_data_with_gap

#---------------------------------------------------------------------------
----
# Load Data with Additional Features
#---------------------------------------------------------------------------
----
COMPANY = 'CBA.AX'
TRAIN_START = '2022-08-01'
TRAIN_END = '2024-08-23'

# Load and process data
X_train, X_test, y_train, y_test, scalers = load_and_process_data_with_gap(
    ticker=COMPANY,
    start_date=TRAIN_START,
    end_date=TRAIN_END,
    handle_nan='drop',
    split_method='date',
    test_ratio=0.2,
    scale_data=True,
    save_local=True,
    load_local=True,
    local_dir='stock_data',
    feature_columns=None  # Use all available features
)

#---------------------------------------------------------------------------
----
# Prepare Data
#---------------------------------------------------------------------------
----
PREDICTION_DAYS = 60

# Print the original shape of the training data
print("Original shape of X_train:", X_train.shape)

# Number of features (columns)
n_features = X_train.shape[1]

# Determine the number of samples and time steps
n_samples = X_train.shape[0]
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# Calculate possible time steps based on the total number of elements
n_timesteps = X_train.size // (n_samples * n_features)

print(f"Calculated time steps: {n_timesteps}")

# Reshape data for LSTM model
X_train = np.reshape(X_train, (n_samples, n_timesteps, n_features))

print("Reshaped X_train shape:", X_train.shape)

# Repeat the process for X_test
print("Original shape of X_test:", X_test.shape)
n_samples_test = X_test.shape[0]
X_test = np.reshape(X_test, (n_samples_test, n_timesteps, n_features))
print("Reshaped X_test shape:", X_test.shape)

#-----------------------------------------------------------------------
----
# Build the Model
#-----------------------------------------------------------------------
----
# Initialize the Sequential model
model = Sequential()

# Add the first LSTM layer with dropout
model.add(LSTM(units=150, return_sequences=True, input_shape=(n_timesteps,
n_features)))
model.add(Dropout(0.2))

# Add the second LSTM layer with dropout
model.add(LSTM(units=100, return_sequences=False))
model.add(Dropout(0.2))

# Add the output layer
model.add(Dense(units=1))

# Compile the model using Adam optimizer and Huber loss
model.compile(optimizer='adam', loss=Huber())

# Early stopping to prevent overfitting
early_stopping = EarlyStopping(monitor='val_loss', patience=5,
restore_best_weights=True)

# Train the model with validation and early stopping
history = model.fit(X_train, y_train, epochs=50, batch_size=32, verbose=1,
validation_split=0.2, callbacks=[early_stopping])

#-----------------------------------------------------------------------
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# Plot the Training and Validation Loss
#-----------------------------------------------------------------------
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plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

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#------------------------------------------------------------------------
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# Test the Model Accuracy on Existing Data
#------------------------------------------------------------------------
----
# Predict prices using the test set
predicted_prices = model.predict(X_test)

# Print raw predictions before inverse_transform
print("Raw predictions before inverse_transform:", predicted_prices[:5])

# Assuming y_train/y_test were scaled separately with a specific scaler for
y
y_scaler = MinMaxScaler()
y_train = y_train.reshape(-1, 1)
y_scaler.fit(y_train)

# Inverse transform the predictions to get actual predicted prices
predicted_prices = y_scaler.inverse_transform(predicted_prices)

# Print inverse-transformed predictions
print("Inverse-transformed predictions:", predicted_prices[:5])

# Display the actual and predicted prices for each day
for i in range(len(predicted_prices)):
    print(f"Day {i + 1}: Actual Price = {y_test[i]}, Predicted Price =
{predicted_prices[i][0]}")

#------------------------------------------------------------------------
----
# Plot the Test Predictions
#------------------------------------------------------------------------
----
actual_prices = y_test.reshape(-1, 1)
actual_prices = y_scaler.inverse_transform(actual_prices)

plt.plot(actual_prices, color="black", label=f"Actual {COMPANY} Price")
plt.plot(predicted_prices, color="green", label=f"Predicted {COMPANY}
Price")
plt.title(f"{COMPANY} Share Price")
plt.xlabel("Time")
plt.ylabel(f"{COMPANY} Share Price")
plt.legend()
plt.show()

#------------------------------------------------------------------------
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# Predict Next Day
#------------------------------------------------------------------------
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# Use the last PREDICTION_DAYS days from the test set to predict the next
day's price
real_data = X_test[-PREDICTION_DAYS:]
real_data = np.reshape(real_data, (real_data.shape[0], real_data.shape[1],
n_features))

# Predict the next day's price
prediction = model.predict(real_data)
prediction = y_scaler.inverse_transform(prediction)
print(f"Next Day Prediction: {prediction[0][0]}")
```