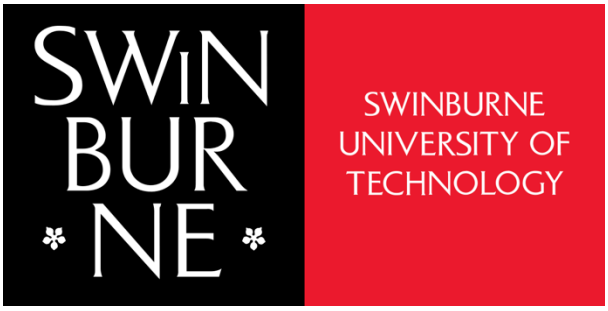

Intelligent System

Assignment 1 - Option B

Week 4 Report

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Environment Setup

Setting up and install required dependencies

In order to create a **virtual environment** for Python, which is a workspace that is **well-organized** with **necessary libraries installed** and **adaptable** for the current task, Anaconda is chosen as the main virtual environment distributor. Anaconda, along with Pycharm and venv, are the three **most recognised distributors** when it comes to creating a safe and clean environment for deploying Python (and R) code. Anaconda offers an **isolated**, **customisable workspace** with **pre-installed packages** for data scientists. It also supports **cross-platform**, seamless **package management** via Conda, integration with Jupyter and Intellisense, and is also a tool for creating **scalability, security, and reproducibility** code.

1. Create a new environment using Conda CLI

There are several different procedures to create an environment, but the given procedure below will **encapsulate** all of the **required steps** to create **a safe and clean environment** using Conda.

- Navigate to the Github repository that contains the source code for both P1 and V0.1.
- Once navigated, download the source code by clicking on **Code → Download ZIP** or use the following command in the **CLI (Terminal):**

git clone https://github.com/cobeo2004/cos30018.git

- Once the source code is successfully cloned (downloaded), navigate to the Week 2/v0.2 folder and execute the file conda-config.sh using the following command:

bash conda-config.sh

- The given file config.sh will execute the following procedure:
  - Generate an environment with a pre-defined name (you can change the name if you want to) in Python 3.10.9 by using the command: conda create -n cos30018_env_w2_v0.2 python=3.10.9
  - Activate the created environment using: conda activate cos30018_env_w2_v0.2.
  - Check and validate if the conda environment is successfully initialized by running conda info –envs for listing conda environments and see which environment that we are in and current Python version using python –version.

```
❯ conda info --envs && python --version
# conda environments:
#
base                  *  /Users/cobeo/miniconda3
cos30018-env-w1-p2       /Users/cobeo/miniconda3/envs/cos30018-env-w1-p2
cos30018-env-w1-v0.1     /Users/cobeo/miniconda3/envs/cos30018-env-w1-v0.1
cos30019-env-w1-p1       /Users/cobeo/miniconda3/envs/cos30019-env-w1-p1
cos30019_env_w2_v0.2     /Users/cobeo/miniconda3/envs/cos30019_env_w2_v0.2
fastapi-env              /Users/cobeo/miniconda3/envs/fastapi-env

Python 3.10.6
```

*Figure 1: Results when running both **conda info –envs** and **python --version***

2. Installing required dependencies

Once the **environment** is **successfully initialized**, we can start **installing** the **dependencies (libraries)** that are **required by the program**. There are multiple pathways to install dependencies in Python, but the **most popular steps** are:

- Scan through the code to find out the required dependencies; for example, consider the file stock_prediction.py. We could see that there are quite a few required dependencies, such as: numpy matplotlib pandas tensorflow scikit-learn pandas-datareader yfinance TA-lib.

```python
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
# import pandas_datareader as pdr
# import datetime as dt
import yfinance as yf
import talib as ta

from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
# from sklearn import metrics

# import tensorflow as tf
# from tensorflow.keras.models import Sequential, Model
# from tensorflow.keras.layers import Dense, LSTM, Dropout, InputLayer, Input, Activation
# from tensorflow.keras.callbacks import EarlyStopping
# from tensorflow.keras.utils import plot_model

import pickle
import os
from typing_extensions import Annotated, Doc, TypeVar, Literal, Tuple
```

Figure 2: Required Dependencies in stock_prediction.py

- Once dependencies are scanned, use the following command to install the dependencies: pip install numpy matplotlib pandas tensorflow scikit-learn pandas-datareader yfinance TA-lib.
- Another step is to list all required libraries into a requirements.txt file, and using the following command to install the required dependencies: pip install -U -r requirements.txt.

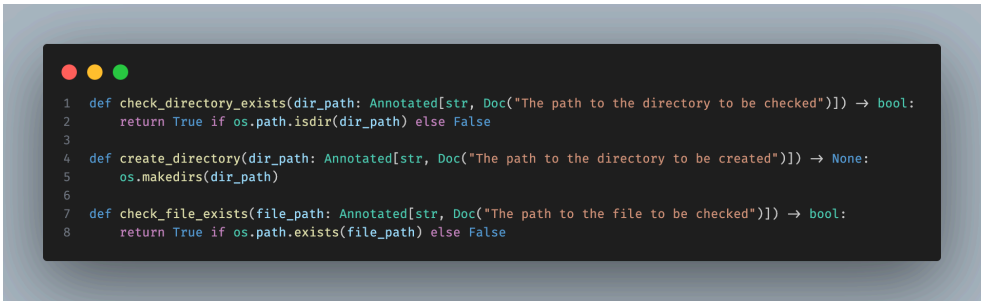
```
numpy
matplotlib
pandas
tensorflow
scikit-learn
pandas-datareader
yfinance
TA-lib

```

Figure 3: Example of requirements.txt

Understanding the Data Processing I

1. Utility functions to ensure directory exists

Codebase



```python
def check_directory_exists(dir_path: Annotated[str, Doc("The path to the directory to be checked")]) -> bool:
    return True if os.path.isdir(dir_path) else False

def create_directory(dir_path: Annotated[str, Doc("The path to the directory to be created")]) -> None:
    os.makedirs(dir_path)

def check_file_exists(file_path: Annotated[str, Doc("The path to the file to be checked")]) -> bool:
    return True if os.path.exists(file_path) else False
```

Figure 4: Utility functions for ensuring the given directory is exists

Parameters

- check_directory_exists():
  - dir_path: str: The path to the directory that needs to be checked if it exists or not.
- check_file_exists():
  - dir_path: str: The path to the file that needs to be checked if it exists or not.
- create_directory():
  - dir_path: str: The path to the directory that needs to be created.

Functionalities

- check_directory_exists() & create_directory(): The purpose of these two functions are two check if the given dir_path is exists or not using os.path.isdir(), if not then the check_directory_exists() will return a False and use create_directory() to create a folder based on the given dir_path, otherwise return True.
- check_file_exists(): This function will check if the file exists using os.path.exists() function, it will return True if exists otherwise return False.

2. Utility function to read and write objects using Pickle

Codebase

```python
T = TypeVar("T", bound=Literal["load", "save"])
U = TypeVar("U", any, object)
def save_or_load_object(obj: Annotated[U | None, Doc("The object to be saved or loaded")],
                        fn: Annotated[str, Doc("The filename to the directory to be checked")],
                        mode: Annotated[T, Doc("The mode to be used")]) -> U | None:
    if mode == "save":
        with open(fn, "wb") as i:
            pickle.dump(obj, i)
    elif mode == "load":
        if obj is None:
            with open(fn, "rb") as i:
                return pickle.load(i)
        else:
            raise ValueError("obj must be None when mode is load")
    else:
        raise ValueError("Invalid mode")
```

Figure 5: Utility function to read / write objects using Pickle

Parameters

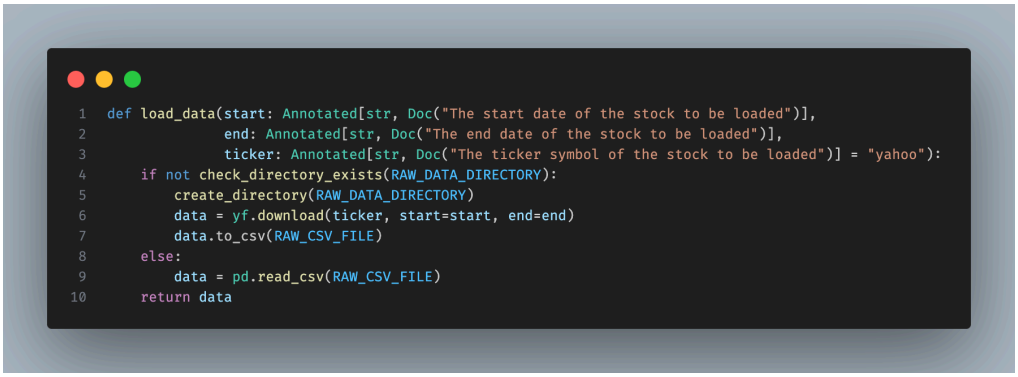
- obj: <U extends any | object> | undefined: The object to be saved or loaded, if the mode set to **load** then the obj should be undefined (None).
- fn: str: The path to the file to be used for saving or loading objects.
- mode: <T extends “load” | “save”>: The mode to be used, load stands for loading from the existing object, save for saving the object to the provided file.

Functionalities

- The load_and_save_object() function does the following procedure:
  + If the mode is set to save, the function will start opening up the file defined in fn parameter. Once the file is successfully opened, it will write all of the given objects defined in obj by using pickle.dump() to ensure that the object will be type-safe when loading the object from the file.
  + If the mode is set to load, the function will start reading from the file defined in fn and load the object using pickle.load() function.

3. Function to load and save data from yfinance

Codebase



```python
def load_data(start: Annotated[str, Doc("The start date of the stock to be loaded")],
              end: Annotated[str, Doc("The end date of the stock to be loaded")],
              ticker: Annotated[str, Doc("The ticker symbol of the stock to be loaded")] = "yahoo"):
    if not check_directory_exists(RAW_DATA_DIRECTORY):
        create_directory(RAW_DATA_DIRECTORY)
        data = yf.download(ticker, start=start, end=end)
        data.to_csv(RAW_CSV_FILE)
    else:
        data = pd.read_csv(RAW_CSV_FILE)
    return data
```

Figure 6: Function to load data from yfinance

Parameters

- start: str: The start date in **string** of the stock to be downloaded.
- end: str: The end date in **string** of the stock to be downloaded.
- ticker: str: The start date in **string** of the stock to be downloaded.

Functionalities

- The major purpose of this function is to check if the **unprocessed CSV file** that contains the stock data from the **start date** and **end date** is existed in the file or not, if it is not existed then it will **download** the data from yfinance and **save** it to the directory that contains **unprocessed CSV data**. Otherwise, it will **load** the **unprocessed CSV File**. The following procedures are:
  + The code will check if the directory that contains **unprocessed CSV file** exists, if not then it will start to create the directory and download the **CSV** from the yfinance. Once it's downloaded then it will convert the data to **CSV Format** and save it to the created directory.
  + However, in the case where the directory exists then it will read the file in that directory.

4. Function to validate data

Codebase

```python
def validate_data() -> pd.DataFrame:
    # Check if the prepared data directory exists, if not then create it
    if not check_directory_exists(PREPARED_DATA_DIRECTORY):
        create_directory(PREPARED_DATA_DIRECTORY)

    if check_file_exists(PREPARED_CSV):
        print('Loading Prepared Data ... ')
        df = pd.read_csv(PREPARED_CSV)
    else:
        print('Processing Raw Data ... ')
        # Read the raw data
        df = pd.read_csv(RAW_CSV_FILE)
        # Convert the date column to datetime
        df['Date'] = pd.to_datetime(df['Date'])
        # Set the date column as the index
        df.set_index('Date', inplace=True)
        # Adding RSI, EMA20(EMA for 20 days), EMA100(EMA for 100 days), EMA200(EMA for 200 days)
        df['RSI'] = ta.RSI(df['Close'], timeperiod=14)
        df['EMA20'] = ta.EMA(df['Close'], timeperiod=20)
        df['EMA100'] = ta.EMA(df['Close'], timeperiod=100)
        df['EMA200'] = ta.EMA(df['Close'], timeperiod=200)

        # Calculate the target value by subtracting the open price
        # from the adjusted close price and shifting it by 1 day
        df['Target'] = df['Adj Close'] - df['Open']
        df['Target'] = df['Target'].shift(-1)

        # Convert the target class to binary class if the target is greater than 0
        df['TargetClass'] = np.where(df['Target'] > 0, 1, 0)
        # Shift the adjusted close price by 1 day
        df['TargetNextClose'] = df['Adj Close'].shift(-1)

        # Drop the NaN values
        df.dropna(inplace=True)

        # Convert to csv and save to the folder
        df.to_csv(PREPARED_CSV, index=False)
    return df
```

Figure 7: Function to validate and update the data

Parameters

- There are **no parameters** in this function.

Functionalities

- This function will check if the directory that contains **processed data** exists, if not then it will create a directory used for storing **processed data**.
- Once the directory is created, it will check the existence of the **processed CSV file**. If the **CSV** file exists, it will read the **CSV** file using pd.read_csv() and return it. Otherwise, it will start the following procedure:
    + ***Read the unprocessed CSV file***: It will read the **unprocessed CSV file** stored in the **unprocessed folder**.
    + ***Convert and set index***: After the **unprocessed CSV file** is successfully read, it will convert the value of Date column into the DateTime type and set the value inside the Date column as **index**. This will make it easier to operate time-based searching, simplify the **plotting** procedure and enhance the **data organization**.
    + ***Adding essential indicators to the data***: This function will also add several required technical analysis indicators to the data, such as **Relative Strength Index (RSI)** and several different date ranges (20

days, 100 days and 150 days) of **Exponential Moving Averages (EMA)** using the **built-in functions** provided by TA-lib.

+ ***Calculate target price***: After adding **indicators** to the data, it will start **calculating** the target price by **subtracting** the value of **Adjustment Close Price** and the **Open Price**. Once subtracted, it will shift the value back by one to assume that is the **targeted** price.
+ ***Indicate if the value is increased or not:*** It will calculate the TargetClass based on the **target price** value and indicate if the price **is increased or not**, if the price is increased then the TargetClass value will be 1, otherwise it will be 0.
+ ***Drop all undefined values:*** By using dropna() function, it will look up all of the **undefined** (**NaN**) values and drop it.
+ ***Save processed data***: Once the datasets are **processed**, it will save those datasets into a **CSV File** by using to_csv() function and return the **processed** datasets to the user.

5. Function to split data by date or randomly

Codebase

```python
def split_data_by_ratio(data: Annotated[pd.DataFrame, Doc("The data to be split")],
                        ratio: Annotated[float, Doc("The ratio to be used in percentage: 0.8 for 80% train and 20% test")],
                        is_split_by_date: Annotated[bool, Doc("Choose to split by date or random")] = True) -> Tuple[pd.DataFrame, pd.DataFrame]:
    # Check if the data is split by date
    if is_split_by_date:
        # Calculate the train data size of the train data
        train_size = int(len(data) * ratio)
        # Split the data into train and test data
        train_data, test_data = data[:train_size], data[train_size:]
    else:
        # Split the data into train and test data randomly
        train_data, test_data = train_test_split(data,train_size=1 - (1 - ratio), test_size= 1 - ratio, random_state=42)

    # Print the shape of the train and test data
    print(f"Train data shape: {train_data.shape}")
    print(f"Test data shape: {test_data.shape}")

    return train_data, test_data
```

Figure 8: Function to split data by date (or by random)

Parameters

- data: pandas.DataFrame: The **processed data** that needs to be split into train and test data.
- ratio: float: The percentage of train and test data (0.8 indicates that 80% of data will be used for **training** and 20% of data will be used for **testing**.
- is_split_by_date: bool = True: Indicates that if the data is chosen to **split by date** or **randomly split.** Default set to True.

Functionalities

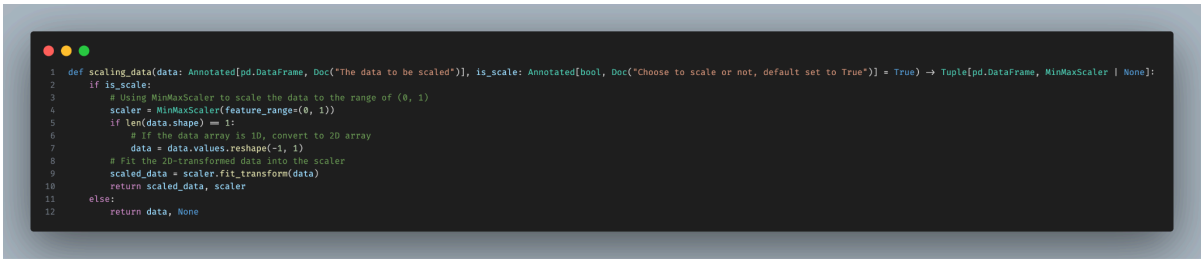
- This function will do the following procedures:
    + ***If is_split_by_date is set to True***: This function will perform calculation based on the **split ratio** (0.8 will equal 80% of **train** data and 20% of **test** data). Once the calculation is finished, the function

will **allocate** the train and test data to the train_data and test_data variables.

+ ***If is_split_by_date is set to False***: This function will use the built-in function provided by scikit-learn, which is train_test_split() to split the data **randomly** based on the given ratio value. The random_state is fixed at 42 to make sure that the splitted data is reproducible.
+ Once the data has been successfully **splitted**, it will then print out the **shape (x,y)** of both train and test data and return it to the user for further usages.

6. Function to scale data

Codebase



```python
def scaling_data(data: Annotated[pd.DataFrame, Doc("The data to be scaled")], is_scale: Annotated[bool, Doc("Choose to scale or not, default set to True")] = True) -> Tuple[pd.DataFrame, MinMaxScaler | None]:
    if is_scale:
        # Using MinMaxScaler to scale the data to the range of (0, 1)
        scaler = MinMaxScaler(feature_range=(0, 1))
        if len(data.shape) == 1:
            # If the data array is 1D, convert to 2D array
            data = data.values.reshape(-1, 1)
        # Fit the 2D-transformed data into the scaler
        scaled_data = scaler.fit_transform(data)
        return scaled_data, scaler
    else:
        return data, None
```

Figure 9: Function to scale the data using MinMaxScaler()

Parameters

- data: pandas.DataFrame: The data object that needs to be scaled.
- is_scale: bool = True: Whether choosing to scale or not.

Functionalities

- This function will check if the is_scale equals to True or not, if it is not then the function will simply return back the data without any **scaling data**. Otherwise, it will do the following procedures:
    + ***Scaling data***: This function will use the MinMaxScaler class provided by scikit-learn to scale the data to the range of (0, 1) by setting the feature_range to a tuple of (0, 1).
    + ***Reshaping data***: After the data is **scaled**, the data will be converted into a two-dimensional array using reshape(-1, 1) function. This procedure is essential as the fit_transform() function only accepts a 2D array.
    + ***Fitting and returning the scaled array***: Once the array is transformed to 2D array, it will be fitted using the fit_transform() function provided by class MinMaxScaler. Once the transform is finished we will return the **scaled data** with the instance of MinMaxScaler for further usage.

Deploying and Testing the Codebase

1. Declaring essential variables

In this step, essential variables are imported into Python code with different usages in order to serve different purposes of the program, which could be categorized into:

- Define the start date, the end date and the ticker (stock) that we wanted to download from yfinance.
- Define the split ratio for splitting the train and test data, and the number of days for looking back.
- Define the directory for storing the raw and prepared datasets.
- Define the files that are used for storing essential information, such as raw data imported from yfinance and the processed data.

```python
# Start, end and ticker for the datasets
start="2015-01-01"
end="2023-08-25"
ticker="TSLA"

# Split ratio, 0.8 equals to 80% data for training and 20% for testing
split_ratio = 0.8

# Number of days to look back for the prediction, could be changed to any value
num_look_back_days = 30

# Define entry directory for the raw and prepared datasets
ENTRY_POINT = f"datasets/{ticker}/from_{start}_to_{end}"
RAW_DATA_DIRECTORY = os.path.join(ENTRY_POINT, "data")
PREPARED_DATA_DIRECTORY = os.path.join(ENTRY_POINT, "prepared-data")

# Raw data to be saved as the same for
RAW_CSV_FILE = os.path.join(RAW_DATA_DIRECTORY, f"raw_data_from_{start}_to_{end}_of_{ticker}_stock.csv")

# Prepared data to be saved as the same for
PREPARED_CSV = os.path.join(PREPARED_DATA_DIRECTORY, f"prepared_data_from_{start}_to_{end}_of_{ticker}_stock.csv")
PREPARED_TRAIN_ALL = os.path.join(PREPARED_DATA_DIRECTORY, f"xytrain_data_{start}-{end}-{ticker}_stock.npz")
PREPARED_TRAIN_DATASET = os.path.join(PREPARED_DATA_DIRECTORY, f"train_dataset_of_{ticker}_from_{start}_to_{end}.csv")
PREPARED_TEST_DATASET = os.path.join(PREPARED_DATA_DIRECTORY, f"test_dataset_of_{ticker}_from_{start}_to_{end}.csv")
PREPARED_SCALER_FEATURE = os.path.join(PREPARED_DATA_DIRECTORY, f"feature_scaler_of_{ticker}_from_{start}_to_{end}.pkl")
PREPARED_SCALER_TARGET = os.path.join(PREPARED_DATA_DIRECTORY, f"targe_scaler_of_{ticker}_from_{start}_to_{end}.pkl")
PREPARED_TRAIN_ARRAY = os.path.join(PREPARED_DATA_DIRECTORY, f"xytrain_train_array_of_{ticker}_from_{start}_to_{end}.npz")
PREPARED_TEST_ARRAY = os.path.join(PREPARED_DATA_DIRECTORY, f"xytrain_test_array_of_{ticker}_from_{start}_to_{end}.npz")
```

Figure 10: Declaring essential variables

2. Processing Data using the created functions

```python
data = load_data(start, end, ticker)
df = validate_data()

if check_file_exists(PREPARED_TRAIN_DATASET) and check_file_exists(PREPARED_TEST_DATASET):
    print('Loading Existed Train and Test Data ... ')
    train_data = pd.read_csv(PREPARED_TRAIN_DATASET)
    test_data = pd.read_csv(PREPARED_TEST_DATASET)

    print(f"Train data shape: {train_data.shape}")
    print(f"Test data shape: {test_data.shape}")

    train_feature_scale = save_or_load_object(None, PREPARED_SCALER_FEATURE, "load")
    train_target_scale = save_or_load_object(None, PREPARED_SCALER_TARGET, "load")
    train_arrays = np.load(PREPARED_TRAIN_ARRAY)
    x_train = train_arrays['x_train']
    y_train = train_arrays['y_train']

    test_arrays = np.load(PREPARED_TEST_ARRAY)
    x_test = test_arrays['x_test']
    y_test = test_arrays['y_test']
else:
    print('Processing Train and Test Data ... ')
    train_data, test_data = split_data_by_ratio(df, split_ratio)

    feature_cols = ['Open', 'High', 'Low', 'RSI', 'EMA20', 'EMA100', 'EMA200']
    target_cols = 'TargetNextClose'

    scaled_train_data, train_feature_scale = scaling_data(train_data[feature_cols])
    converted_2d_train_data = train_data[target_cols].values.reshape(-1, 1)
    scaled_train_target, train_target_scale = scaling_data(converted_2d_train_data)

    x_train, y_train = [], []
    for i in range(num_look_back_days, len(scaled_train_data)):
        x_train.append(scaled_train_data[i-num_look_back_days:i])
        y_train.append(scaled_train_target[i])

    x_train, y_train = np.array(x_train), np.array(y_train)

    scaled_test_data = train_feature_scale.transform(test_data[feature_cols])
    converted_2d_test_data = test_data[target_cols].values.reshape(-1, 1)
    scaled_test_target = train_target_scale.transform(converted_2d_test_data)

    x_test, y_test = [], []
    for i in range(num_look_back_days, len(scaled_test_data)):
        x_test.append(scaled_test_data[i-num_look_back_days:i])
        y_test.append(scaled_test_target[i])

    x_test, y_test = np.array(x_test), np.array(y_test)

    train_data.to_csv(PREPARED_TRAIN_DATASET, index=False)
    test_data.to_csv(PREPARED_TEST_DATASET, index=False)

    save_or_load_object(train_feature_scale, PREPARED_SCALER_FEATURE, "save")
    save_or_load_object(train_target_scale, PREPARED_SCALER_TARGET, "save")

    np.savez(PREPARED_TRAIN_ARRAY, x_train=x_train, y_train=y_train)
    np.savez(PREPARED_TEST_ARRAY, x_test=x_test, y_test=y_test)
```

Figure 11: Procedure to process data

The given procedure, which is the **heart** to execute successfully the program, does the following steps:

- ***Load and validate data***: The procedure initially calls to the defined load_data() function, which will either load the existing **raw** data or **download** the data if it does not exist. Once the data is loaded **successfully**, it will call the validate_data() function to process and validate the data to be in the right format, which adds in extra **technical analysis indicators** and **target values**.
- ***Check the existence of the prepared datasets***: After the data is validated, it will check if the **train and test datasets** exist. If the datasets are existed, it will do the following steps:

    + Load from the **processed CSV file** the existing datasets, including train and test datasets.
    + Print out the shapes of both **train and test** datasets for validation.
    + Load the saved scaler values of both **feature** and **target.**
    + Retrieve the value from the **x and y array** of both **train and test** arrays.
- In case where the datasets are not existed, the following logic will be executed:
    + The **validated data** will be split into **train and test** data using the defined split_data_by_ratio() function. With the split rate defined at 0.8 (80% of train data, 20% of test data).
    + Scale the training data for the **features** using the defined scaling_data() function and based on the defined feature_cols columns.
    + Make **training arrays** by creating a sequence for each sample based on the defined variable num_look_back_days.
    + Scale the testing data for the **features** and **target** using the defined scaling_data() function and based on the defined feature_cols and target_cols columns.
    + Make **test arrays** by creating a sequence of each sample based on the defined variable num_look_back_days.
    + Save the train and test data to a CSV file by using the to_csv()function from pandas and save the feature and target scalers using the defined save_or_load_object()function.
    + Save the created **train and test** arrays to a .npz file using savez()function from numpy.

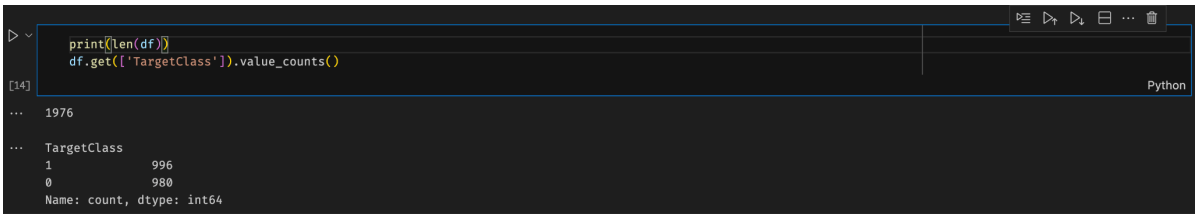
3. Result

```
print("Data Preparation Completed!")
print("Data: ", type(data))
print("Data: ", type(df))
print("Train Data: ", train_data.shape)
print("Test Data: ", test_data.shape)
print("Train Feature Scaler: ", type(train_feature_scale))
print("Train Target Scaler: ", type(train_target_scale))
print("x_train: ", x_train.shape)
print("y_train: ", y_train.shape)
print("x_test: ", x_test.shape)
print("y_test: ", y_test.shape)
```

[12] Python

```
Data Preparation Completed!
Data:  <class 'pandas.core.frame.DataFrame'>
Data:  <class 'pandas.core.frame.DataFrame'>
Train Data:  (1580, 13)
Test Data:  (396, 13)
Train Feature Scaler:  <class 'sklearn.preprocessing._data.MinMaxScaler'>
Train Target Scaler:  <class 'sklearn.preprocessing._data.MinMaxScaler'>
x_train:  (1550, 30, 7)
y_train:  (1550, 1)
x_test:  (366, 30, 7)
y_test:  (366, 1)
```

Figure 12: Type and Shape of the processed data

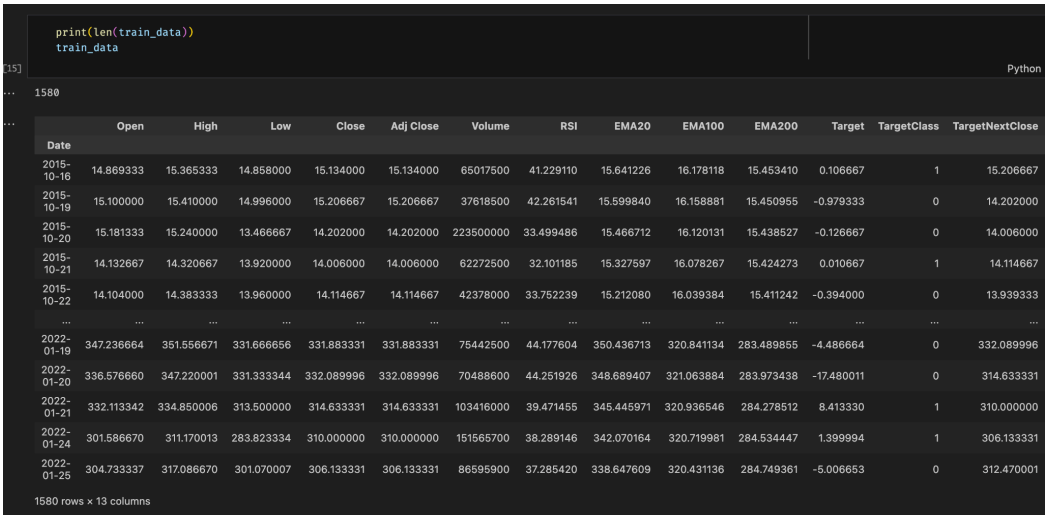


```
print(len(df))
df.get(['TargetClass']).value_counts()
```

[14] Python

```
1976

TargetClass
1             996
0             980
Name: count, dtype: int64
```

Figure 13: Value counts for the transformed TargetClass



```
print(len(train_data))
train_data
```

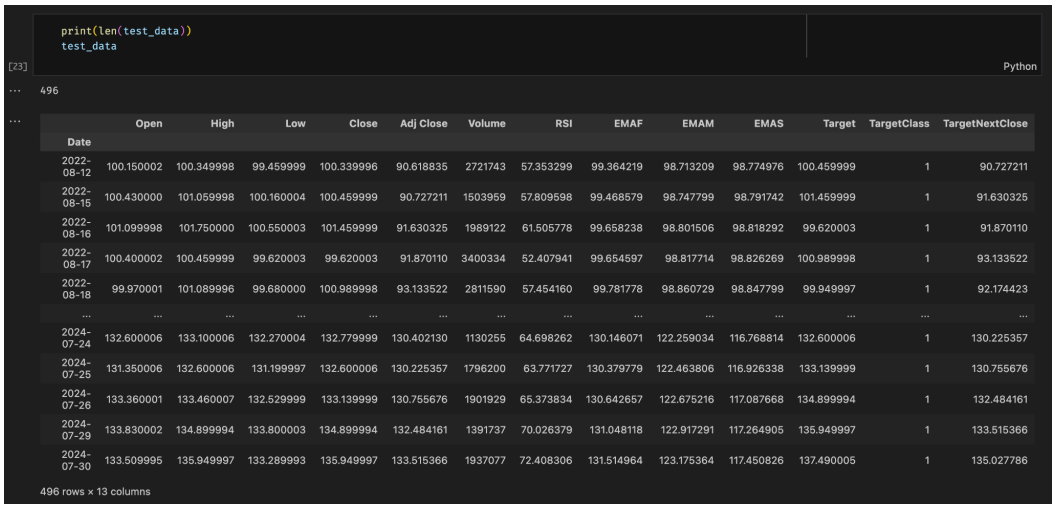
[15] Python

```
1580
```

Date	Open	High	Low	Close	Adj Close	Volume	RSI	EMA20	EMA100	EMA200	Target	TargetClass	TargetNextClose
2015-10-16	14.869333	15.365333	14.858000	15.134000	15.134000	65017500	41.229110	15.641226	16.178118	15.453410	0.106667	1	15.206667
2015-10-19	15.100000	15.410000	14.996000	15.206667	15.206667	37618500	42.261541	15.599840	16.158881	15.450955	-0.979333	0	14.202000
2015-10-20	15.181333	15.240000	13.466667	14.202000	14.202000	223500000	33.499486	15.466712	16.120131	15.438527	-0.126667	0	14.006000
2015-10-21	14.132667	14.320667	13.920000	14.006000	14.006000	62272500	32.101185	15.327597	16.078267	15.424273	0.010667	1	14.114667
2015-10-22	14.104000	14.383333	13.960000	14.114667	14.114667	42378000	33.752239	15.212080	16.039384	15.411242	-0.394000	0	13.939333
...	...	...	...	...	...	...	...	...	...	...	...	...	...
2022-01-19	347.236664	351.556671	331.666656	331.883331	331.883331	75442500	44.177604	350.436713	320.841134	283.489855	-4.486664	0	332.089996
2022-01-20	336.576660	347.220001	331.333344	332.089996	332.089996	70488600	44.251926	348.689407	321.063884	283.973438	-17.480011	0	314.633331
2022-01-21	332.113342	334.850006	313.500000	314.633331	314.633331	103416000	39.471455	345.445971	320.936546	284.278512	8.413330	1	310.000000
2022-01-24	301.586670	311.170013	283.823334	310.000000	310.000000	151565700	38.289146	342.070164	320.719981	284.534447	1.399994	1	306.133331
2022-01-25	304.733337	317.086670	301.070007	306.133331	306.133331	86595900	37.285420	338.647609	320.431136	284.749361	-5.006653	0	312.470001

1580 rows × 13 columns

Figure 14: Length of the train data and the train data informations



```
print(len(test_data))
test_data
```

[23] Python

```
496
```

Date	Open	High	Low	Close	Adj Close	Volume	RSI	EMAF	EMAM	EMAS	Target	TargetClass	TargetNextClose
2022-08-12	100.150002	100.349998	99.459999	100.339996	90.618835	2721743	57.353299	99.364219	98.713209	98.774976	100.459999	1	90.727211
2022-08-15	100.430000	101.059998	100.160004	100.459999	90.727211	1503959	57.809598	99.468579	98.747799	98.791742	101.459999	1	91.630325
2022-08-16	101.099998	101.750000	100.550003	101.459999	91.630325	1989122	61.505778	99.658238	98.801506	98.818292	99.620003	1	91.870110
2022-08-17	100.400002	100.459999	99.620003	99.620003	91.870110	3400334	52.407941	99.654597	98.817714	98.826269	100.989998	1	93.133522
2022-08-18	99.970001	101.089996	99.680000	100.989998	93.133522	2811590	57.454160	99.781778	98.860729	98.847799	99.949997	1	92.174423
...	...	...	...	...	...	...	...	...	...	...	...	...	...
2024-07-24	132.600006	133.100006	132.270004	132.779999	130.402130	1130255	64.698262	130.146071	122.259034	116.768814	132.600006	1	130.225357
2024-07-25	131.350006	132.600006	131.199997	132.600006	130.225357	1796200	63.771727	130.379779	122.463806	116.926338	133.139999	1	130.755676
2024-07-26	133.360001	133.460007	132.529999	133.139999	130.755676	1901929	65.373834	130.642657	122.675216	117.087668	134.899994	1	132.484161
2024-07-29	133.830002	134.899994	133.800003	134.899994	132.484161	1391737	70.026379	131.048118	122.917291	117.264905	135.949997	1	133.515366
2024-07-30	133.509995	135.949997	133.289993	135.949997	133.515366	1937077	72.408306	131.514964	123.175364	117.450826	137.490005	1	135.027786

496 rows × 13 columns

Figure 15: Length of the test data and the test data informations

```
print("Actual Ratio: ", split_ratio)
print("Received train ratio: ", len(train_data) / len(df))
print("Received test ratio: ", len(test_data) / len(df))
```

```
Actual Ratio:  0.8
Received train ratio:  0.7995951417004049
Received test ratio:  0.20040485829959515
```

Figure 16: Expected and actual train / test radio

```
plt.figure(figsize=(12,6))
plt.plot(df.index, df['Close'])
plt.title(f'{ticker} Stock Price')
plt.xlabel('Date')
plt.ylabel('Price')
plt.grid(True)
plt.show()
```

Figure 17: The processed close price of the TSLA stock

```
plt.figure(figsize=(12,6))
plt.plot(df.index, df['Close'], label='Close Price')
plt.plot(df.index, df['EMA20'], label='20-day EMA')
plt.plot(df.index, df['EMA100'], label='100-day EMA')
plt.plot(df.index, df['EMA200'], label='200-day EMA')
plt.title(f'{ticker} Stock Price with Moving Averages')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend()
plt.grid(True)
plt.show()
```

Figure 18: TSLA Stock with 20 / 100 / 150 days index of EMA

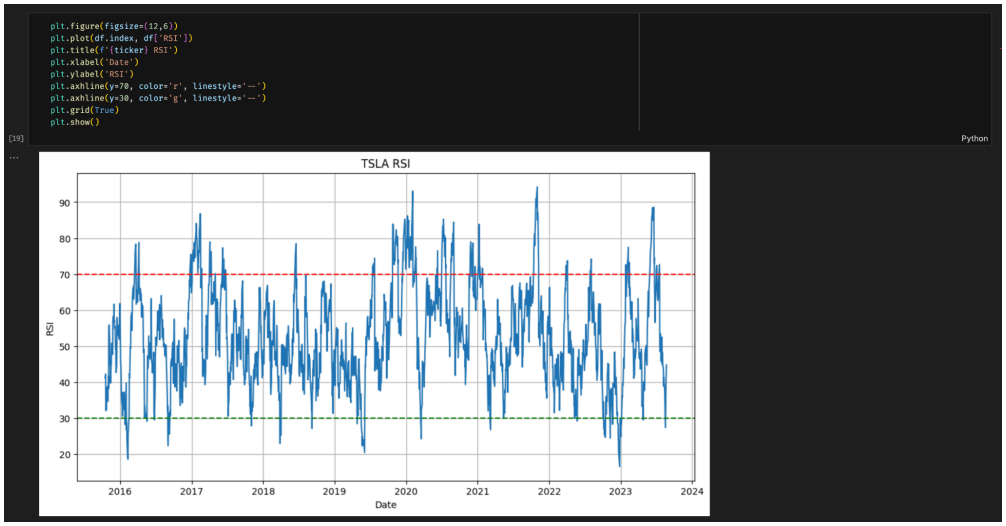


Figure 19: RSI Index of the TSLA