

Configuration Manual

MSc Research Project
Data Analytics

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School of Computing
National College of Ireland

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National College of Ireland
MSc Project Submission Sheet
School of Computing



Student Name: Roopak Mallik

Student ID: 23433639

Programme: MSc Data Analytics **Year:** 2025-2026

Module: Research Practicum/ Master Thesis

Lecturer: Dr. David Hamill

Submission Due Date: 11th December 2025

Project Title: A Comparative Study of Reinforcement Learning Algorithms and Custom Technical Indicators for Short-Term Stock Trading

1284 9

Word Count: **Page Count:**

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Signature: Roopak Mallik

Date: 8th December 2025

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National College of Ireland

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Research Practicum/ Master Thesis

Configuration Manual: A Comparative Study of Reinforcement Learning Algorithms and Custom Technical Indicators for Short-Term Stock Trading

Roopak Mallik/23433639	MSc Data Analytics	8th December 2025
NA	NA	NA

This section is a supplement to the main assignment, to be used if AI was used in any capacity in the creation of your assignment; if you have queries about how to do this, please contact your lecturer. For an example of how to fill these sections out, please click [here](#).

AI Acknowledgment

This section acknowledges the AI tools that were utilized in the process of completing this assignment.

Tool Name	Brief Description	Link to tool
NA	NA	NA

Description of AI Usage

This section provides a more detailed description of how the AI tools were used in the assignment. It includes information about the prompts given to the AI tool, the responses received, and how these responses were utilized or modified in the assignment. **One table should be used for each tool used.**

[Insert Tool Name]	
[Insert Description of use]	
[Insert Sample prompt]	[Insert Sample response]

Evidence of AI Usage

This section includes evidence of significant prompts and responses used or generated through the AI tool. It should provide a clear understanding of the extent to which the AI tool was used in the assignment. Evidence may be attached via screenshots or text.

Additional Evidence:

[Place evidence here]

Additional Evidence:

[Place evidence here]

Configuration Manual: A Comparative Study of Reinforcement Learning Algorithms and Custom Technical Indicators for Short-Term Stock Trading

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National College of Ireland
Supervisor: Dr. David Hamill

This configuration manual provides detailed information to ensure reproducibility and consistency across environments. It has all the specific required software tools, settings, and configurations required to replicate the experimental setup for training and evaluating the proposed framework.

1. System Requirements

This project was developed and implemented in multiple Jupyter Notebooks using Visual Studio Code on a MacBook Air M3, equipped with 16 GB of unified memory and a 256 GB SSD.

1.1 Hardware Requirements

CPU:

- Minimum: 4-core CPU.
- Recommended: 6-core or higher.

GPU:

- Minimum: None required (CPU-only training will work).

RAM:

- Minimum: 8 GB.
- Recommended: 16 GB or more.

Storage:

- Minimum: 20 GB free space.
- Recommended: 50 GB or more (SSD preferred).

1.2 Software Requirements

To implement, train and evaluate the reinforcement learning models developed in this project for trading, several software components, libraries and development tools are required. These tools ensure smooth data acquisition, environment setup, model execution and result visualization. The following list outlines the essential software requirements:

Operating System:

- macOS (Ventura or later).
- Windows 10/11 (64-bit).
- Linux (Ubuntu 20.04 or later).

All operating systems must support Python environments and the associated machine learning libraries.

Python Environment:

- Python Version:
 - Python 3.10 or 3.11 (recommended for compatibility with Stable-Baselines3 and Gymnasium).
- Environment Managers (any one):
 - venv (built-in).
 - Anaconda / Miniconda (recommended for dependency isolation).

Required Python Libraries:

These libraries support data preprocessing, financial indicator computation, reinforcement learning algorithms and visualisation.

Purpose	Libraries
Data handling & numerical computations	pandas, numpy
Data acquisition	yfinance
Technical indicators	Finta or ta
Reinforcement learning	stable-baselines3, gymnasium, gym-anytrading
Vectorised environments	stable_baselines3.common.vec_env
Plotting & visualisation	matplotlib, plotly
Performance analysis (optional)	quantstats
Jupyter environment	jupyterlab or notebook

Table 1. Required Libraries

Development Tools:

- Visual Studio Code or any another code editor.

Reinforcement Learning Frameworks:

- Stable-Baselines3 (SB3):
 - Provides implementations for DQN, PPO, and A2C algorithms used in the project.
- OpenAI Gymnasium:
 - Used for creating custom trading environments.
- gym-anytrading:
 - Used as the base environment for financial time-series simulations.

2. Code Editor Setup

Use Visual Studio Code or any other code editor like Pycharm.

Link to download [Visual Studio Code](#).

3. Data Gathering

This section guides you on how to download and prepare the dataset from starting to final stage.

3.1 Dataset Source

The historical stock market data used in this project was collected through the Yahoo Finance (YFinance) API, an open-source Python library that provides convenient access to publicly available financial datasets. The API was selected due to its reliability, ease of integration and suitability for academic research, allowing seamless retrieval of daily stock prices without licensing restrictions. For more information, refer to documentation available at [yfinance](#).

3.2 Data Collection Procedure

To acquire the data locally on your workstation, begin by executing the following command to install the library on your system as shown in Figure 1. To download via pip on **Windows** simply run the command in command prompt or terminal, '**pip install yfinance**'. For **MacOS** run the command '**pip3 install yfinance**'.



Figure 1. Installing yfinance library

The datasets were acquired programmatically using Python through publicly accessible financial data APIs. A custom data-collection workflow was created in the accompanying '**fetch_data.ipynb**' notebook, which automated the retrieval of daily stock market information. Data points collected included:

- Daily opening and closing prices.
- High and low values for each trading day.
- Trading volume.

The data acquisition process followed a structured pipeline:

- **API Request Construction:** API calls were generated using stock ticker symbols and date ranges for AMD, Intel and Nvidia. An example on how to gather historical stock data of a company is shown in Figure 2.
- **Fetching:** The system retrieved data at the daily level and exported the results into CSV format for each company.
- **File Storage:** The resulting datasets were stored as:
 - intel_stock_data_jan_to_aug_2025.csv
 - amd_stock_data_jan_to_aug_2025.csv
 - nvda_stock_data_jan_to_aug_2025.csv
- **Verification:** Each dataset was checked for completeness, missing values, duplicate entries and consistency.

```
# Stock tickers
tickers = ["NVDA"]

# Fetching daily stock data from Jan 1, 2025 to Aug 31, 2025
nvda_data = yf.download(tickers, start="2025-01-01", end="2025-08-31", interval="1d")

# Reset index to make the timestamp a separate column
nvda_data = nvda_data.reset_index()

nvda_data.columns = ['Date', 'Open', 'High', 'Low', 'Close', 'Volume']

nvda_data.head()
```

/var/folders/gl/gtqpk9s52v7_d3g5hfr_v3940000gn/T/ipykernel_3697/1839666459.py:5: FutureWarning:
nvda_data = yf.download(tickers, start="2025-01-01", end="2025-08-31", interval="1d")
[*****100%*****] 1 of 1 completed

	Date	Open	High	Low	Close	Volume
0	2025-01-02	138.279877	138.849760	134.600685	135.970382	198247200
1	2025-01-03	144.438538	144.868437	139.699564	139.979502	229322500
2	2025-01-06	149.397446	152.126862	147.787811	148.557632	265377400
3	2025-01-07	140.109467	153.096642	139.979490	152.996658	351782200
4	2025-01-08	140.079483	143.918643	137.530035	142.548946	227349900

Figure 2. API call to gather historical daily data for Nvidia

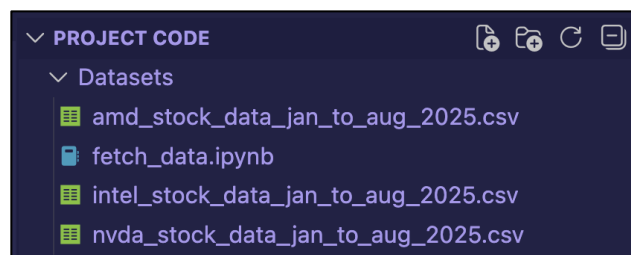


Figure 3. Data Collection as CSV file format

4. Execution

Prior to executing the main Reinforcement Learning for Trading scripts, a preliminary analysis was conducted to understand the characteristics of the collected datasets. The '**General_Analysis.ipynb**' file contains several visualizations and basic steps undertaken to explore and understand the data properties.

4.1 Library Installation and Execution Requirements

To ensure proper reproducibility of the reinforcement learning experiments conducted in this study, all software dependencies and library versions must be installed prior to running the notebooks. The project was developed in Python (version 3.10+), using a combination of scientific computing, machine learning, and reinforcement learning frameworks.

Refer to the official documentation available in Table 2 for the exact steps to install the libraries.

Library	Documentation Link
gymnasium (as gym)	https://gymnasium.farama.org/
gym_anytrading	Gym Trading Environment (similar functionality)
stable_baselines3	Stable Baselines3 Docs
finta	finta PyPI Page (includes installation and usage)
quantstats (as qs)	QuantStats GitHub/Documentation
pandas (as pd)	The Official Documentation of Pandas
numpy (as np)	NumPy Documentation
matplotlib.pyplot(as plt)	Matplotlib Documentation
os	Python os Module Documentation

Table 2. Library Documentation

4.2 Executing the files

The **RL Algorithms** folder is organized into two main directories: **Standard** and **Custom Indicators**. Each directory contains three algorithm-specific folders: **A2C**, **DQN**, and **PPO**.

The Standard folder houses reinforcement learning implementations applied to traditional **OHLCV datasets**, with files named intuitively (e.g., **A2C_on_AMD.ipynb**, **PPO_on_Intel.ipynb**). Similarly, the Custom Indicators folder follows the same structure but **incorporates technical indicators** into the trading algorithms, reflected in its naming convention (e.g., **A2C_on_AMD_Custom_Indicators.ipynb**, **PPO_on_Intel_Custom_Indicators.ipynb**).

Each notebook is fully **self-contained and can be executed independently**. To run any file, simply copy the dataset path from the Datasets folder (stored in CSV format) and paste it into your chosen algorithm notebook. The dataset loads via pandas, and you can then execute the cells sequentially. In total, there are 18 notebooks, 9 utilizing standard datasets and 9 incorporating custom technical indicators. Figures 4 and 5 provide visual examples of loading specific stock data into these implementations.

The environment operates with a 2-day window size and evaluates agent performance using Nvidia, AMD, and Intel stock data from January to August 2025. The model trains on days 50-130 and is tested on a separate period spanning days 131-165 as shown in Figures 9 and 10.

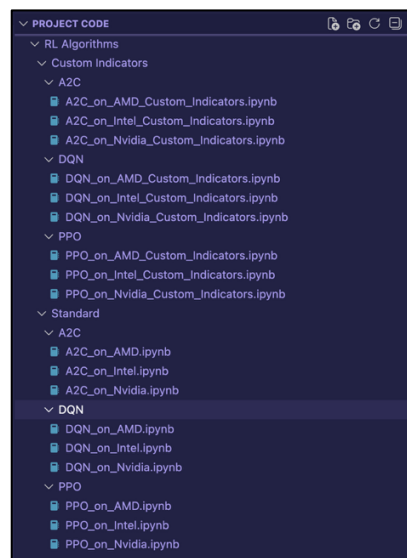


Figure 4. Layout of RL Algorithm Files

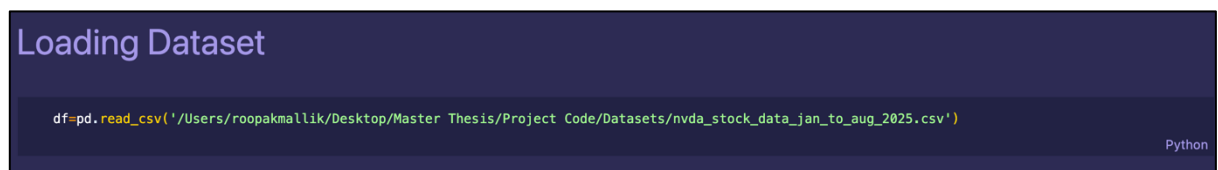


Figure 5. Loading a stock dataset for algorithmic trading

Steps for files using Standard Datasets:

1. Importing Libraries.
2. Loading Dataset and Pre-Processing.
3. Building Trading Environment.
4. Training the Reinforcement Learning Model (A2C, DQN or PPO).
5. Evaluating Model Performance using Time Series Graph.

Importing Libraries

```
import gymnasium as gym
import gym_anytrading
from gym_anytrading.envs import StocksEnv

from stable_baselines3.common.vec_env import DummyVecEnv
from stable_baselines3 import A2C
from stable_baselines3.common.sb2_compat.rmsprop_tf_like import RMSpropTFLike

from finta import TA
import quantstats as qs

import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

Python

Gym has been unmaintained since 2022 and does not support NumPy 2.0 amongst other critical functionality. Please upgrade to Gymnasium, the maintained drop-in replacement of Gym, or contact the authors of your software and request that they upgrade. Users of this version of Gym should be able to simply replace 'import gym' with 'import gymnasium as gym' in the vast majority of cases. See the migration guide at https://gymnasium.farama.org/introduction/migration_guide/ for additional information.

Figure 6. Importing Libraries

```
df=pd.read_csv('/Users/roopakmallik/Desktop/Master Thesis/Project Code/Datasets/amd_stock_data_jan_to_aug_2025.csv')
```

Python

```
df.head(10)
```

Python

Unnamed: 0	Date	Open	High	Low	Close	Volume
0	2025-01-02	120.629997	123.139999	119.440002	122.290001	34256200
1	2025-01-03	125.370003	125.559998	121.419998	121.650002	36785300
2	2025-01-06	129.550003	130.729996	127.360001	129.070007	48020200
3	2025-01-07	127.330002	131.710007	126.849998	130.509995	39220400
4	2025-01-08	121.839996	125.300003	120.120003	124.510002	46723100
5	2025-01-10	116.040001	118.709999	114.449997	118.180000	59415600
6	2025-01-13	117.320000	117.480003	114.410004	115.279999	39128900
7	2025-01-14	116.089996	118.660004	114.500000	118.000000	37005300
8	2025-01-15	119.959999	120.419998	117.459999	117.550003	38185800
9	2025-01-16	118.440002	121.089996	118.250000	120.239998	29414100

```
df=df.drop(columns=['Unnamed: 0'])
```

Python

```
df['Date'] = pd.to_datetime(df['Date'])
```

Python

```
df = df.astype({'Volume': 'float64'})
```

Python

```
df.set_index('Date', inplace=True)
df.info()
```

Figure 7. Loading Dataset and Pre-Processing

Building Gym Environment

```
env = StocksEnv(df=df, window_size=2, frame_bound=(50,130))
```

```
env.signal_features
```

```
array([[ 9.9639999e+01,  0.0000000e+00],
       [ 1.0260000e+02,  2.9599991e+00],
       [ 1.0385000e+02,  1.2500000e+00],
       [ 1.0442000e+02,  5.6999969e-01],
       [ 1.0512000e+02,  7.0000458e-01],
       [ 1.0533000e+02,  2.0999908e-01],
```

Figure 8. Building Trading Environment

The screenshot shows a Jupyter Notebook titled "Training". It contains two code cells. The first cell (index 14) defines the environment and the model:

```
env_maker = Lambda: StocksEnv(df=df, window_size=2, frame_bound=(50,130))
env = DummyVecEnv([env_maker])

model = A2C('MlpPolicy', env, verbose=1)
model.learn(total_timesteps=20000)
```

The second cell (index 15) shows the output of the training process, indicating it is using the CPU device and displaying two tables of performance metrics.

time/	
fps	1474
iterations	100
time_elapsed	0
total_timesteps	5000
train/	
entropy_loss	-0.688
explained_variance	0.0288
learning_rate	0.0007
n_updates	99
policy_loss	2.2
value_loss	12.1

time/	
fps	1192
iterations	200
time_elapsed	0
total_timesteps	10000
train/	
entropy_loss	-0.693
explained_variance	-0.0606
learning_rate	0.0007

Figure 9. Training the Reinforcement Learning Model (A2C, DQN or PPO).

The screenshot shows a Jupyter Notebook titled "Evaluation". It contains two code cells. The first cell (index 16) defines the evaluation environment and the evaluation loop:

```
env=StocksEnv(df=df, window_size=2, frame_bound=(131, 165))
obs, info = env.reset()
while True:
    obs_input = obs[np.newaxis, ...]
    action, _states = model.predict(obs_input)
    obs, rewards, terminated, truncated, info = env.step(action)
    done = terminated or truncated
    if done:
        print("info:", info)
        break
```

The second cell (index 17) shows the output of the evaluation process, displaying the information returned by the environment:

```
info: {'total_reward': np.float32(22.12001), 'total_profit': np.float32(1.0385008), 'position': <Positions.Long: 1>}
```

The third cell (index 17) shows the code for rendering the environment:

```
plt.figure(figsize=(15,6))
plt.cla()
env.render_all()
plt.show()
```

Figure 10. Evaluating Model Performance using Time Series Graph

Figures 6 through 10 provide a comprehensive, step-by-step guide to implementing reinforcement learning algorithms for trading using standard OHLCV (Open, High, Low, Close, Volume) datasets.

Steps for files with inclusion of Custom Indicators in Standard Datasets:

1. Importing Libraries.
2. Loading Dataset and Pre-Processing.
3. Calculating SMA, RSI and OBV.
4. Building Trading Environment.
5. Adding five features, 'Low','Volume','SMA','RSI','OBV'.
6. Training the Reinforcement Learning Model (A2C, DQN or PPO).
7. Evaluating Model Performance using Time Series Graph.

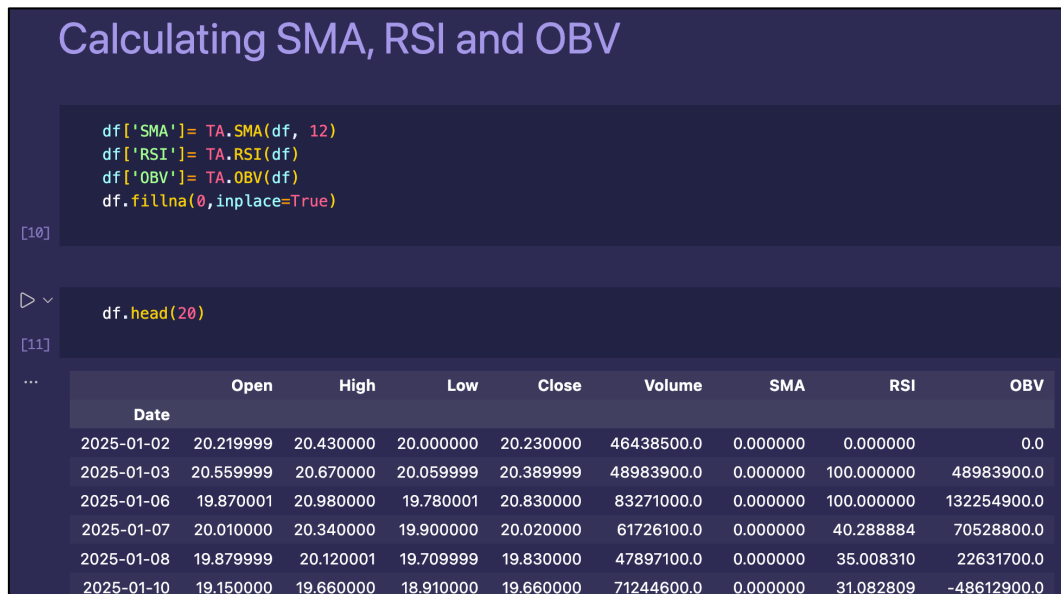


Figure 11. Calculating SMA, RSI and OBV



Figure 12. Selecting Low, Volume, SMA, RSI and OBV as Custom Technical Indicators

As illustrated in Figures 11 and 12, implementing custom technical indicators requires just two additional steps: computing and adding the custom indicators, then selecting five key features (Low, Volume, SMA, RSI and OBV). Beyond these modifications, the execution process follows the same procedure as the standard implementation.