Tugas 3 MA4072 - Pembelajaran Mendalam

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Notebook ini dijalankan menggunakan Google Colab, menjalankan notebook ini di Local Machine mungkin akan mendapatkan hasil yang sedikit berbeda

Akan dibuat 3 model CNN berbeda, yaitu 3 konfigurasi berbeda dari satu arsitektur yang sama dengan keterangan sebagai berikut:

1. lapisan *dropout* dengan rasio **0.25** dan **0.5**, lapisan *Fully Connected* sebesar **64**, serta optimisasi **SGD**,
2. lapisan *dropout* dengan rasio **0.5** dan **0.5**, lapisan *Fully Connected* sebesar **64** serta optimisasi **RMSprop**, dan
3. lapisan *dropout* dengan rasio **0.5** dan **0.75**, lapisan *Fully Connected* sebesar **128** serta optimisasi **NADAM**.

Ketiga model ini akan diuji menggunakan data harga saham SPDR S&P 500 trust (SPY) yang didapatkan dari https://finance.yahoo.com/quote/SPY. Data berupa 7372 entri harga saham dari bulan Januari 1993 sampai Mei 2022, berupa nilai saham ketika pasar dibuka (*Open*), harga tertinggi pada hari itu (*High*), harga terendah (*Low*), dan ketika pasar ditutup (*Close*). Terdapat juga harga saham ketika ditutup yang sudah disesuaikan dengan aksi perusahaan seperti deviden dan close split (*Adj. Close*) serta volume yaitu jumlah lembar saham yang diperdagangkan di hari tersebut.

Dependencies

In [ ]:
```
!pip install ta
```

```
Requirement already satisfied: ta in /usr/local/lib/python3.7/dist-packag
es (0.10.1)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-pac
kages (from ta) (1.21.6)
Requirement already satisfied: pandas in /usr/local/lib/python3.7/dist-pa
ckages (from ta) (1.3.5)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/d
ist-packages (from pandas->ta) (2022.1)
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/p
ython3.7/dist-packages (from pandas->ta) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-
packages (from python-dateutil>=2.7.3->pandas->ta) (1.15.0)
```

In [ ]:
```
!pip install imbalanced-learn
```

```
Requirement already satisfied: imbalanced-learn in /usr/local/lib/python
3.7/dist-packages (0.8.1)
Requirement already satisfied: numpy>=1.13.3 in /usr/local/lib/python3.7/
dist-packages (from imbalanced-learn) (1.21.6)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/d
ist-packages (from imbalanced-learn) (1.1.0)
Requirement already satisfied: scipy>=0.19.1 in /usr/local/lib/python3.7/
dist-packages (from imbalanced-learn) (1.4.1)
Requirement already satisfied: scikit-learn>=0.24 in /usr/local/lib/pytho
n3.7/dist-packages (from imbalanced-learn) (1.0.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/pyt
hon3.7/dist-packages (from scikit-learn>=0.24->imbalanced-learn) (3.1.0)
```

In [ ]:

```
import torch
import pandas as pd
import numpy as np
import random
import matplotlib.pyplot as plt
import ta
from sklearn.model_selection import train_test_split
import random
import sklearn
from collections import Counter
from imblearn.over_sampling import SMOTE
import matplotlib.dates as mdates
import numpy as np
import datetime as dt
```

SEED

In [ ]:

```
torch.manual_seed(13520157)
random.seed(13520157)
np.random.seed(13520157)
```

GLOBAL VARIABLE

In [ ]:

```
WINDOW_SIZE = 14 # LABELING WINDOW
INTERVAL_START = 3 # UNTUK IMAGE CREATION
INTERVAL_END = INTERVAL_START + 15 - 1 # 15 INTERVAL
```

Function and Procedure

In [ ]:

```
def dolabelling(dataframe):
  dataframe["Label"] = "HOLD" # HOLD by default
  dataframe["LabelEncode"] = 0
  windowSize = WINDOW_SIZE
  counterRow = 10
  while (counterRow < len(dataframe.index)):
    counterRow += 1
    if (counterRow >= windowSize): # START AT 0
      windowBeginIndex = counterRow - windowSize
      windowEndIndex = windowBeginIndex + windowSize - 1 if windowBeginIn
      windowMiddleIndex = (windowBeginIndex + windowEndIndex)//2
      maxIndex = 0 # Scope Extension
      minIndex = 0 # Scope Extension
      maxVal = 0.0 # Lets be real, no stock is going lower than 0
      minVal = np.finfo(dataframe["Close"].dtype).max
      for i in range(windowBeginIndex, windowEndIndex):
        number = dataframe.iloc[i, dataframe.columns.get_loc("Close")] #
        if (number < minVal):
          minVal = number
          minIndex = i
        if (number > maxVal):
          maxVal = number
          maxIndex = i
      if (maxIndex == windowMiddleIndex):
        dataframe.iloc[maxIndex, dataframe.columns.get_loc("Label")] = "S
        dataframe.iloc[maxIndex, dataframe.columns.get_loc("LabelEncode")
      elif (minIndex == windowMiddleIndex):
        dataframe.iloc[minIndex, dataframe.columns.get_loc("Label")] = "B
        dataframe.iloc[minIndex, dataframe.columns.get_loc("LabelEncode")

def retnormed(dataframe):
  return (dataframe-dataframe.min())/(dataframe.max() - dataframe.min())

def print_eval(cf_matrix, classes):
    fpm = np.sum(cf_matrix, axis=0)
    fnm = np.sum(cf_matrix, axis=1)
    rec = [(cf_matrix[i][i]) / (fnm[i] + 1e-10) for i in range(len(cf_mat
    prec = [(cf_matrix[i][i]) / (fpm[i] + 1e-10)for i in range(len(cf_mat
    f1 = [2 * prec[i] * rec[i] / (prec[i] + rec[i] + 1e-10) for i in rang
    raw_m = np.vstack((rec, prec, f1))
    acc = np.trace(cf_matrix) / (np.sum(cf_matrix) + 1e-10)
    print(f"\nTotal Accuracy: {acc:.4f}")
    print(pd.DataFrame(raw_m, index = ["Recall", "Precision", "F1 Score"]

def do_financial_run(pred, date, closeprice, initial, stockname, model):
  plt.figure(figsize=(12, 6))
  plt.title(f"{model} Financial Run ({stockname})")
  plt.xlabel("Date")
  plt.ylabel("Net Worth (USD)")
  plt.figure(1).patch.set_facecolor("white")
  cdate = list(map(dt.datetime.strptime, date, len(date.index)*['%Y-%m-%d
  balance = initial
  curstock = 0
  networth = 10000
  xlogger, ylogger = np.array([]), np.array([])
  for i in range(len(pred)):
    if pred[i] == 1: # SELL
      balance += curstock * closeprice[i]
      curstock = 0
    elif pred[i] == 2:
      while (balance > closeprice[i]):
        balance -= closeprice[i]
        curstock += 1
```

```
        curstock += 1
    networth = balance + curstock * closeprice[i]
    xlogger = np.append(xlogger, cdate[i])
    ylogger = np.append(ylogger, networth)
  print(f"\nInitial Net Worth: ${initial}, At The End: ${networth:.2f}\n"
  plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%Y-%m-%d'))
  plt.gca().xaxis.set_major_locator(mdates.YearLocator())
  plt.plot(xlogger, ylogger)
  plt.gcf().autofmt_xdate()
  plt.show()
```

In [ ]:
```
# KOMPATIBEL DENGAN SELURUH CSV YANG DIUNDUH MELALUI YAHOO FINANCE
STOCKNAME = "SPY"
df = pd.read_csv('/content/SPY.csv')
```

In [ ]:
```
df.head(5)
```

Out[ ]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	1993-01-29	43.96875	43.96875	43.75000	43.93750	25.547981	1003200
1	1993-02-01	43.96875	44.25000	43.96875	44.25000	25.729704	480500
2	1993-02-02	44.21875	44.37500	44.12500	44.34375	25.784195	201300
3	1993-02-03	44.40625	44.84375	44.37500	44.81250	26.056751	529400
4	1993-02-04	44.96875	45.09375	44.46875	45.00000	26.165777	531500

In [ ]:
```
dolabelling(df)
```

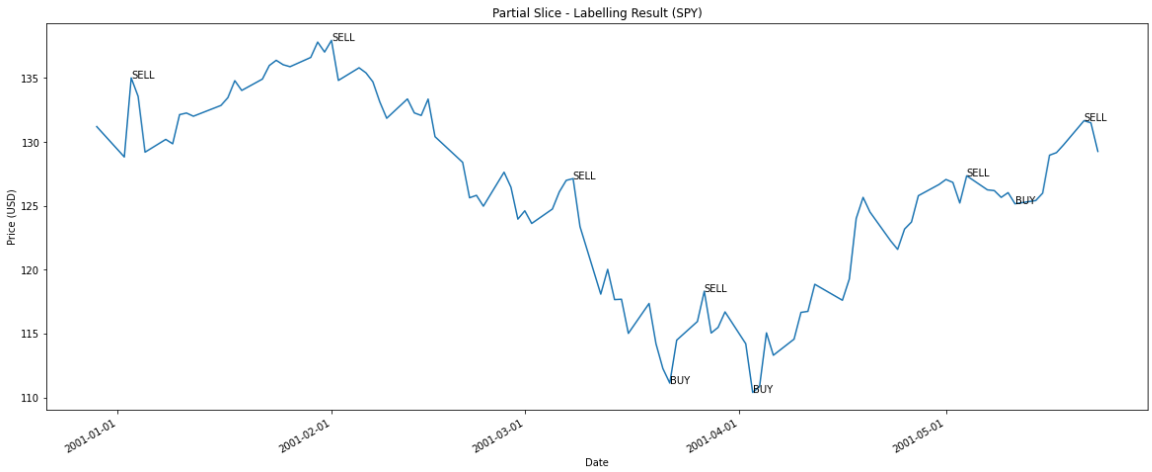
In [ ]:
```
df
```

Out[ ]:

	Date	Open	High	Low	Close	Adj Close	Volume	Labe
0	1993-01-29	43.968750	43.968750	43.750000	43.937500	25.547981	1003200	HOL
1	1993-02-01	43.968750	44.250000	43.968750	44.250000	25.729704	480500	HOL
2	1993-02-02	44.218750	44.375000	44.125000	44.343750	25.784195	201300	HOL
3	1993-02-03	44.406250	44.843750	44.375000	44.812500	26.056751	529400	HOL
4	1993-02-04	44.968750	45.093750	44.468750	45.000000	26.165777	531500	HOL
...	...	...	...	...	...	...	...	
7367	2022-05-02	412.070007	415.920013	405.019989	414.480011	414.480011	158312500	HOL
7368	2022-05-03	415.010010	418.929993	413.359985	416.380005	416.380005	100028200	HOL
7369	2022-05-04	417.079987	429.660004	413.709991	429.059998	429.059998	144247900	HOL
7370	2022-05-05	424.549988	425.000000	409.440002	413.809998	413.809998	172929100	HOL
7371	2022-05-06	411.100006	414.799988	405.730011	411.339996	411.339996	151671300	HOL

7372 rows × 9 columns

In [ ]:
```
slices = df[2000:2100]
plt.figure(figsize=(20, 8))
plt.title("Partial Slice - Labelling Result (" + STOCKNAME + ")")
plt.ylabel("Price (USD)")
plt.xlabel("Date")
plt.figure(1).patch.set_facecolor("white")
cdate = list(map(dt.datetime.strptime, slices["Date"], len(slices["Date"]
plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%Y-%m-%d'))
plt.gca().xaxis.set_major_locator(mdates.MonthLocator())
plt.plot(cdate, slices["Close"])
plt.gcf().autofmt_xdate()
for i in range(2000, 2100):
  if slices.loc[i]["Label"] ≠ "HOLD":
    plt.annotate(slices.loc[i]["Label"], xy=(cdate[i-2000], slices.loc[i,
plt.show()
```



Feature Generation

Momentum: RSI Williams %R ROC Stoch PPO PVO

Volume: CMF

Volatility: ATR

Trend: ADX WMA EMA SMA TRIX CCI MACD

RSI

In [ ]:
```
rsiTable = df[["Close"]]
for i in range(INTERVAL_START, INTERVAL_END+1):
  temp = ta.momentum.RSIIndicator(df["Close"], i, False).rsi()
  rsiTable = rsiTable.join(pd.DataFrame(temp).rename(columns = {'rsi':f'r
rsiTable = rsiTable.drop(columns=["Close"])
rsiTable = rsiTable.dropna() # DROP INVALID
rsiTable = retnormed(rsiTable) # NORMALIZED
```

In [ ]:
```
rsiTable # NORMALIZED, START VALID AT 21
```

Out[ ]:

	rsi_3	rsi_4	rsi_5	rsi_6	rsi_7	rsi_8	rsi_9	rsi_10	rsi_11
16	0.451025	0.386619	0.362193	0.352763	0.349359	0.348312	0.348037	0.347799	0.343436
17	0.816583	0.715459	0.652426	0.613896	0.590059	0.574910	0.565022	0.558386	0.547709
18	0.842931	0.746335	0.683505	0.644011	0.619122	0.603118	0.592618	0.585591	0.574414
19	0.862712	0.768802	0.705685	0.665206	0.639360	0.622596	0.611543	0.604142	0.592536
20	0.626371	0.623216	0.602332	0.584025	0.570929	0.562008	0.556002	0.551934	0.543095
...	...	...	...	...	...	...	...	...	...
7367	0.353388	0.338838	0.328280	0.320422	0.314810	0.310868	0.308073	0.305977	0.300883
7368	0.425905	0.391694	0.371539	0.357974	0.348557	0.341873	0.336995	0.333257	0.326549
7369	0.730059	0.646365	0.594293	0.559060	0.534098	0.515688	0.501622	0.490482	0.476032
7370	0.370953	0.382638	0.382047	0.377681	0.372575	0.367638	0.363084	0.358870	0.350976
7371	0.331015	0.351063	0.355486	0.354299	0.351298	0.347802	0.344265	0.340783	0.333617

7356 rows × 15 columns

Will R

In [ ]:

```
willR = df[["Close"]]
for i in range(INTERVAL_START, INTERVAL_END+1):
  temp = ta.momentum.WilliamsRIndicator(df["High"], df["Low"], df["Close"
  willR = willR.join(pd.DataFrame(temp).rename(columns = {'wr':f'wr_{i}'}
willR = willR.drop(columns=["Close"])
willR = willR.dropna()
willR = retnormed(willR)
```

In [ ]:

```
willR # VALID FROM ROW 21
```

Out[ ]:

	wr_3	wr_4	wr_5	wr_6	wr_7	wr_8	wr_9	wr_10	wr_11
16	0.647059	0.777778	0.777778	0.528302	0.424242	0.378378	0.378378	0.378378	0.378378
17	1.000000	1.000000	1.000000	1.000000	0.867925	0.696970	0.621622	0.621622	0.621622
18	0.965517	0.965517	0.969697	0.980000	0.980000	0.924528	0.742424	0.662162	0.662162
19	0.956522	0.967742	0.967742	0.971429	0.980769	0.980769	0.962264	0.772727	0.689189
20	0.357143	0.666667	0.742857	0.742857	0.769231	0.839286	0.839286	0.839286	0.712121
...	...	...	...	...	...	...	...	...	...
7367	0.384241	0.384241	0.384241	0.384241	0.286147	0.210269	0.210269	0.210269	0.210269
7368	0.544845	0.461414	0.461414	0.461414	0.461414	0.343618	0.252501	0.252501	0.252501
7369	0.975649	0.975649	0.975649	0.975649	0.975649	0.975649	0.727163	0.534341	0.534341
7370	0.216122	0.356737	0.356737	0.356737	0.356737	0.356737	0.356737	0.265881	0.195377
7371	0.234433	0.234433	0.256494	0.256494	0.256494	0.256494	0.256494	0.256494	0.191168

7356 rows × 15 columns

ROC

In [ ]:
```
rocTable = df[["Close"]]
for i in range(INTERVAL_START, INTERVAL_END+1):
  temp = ta.momentum.roc(df["Close"], i, False)
  rocTable = rocTable.join(pd.DataFrame(temp).rename(columns = {'roc':f'r
rocTable = rocTable.drop(columns=["Close"])
rocTable = rocTable.dropna()
rocTable = retnormed(rocTable)
```

In [ ]:
```
rocTable # START VALID AT 22
```

Out[ ]:

	roc_3	roc_4	roc_5	roc_6	roc_7	roc_8	roc_9	roc_10	roc_11
17	0.489984	0.552746	0.552693	0.570414	0.559006	0.558795	0.581148	0.544569	0.530903
18	0.485119	0.548534	0.560074	0.577386	0.626737	0.583226	0.574508	0.546068	0.549883
19	0.492178	0.542351	0.554386	0.582632	0.632023	0.651715	0.596412	0.538831	0.549903
20	0.440628	0.536375	0.537797	0.566860	0.626808	0.646315	0.652086	0.548970	0.533817
21	0.482152	0.541823	0.577968	0.594304	0.654558	0.686271	0.690604	0.634884	0.580947
...	...	...	...	...	...	...	...	...	...
7367	0.416425	0.487426	0.421442	0.461613	0.446794	0.426023	0.439665	0.450779	0.452196
7368	0.350845	0.492354	0.506689	0.458782	0.522594	0.472616	0.451734	0.428109	0.460538
7369	0.573881	0.506506	0.577057	0.602190	0.580884	0.615222	0.556679	0.489617	0.488818
7370	0.433023	0.510625	0.421484	0.507061	0.564371	0.510892	0.536835	0.447149	0.417895
7371	0.398687	0.477116	0.500885	0.434200	0.543184	0.568523	0.509205	0.491065	0.435823

7355 rows × 15 columns

STOCH

In [ ]:
```
stochTable = df[["Close"]]
for i in range(INTERVAL_START, INTERVAL_END+1):
  temp = ta.momentum.stoch(df["High"], df["Low"], df["Close"], i, 3, Fals
  stochTable = stochTable.join(pd.DataFrame(temp).rename(columns = {'stoc
stochTable = stochTable.drop(columns=["Close"])
stochTable = stochTable.dropna()
stochTable = retnormed(stochTable)
```

In [ ]:
```
stochTable # START AT 21
```

Out[ ]:

	stoch_k_3	stoch_k_4	stoch_k_5	stoch_k_6	stoch_k_7	stoch_k_8	stoch_k_9	stoch_k_10
16	0.647059	0.777778	0.777778	0.528302	0.424242	0.378378	0.378378	0.378378
17	1.000000	1.000000	1.000000	1.000000	0.867925	0.696970	0.621622	0.621622
18	0.965517	0.965517	0.969697	0.980000	0.980000	0.924528	0.742424	0.662162
19	0.956522	0.967742	0.967742	0.971429	0.980769	0.980769	0.962264	0.772727
20	0.357143	0.666667	0.742857	0.742857	0.769231	0.839286	0.839286	0.839286
...	...	...	...	...	...	...	...	...
7367	0.384241	0.384241	0.384241	0.384241	0.286147	0.210269	0.210269	0.210269
7368	0.544845	0.461414	0.461414	0.461414	0.461414	0.343618	0.252501	0.252501
7369	0.975649	0.975649	0.975649	0.975649	0.975649	0.975649	0.727163	0.534341
7370	0.216122	0.356737	0.356737	0.356737	0.356737	0.356737	0.356737	0.265881
7371	0.234433	0.234433	0.256494	0.256494	0.256494	0.256494	0.256494	0.256494

7356 rows × 15 columns

PPO

In [ ]:

```
ppoTable = df[["Close"]]
for i in range(INTERVAL_START, INTERVAL_END+1):
  temp = ta.momentum.PercentagePriceOscillator(df["Close"], window_sign=i
  ppoTable = ppoTable.join(pd.DataFrame(temp).rename(columns = {'PPO_12_2
ppoTable = ppoTable.drop(columns=["Close"])
ppoTable = ppoTable.dropna()
ppoTable = retnormed(ppoTable)
```

In [ ]:

```
ppoTable # VALID START AT 25
```

Out[ ]:

	PPO_12_26_3	PPO_12_26_4	PPO_12_26_5	PPO_12_26_6	PPO_12_26_7	PPO_12_26_8	PPC
25	0.786103	0.786103	0.786103	0.786103	0.786103	0.786103	
26	0.796188	0.796188	0.796188	0.796188	0.796188	0.796188	
27	0.804806	0.804806	0.804806	0.804806	0.804806	0.804806	
28	0.808839	0.808839	0.808839	0.808839	0.808839	0.808839	
29	0.804010	0.804010	0.804010	0.804010	0.804010	0.804010	
...	...	...	...	...	...	...	
7367	0.594917	0.594917	0.594917	0.594917	0.594917	0.594917	
7368	0.588983	0.588983	0.588983	0.588983	0.588983	0.588983	
7369	0.606433	0.606433	0.606433	0.606433	0.606433	0.606433	
7370	0.596966	0.596966	0.596966	0.596966	0.596966	0.596966	
7371	0.587028	0.587028	0.587028	0.587028	0.587028	0.587028	

7347 rows × 15 columns

PVO

In [ ]:
```
pvoTable = df[["Close"]]
for i in range(INTERVAL_START, INTERVAL_END+1):
  temp = ta.momentum.PercentageVolumeOscillator(df["Volume"], window_sign
  pvoTable = pvoTable.join(pd.DataFrame(temp).rename(columns = {'PVO_12_2
pvoTable = pvoTable.drop(columns=["Close"])
pvoTable = pvoTable.dropna()
pvoTable = retnormed(pvoTable)
```

In [ ]:
```
pvoTable # VALID START AT 25
```

Out[ ]:

	PVO_12_26_3	PVO_12_26_4	PVO_12_26_5	PVO_12_26_6	PVO_12_26_7	PVO_12_26_8	PV
25	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
26	0.022751	0.022751	0.022751	0.022751	0.022751	0.022751	
27	0.053517	0.053517	0.053517	0.053517	0.053517	0.053517	
28	0.037032	0.037032	0.037032	0.037032	0.037032	0.037032	
29	0.221322	0.221322	0.221322	0.221322	0.221322	0.221322	
...	...	...	...	...	...	...	
7367	0.539143	0.539143	0.539143	0.539143	0.539143	0.539143	
7368	0.522357	0.522357	0.522357	0.522357	0.522357	0.522357	
7369	0.536173	0.536173	0.536173	0.536173	0.536173	0.536173	
7370	0.561699	0.561699	0.561699	0.561699	0.561699	0.561699	
7371	0.566636	0.566636	0.566636	0.566636	0.566636	0.566636	

7347 rows × 15 columns

CMF

In [ ]:
```
cmfTable = df[["Close"]]
for i in range(INTERVAL_START, INTERVAL_END+1):
  temp = ta.volume.ChaikinMoneyFlowIndicator(df["High"], df["Low"], df["C
  cmfTable = cmfTable.join(pd.DataFrame(temp).rename(columns = {'cmf':f'cm
cmfTable = cmfTable.drop(columns=["Close"])
cmfTable = cmfTable.dropna()
cmfTable = retnormed(cmfTable)
```

In [ ]:
```
cmfTable # VALID START AT 21
```

Out[ ]:

	cmf_3	cmf_4	cmf_5	cmf_6	cmf_7	cmf_8	cmf_9	cmf_10	cmf_11
16	0.647067	0.614201	0.618614	0.504624	0.484957	0.466690	0.557039	0.532561	0.473426
17	0.643745	0.664839	0.626017	0.648719	0.507976	0.476503	0.484415	0.551779	0.556323
18	0.591613	0.662175	0.680861	0.658623	0.659220	0.502935	0.496592	0.484122	0.578583
19	0.897017	0.633892	0.683043	0.723084	0.674867	0.665911	0.528065	0.500978	0.514120
20	0.607315	0.666140	0.578366	0.673174	0.689929	0.641363	0.653338	0.500678	0.499240
...	...	...	...	...	...	...	...	...	...
7367	0.565419	0.494197	0.398378	0.512107	0.417952	0.351762	0.348290	0.385931	0.401844
7368	0.484371	0.559875	0.498759	0.423572	0.511470	0.409605	0.374917	0.354318	0.403575
7369	0.817312	0.614592	0.660155	0.614260	0.524085	0.583231	0.507038	0.452214	0.448333
7370	0.570900	0.659503	0.525756	0.589562	0.540263	0.453830	0.532300	0.451756	0.424214
7371	0.591926	0.584046	0.654995	0.558332	0.596601	0.541018	0.485159	0.533283	0.482374

7356 rows × 15 columns

ATR

In [ ]:

```
atrTable = df[["Close"]]
for i in range(INTERVAL_START, INTERVAL_END+1):
  temp = ta.volatility.AverageTrueRange(df["High"], df["Low"], df["Close"
  atrTable = atrTable.join(pd.DataFrame(temp).rename(columns = {'atr':f'a
atrTable = atrTable.drop(columns=["Close"])
atrTable = atrTable.dropna()
atrTable = retnormed(atrTable)
```

In [ ]:

```
atrTable # PRACTICALLY VALID AT 21
```

Out[ ]:

	atr_3	atr_4	atr_5	atr_6	atr_7	atr_8	atr_9	atr_10	atr_11
0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.010542	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
3	0.013775	0.014041	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
4	0.017617	0.017380	0.017619	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
...	...	...	...	...	...	...	...	...	...
7367	0.487361	0.507766	0.514885	0.519952	0.527231	0.536412	0.547206	0.559350	0.572606
7368	0.400069	0.441867	0.463391	0.478199	0.492201	0.506229	0.520635	0.535542	0.550960
7369	0.481941	0.506198	0.518136	0.527089	0.537258	0.548527	0.560805	0.573985	0.587951
7370	0.586046	0.594667	0.595852	0.597418	0.602423	0.609830	0.619065	0.629753	0.641615
7371	0.513087	0.545399	0.560514	0.570971	0.581968	0.593638	0.606019	0.619092	0.632803

7372 rows × 15 columns

ADX

In [ ]:
```
adxTable = df[["Close"]]
for i in range(INTERVAL_START, INTERVAL_END+1):
  temp = ta.trend.ADXIndicator(df["High"], df["Low"], df["Close"], window
  adxTable = adxTable.join(pd.DataFrame(temp).rename(columns = {'adx':f'a
adxTable = adxTable.drop(columns=["Close"])
adxTable = adxTable.dropna()
adxTable = retnormed(adxTable)
```

```
/usr/local/lib/python3.7/dist-packages/ta/trend.py:769: RuntimeWarning: i
nvalid value encountered in double_scalars
  dip[idx] = 100 * (self._dip[idx] / value)
/usr/local/lib/python3.7/dist-packages/ta/trend.py:774: RuntimeWarning: i
nvalid value encountered in double_scalars
  din[idx] = 100 * (self._din[idx] / value)
```

In [ ]:
```
adxTable # PRACTICALLY START AT 43
```

Out[ ]:

	adx_3	adx_4	adx_5	adx_6	adx_7	adx_8	adx_9	adx_10	adx_11
0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
3	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
...	...	...	...	...	...	...	...	...	...
7367	0.519306	0.529379	0.522653	0.508856	0.493761	0.478799	0.465118	0.453317	0.436702
7368	0.438403	0.483537	0.496692	0.495696	0.489107	0.480042	0.470521	0.461658	0.446934
7369	0.425647	0.422110	0.423375	0.422019	0.419830	0.426302	0.428044	0.427589	0.419718
7370	0.304959	0.317865	0.348849	0.368076	0.379684	0.394737	0.403231	0.408092	0.404663
7371	0.266682	0.282404	0.317843	0.343362	0.360743	0.379617	0.391687	0.399647	0.398900

7372 rows × 15 columns

WMA

In [ ]:
```
wmaTable = df[["Close"]]
for i in range(INTERVAL_START, INTERVAL_END+1):
  temp = ta.trend.WMAIndicator(df["Close"], window=i, fillna=False).wma()
  wmaTable = wmaTable.join(pd.DataFrame(temp).rename(columns = {'wma':f'w
wmaTable = wmaTable.drop(columns=["Close"])
wmaTable = wmaTable.dropna()
wmaTable = retnormed(wmaTable)
```

In [ ]:
```
wmaTable # START VALID AT 21
```

Out[ ]:

	wma_3	wma_4	wma_5	wma_6	wma_7	wma_8	wma_9	wma_10	wma_11
16	0.000156	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
17	0.000841	0.000606	0.000529	0.000464	0.000319	0.000204	0.000140	0.000097	0.000056
18	0.001369	0.001103	0.001005	0.000903	0.000721	0.000501	0.000347	0.000251	0.000173
19	0.001730	0.001478	0.001385	0.001285	0.001087	0.000846	0.000613	0.000447	0.000326
20	0.001670	0.001579	0.001539	0.001473	0.001301	0.001067	0.000831	0.000613	0.000441
...	...	...	...	...	...	...	...	...	...
7367	0.858486	0.860927	0.861702	0.863344	0.864875	0.867372	0.870628	0.874283	0.877994
7368	0.856506	0.859533	0.860816	0.861378	0.862604	0.864213	0.866644	0.869814	0.873506
7369	0.873541	0.870050	0.869642	0.869107	0.868447	0.868954	0.869977	0.871885	0.874674
7370	0.866434	0.866200	0.864921	0.865354	0.865443	0.865674	0.866723	0.868199	0.870513
7371	0.856737	0.859653	0.860454	0.860353	0.861204	0.862069	0.862955	0.864495	0.866482

7356 rows × 15 columns

EMA

In [ ]:

```
emaTable = df[["Close"]]
for i in range(INTERVAL_START, INTERVAL_END+1):
  temp = ta.trend.EMAIndicator(df["Close"], window=i, fillna=False).ema_i
  emaTable = emaTable.join(pd.DataFrame(temp).rename(columns = {'ema':f'e
emaTable = emaTable.drop(columns=["Close"])
emaTable = emaTable.dropna()
emaTable = retnormed(emaTable)
```

In [ ]:

```
emaTable # START VALID AT 21
```

Out[ ]:

	ema_3	ema_4	ema_5	ema_6	ema_7	ema_8	ema_9	ema_10	ema_11
16	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
17	0.000673	0.000525	0.000413	0.000328	0.000263	0.000214	0.000176	0.000147	0.000125
18	0.001117	0.000926	0.000761	0.000624	0.000515	0.000429	0.000361	0.000307	0.000265
19	0.001411	0.001225	0.001040	0.000877	0.000740	0.000628	0.000538	0.000465	0.000406
20	0.001414	0.001289	0.001131	0.000975	0.000837	0.000719	0.000621	0.000541	0.000475
...	...	...	...	...	...	...	...	...	...
7367	0.859674	0.863222	0.866992	0.870848	0.874667	0.878367	0.881899	0.885235	0.888365
7368	0.859805	0.862165	0.865122	0.868403	0.871811	0.875220	0.878547	0.881746	0.884787
7369	0.874499	0.873243	0.873644	0.875039	0.877014	0.879308	0.881756	0.884251	0.886725
7370	0.864253	0.865804	0.867576	0.869697	0.872083	0.874627	0.877240	0.879854	0.882424
7371	0.856281	0.859059	0.861628	0.864248	0.866954	0.869713	0.872479	0.875213	0.877882

7356 rows × 15 columns

SMA

In [ ]:
```
smaTable = df[["Close"]]
for i in range(INTERVAL_START, INTERVAL_END+1):
  temp = ta.trend.SMAIndicator(df["Close"], window=i, fillna=False).sma_i
  smaTable = smaTable.join(pd.DataFrame(temp).rename(columns = {'sma':f's
smaTable = smaTable.drop(columns=["Close"])
smaTable = smaTable.dropna()
smaTable = retnormed(smaTable)
```

In [ ]:
```
smaTable # START VALID AT 21
```

Out[ ]:

	sma_3	sma_4	sma_5	sma_6	sma_7	sma_8	sma_9	sma_10	sma_11
16	0.000000	0.000000	0.000000	0.000000	0.000113	0.000271	0.000322	0.000377	0.000423
17	0.000529	0.000487	0.000375	0.000301	0.000000	0.000072	0.000201	0.000283	0.000271
18	0.001009	0.000937	0.000808	0.000649	0.000289	0.000000	0.000048	0.000196	0.000205
19	0.001562	0.001334	0.001197	0.001034	0.000608	0.000271	0.000000	0.000073	0.000139
20	0.001586	0.001677	0.001457	0.001310	0.000897	0.000515	0.000209	0.000000	0.000000
...	...	...	...	...	...	...	...	...	...
7367	0.863667	0.863730	0.863253	0.867449	0.869485	0.876162	0.883588	0.889723	0.893305
7368	0.854879	0.863216	0.863383	0.862782	0.866300	0.869894	0.876292	0.883068	0.888740
7369	0.867996	0.863938	0.868826	0.867768	0.866481	0.870767	0.873974	0.879434	0.885361
7370	0.867481	0.864982	0.862362	0.866437	0.865726	0.866517	0.870824	0.873803	0.878827
7371	0.863606	0.863170	0.862058	0.860101	0.863771	0.865141	0.866402	0.870389	0.873177

7356 rows × 15 columns

TRIX

In [ ]:
```
trixTable = df[["Close"]]
for i in range(INTERVAL_START, INTERVAL_END+1):
  temp = ta.trend.TRIXIndicator(df["Close"], window=i, fillna=False).trix
  trixTable = trixTable.join(pd.DataFrame(temp).rename(columns = {'trix':
trixTable = trixTable.drop(columns=["Close"])
trixTable = trixTable.dropna()
trixTable = retnormed(trixTable)
```

In [ ]:
```
trixTable # STARTING AT 64
```

Out[ ]:

	trix_3	trix_4	trix_5	trix_6	trix_7	trix_8	trix_9	trix_10	trix_11
49	0.693248	0.669875	0.645458	0.634754	0.649754	0.666942	0.695803	0.704912	0.707342
50	0.722951	0.697965	0.668013	0.652037	0.661591	0.674846	0.700783	0.707516	0.708141
51	0.727868	0.713343	0.684889	0.667445	0.673618	0.683931	0.707430	0.711946	0.710767
52	0.721835	0.719038	0.695533	0.679357	0.684156	0.692702	0.714458	0.717151	0.714366
53	0.712839	0.718762	0.701005	0.687595	0.692560	0.700393	0.721111	0.722453	0.718354
...	...	...	...	...	...	...	...	...	...
7367	0.571217	0.548331	0.517663	0.498424	0.516336	0.535640	0.565941	0.581284	0.591220
7368	0.600891	0.567308	0.528282	0.502190	0.514482	0.529518	0.556293	0.569039	0.577059
7369	0.700405	0.635340	0.576482	0.536531	0.536392	0.542664	0.562872	0.570324	0.574283
7370	0.671911	0.640640	0.590382	0.550706	0.546906	0.549117	0.565429	0.569279	0.570196
7371	0.629438	0.624852	0.587638	0.552972	0.549782	0.550653	0.564802	0.566258	0.564915

7323 rows × 15 columns

CCI

In [ ]:

```
cciTable = df[["Close"]]
for i in range(INTERVAL_START, INTERVAL_END+1):
  temp = ta.trend.CCIIndicator(df["High"], df["Low"], df["Close"], window
  cciTable = cciTable.join(pd.DataFrame(temp).rename(columns = {'cci':f'c
cciTable = cciTable.drop(columns=["Close"])
cciTable = cciTable.dropna()
cciTable = retnormed(cciTable)
```

In [ ]:

```
cciTable # START AT 21
```

Out[ ]:

	cci_3	cci_4	cci_5	cci_6	cci_7	cci_8	cci_9	cci_10	cci_11
16	0.729730	0.739362	0.741379	0.621951	0.472593	0.446353	0.452100	0.432044	0.443310
17	1.000000	1.000000	0.956019	0.893939	0.834107	0.624969	0.558955	0.526189	0.528353
18	0.906250	0.855263	0.827640	0.813291	0.806452	0.792371	0.665429	0.591096	0.583484
19	0.847826	0.785714	0.750789	0.726930	0.714839	0.711769	0.730806	0.645209	0.609921
20	0.807692	0.739726	0.692308	0.683857	0.666218	0.660058	0.673326	0.677015	0.641129
...	...	...	...	...	...	...	...	...	...
7367	0.093827	0.100711	0.111652	0.173180	0.241616	0.292454	0.329669	0.324437	0.344197
7368	0.738573	0.426397	0.419339	0.410743	0.395292	0.396015	0.408879	0.389529	0.409270
7369	1.000000	1.000000	0.731402	0.731565	0.719192	0.647282	0.597637	0.528314	0.512622
7370	0.243430	0.430724	0.441828	0.413246	0.413026	0.413286	0.421732	0.404010	0.420108
7371	0.060241	0.083390	0.217569	0.218247	0.278521	0.285622	0.301519	0.294034	0.331508

7356 rows × 15 columns

MACD

In [ ]:
```
macdTable = df[["Close"]]
for i in range(INTERVAL_START, INTERVAL_END+1):
  temp = ta.trend.MACD(df["Close"], window_sign=i, fillna=False).macd()
  macdTable = macdTable.join(pd.DataFrame(temp).rename(columns = {'MACD_1:
macdTable = macdTable.drop(columns=["Close"])
macdTable = macdTable.dropna()
macdTable = retnormed(macdTable)
```

In [ ]:
```
macdTable # START AT 25
```

Out[ ]:

	MACD_12_26_3	MACD_12_26_4	MACD_12_26_5	MACD_12_26_6	MACD_12_26_7	MACD_1
25	0.728635	0.728635	0.728635	0.728635	0.728635	0
26	0.730230	0.730230	0.730230	0.730230	0.730230	0
27	0.731601	0.731601	0.731601	0.731601	0.731601	0
28	0.732251	0.732251	0.732251	0.732251	0.732251	0
29	0.731499	0.731499	0.731499	0.731499	0.731499	0
...	...	...	...	...	...	
7367	0.503968	0.503968	0.503968	0.503968	0.503968	0
7368	0.495582	0.495582	0.495582	0.495582	0.495582	0
7369	0.522239	0.522239	0.522239	0.522239	0.522239	0
7370	0.508516	0.508516	0.508516	0.508516	0.508516	0
7371	0.494213	0.494213	0.494213	0.494213	0.494213	0

7347 rows × 15 columns

Merging

In [ ]:
```
MSV = 49 # MOST STARING VALID: TRIX TABLE
```

In [ ]:
```python
imgdat = df[["Date", "Close", "Label", "LabelEncode"]].loc[MSV:]
# Momentum:
imgdat = imgdat.join(rsiTable.loc[MSV:]) # RSI
imgdat = imgdat.join(willR.loc[MSV:]) # Williams %R
imgdat = imgdat.join(rocTable.loc[MSV:]) # ROC
imgdat = imgdat.join(stochTable.loc[MSV:]) # Stoch
imgdat = imgdat.join(ppoTable.loc[MSV:]) # PPO
imgdat = imgdat.join(pvoTable.loc[MSV:]) # PVO

# Volume:
imgdat = imgdat.join(cmfTable.loc[MSV:]) # CMF

# Volatility:
imgdat = imgdat.join(atrTable.loc[MSV:]) # ATR

# Trend:
imgdat = imgdat.join(adxTable.loc[MSV:]) # ADX
imgdat = imgdat.join(wmaTable.loc[MSV:]) # WMA
imgdat = imgdat.join(emaTable.loc[MSV:]) # EMA
imgdat = imgdat.join(smaTable.loc[MSV:]) # SMA
imgdat = imgdat.join(trixTable.loc[MSV:]) # TRIX
imgdat = imgdat.join(cciTable.loc[MSV:]) # CCI
imgdat = imgdat.join(macdTable.loc[MSV:]) # MACD


# SANITY CHECK
imgdat.reset_index(drop=True, inplace=True) # RESET INDEX
imgdat[(imgdat.iloc[:, 4:] >= 0).all(1)] # DELETE ANY BELOW ZERO VALUE
imgdat.iloc[:, 4:] *= 255 # APPROPCHANNEL
```

In [ ]:
```python
imgdat
```

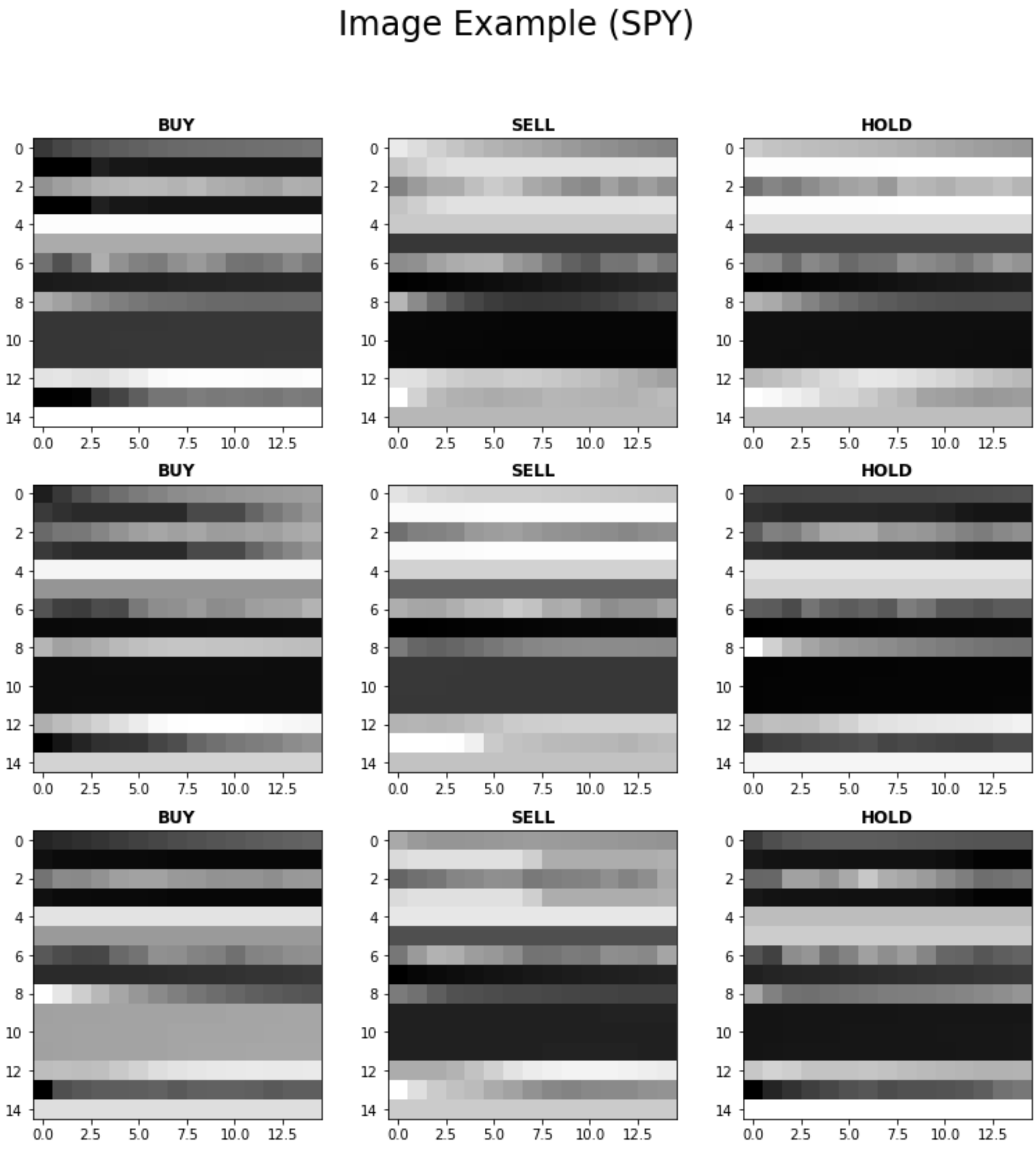
Out[ ]:

	Date	Close	Label	LabelEncode	rsi_3	rsi_4	rsi_5	r
0	1993-04-12	44.906250	HOLD	0	196.444138	175.034311	161.687246	153.009
1	1993-04-13	45.000000	SELL	1	203.874190	182.755940	169.151916	160.092
2	1993-04-14	44.937500	HOLD	0	180.898868	168.382316	158.709575	151.806
3	1993-04-15	44.937500	HOLD	0	180.898868	168.382316	158.709575	151.806
4	1993-04-16	44.937500	HOLD	0	180.898868	168.382316	158.709575	151.806
...	...	...	...	...	...	...	...	
7318	2022-05-02	414.480011	HOLD	0	90.113982	86.403802	83.711473	81.707
7319	2022-05-03	416.380005	HOLD	0	108.605672	99.881948	94.742361	91.283
7320	2022-05-04	429.059998	HOLD	0	186.164983	164.822974	151.544725	142.560
7321	2022-05-05	413.809998	HOLD	0	94.593044	97.572679	97.422021	96.308
7322	2022-05-06	411.339996	HOLD	0	84.408752	89.520961	90.648851	90.346

7323 rows × 229 columns

In [ ]:

```
buyimg = imgdat[imgdat["Label"] == "BUY"]
sellimg = imgdat[imgdat["Label"] == "SELL"]
holdimg = imgdat[imgdat["Label"] == "HOLD"]
fig, ax = plt.subplots(3,3, figsize=(13, 13))
fig.set_facecolor("white")
fig.suptitle(f"Image Example ({STOCKNAME})", fontsize=24)
for i in range(3):
  pickindex = random.randint(0, len(buyimg.index))
  ax[i, 0].set_title("BUY", fontweight='bold')
  ax[i, 0].imshow(np.array(buyimg.iloc[pickindex, 4:].values.reshape((15,
  pickindex = random.randint(0, len(sellimg.index))
  ax[i, 1].set_title("SELL", fontweight='bold')
  ax[i, 1].imshow(np.array(sellimg.iloc[pickindex, 4:].values.reshape((15
  pickindex = random.randint(0, len(holdimg.index))
  ax[i, 2].set_title("HOLD", fontweight='bold')
  ax[i, 2].imshow(np.array(holdimg.iloc[pickindex, 4:].values.reshape((15
fig.show()
```



Training

Preprocess

Split Dataset

In [ ]:
```
# traindat_le, testdat_le = train_test_split(imgdat_le, test_size=0.2, sh
# traindat_le.reset_index(drop=True, inplace=True)
# testdat_le.reset_index(drop=True, inplace=True)
# inp_train_le, out_train_le = traindat_le.iloc[:, 3:], traindat_le.iloc[
# inp_test_le, out_test_le = testdat_le.iloc[:, 3:], testdat_le.iloc[:, 2
# inp_train_le_tensor = torch.tensor(inp_train_le.values).reshape(len(inp
# out_train_le_tensor = torch.tensor(out_train_le.values).type(torch.Long
# inp_test_le_tensor = torch.tensor(inp_test_le.values).reshape(len(inp_t
# out_test_le_tensor = torch.tensor(out_test_le.values).type(torch.LongTe
scaler = sklearn.preprocessing.StandardScaler()
train_data, test_data = train_test_split(imgdat, test_size=0.2, shuffle=F
train_data.reset_index(drop=True, inplace=True)
in_train, out_train = torch.tensor(scaler.fit_transform(train_data.iloc[:
test_data.reset_index(drop=True, inplace=True)
in_test, out_test = torch.tensor(scaler.transform(test_data.iloc[:, 4:]))
```

SMOTE

In [ ]:
```
# oversampler = SMOTE()
# oversampled_train_inp, oversampled_train_out = oversampler.fit_resample
# oversampled_train_inp_tensor = torch.tensor(oversampled_train_inp.value
# oversampled_train_out_tensor = torch.tensor(oversampled_train_out.value
```

Details

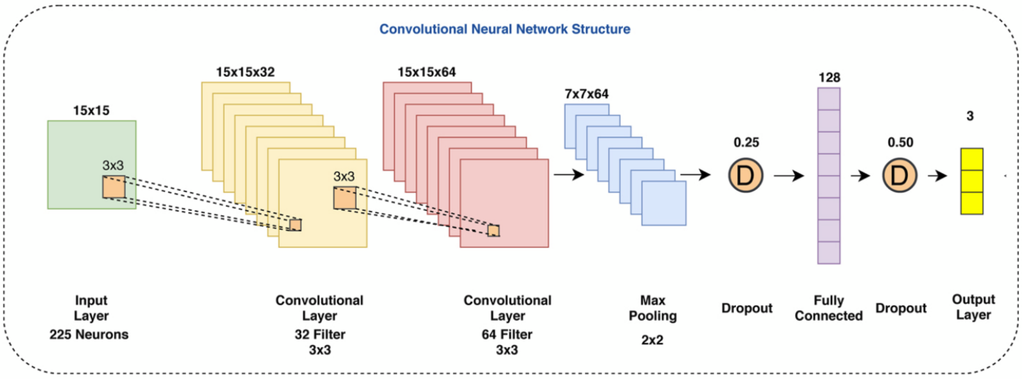


Figure 5: CNN Process

1. 15 x 15
2. 32 @ 15 * 15 (ReLU) (3x3)
3. 64 @ 15 * 15 (ReLU) (3x3)
4. 64 @ 7 * 7 (MaxPooling) (2x2)
5. Dropout 0.25
6. FC 128 (ReLU)
7. Dropout 0.50
8. Output Layer 10 (Softmax)

Loss Function

In [ ]:
```
# def f1_loss_approx(predl, actl):
#   act = torch.nn.functional.one_hot(actl)
#   pred = torch.nn.functional.log_softmax(predl)
#   tp = torch.sum(pred*act, dim=0)
#   fp = torch.sum((1-act)*pred, dim=0)
#   fn = torch.sum(act*(1-pred), dim=0)
#   prec = tp/(tp+fp+1e-10)
#   rec = tp / (tp+fn+1e-10)
#   f1 = 2 * prec * rec / (prec + rec+1e-10)
#   f1 = torch.where(torch.isnan(f1), torch.zeros_like(torch.empty(f1.sha
#   return 1 - torch.mean(f1)

# def modified_ce(pred, act, alpha, gamma=2):
#   c_weight = sklearn.utils.class_weight.compute_class_weight(class_weig
#   c_weight = torch.tensor(c_weight, dtype=torch.float)
#   ce_loss = torch.nn.functional.cross_entropy(pred, act, reduction='non
#   pt = torch.exp(-ce_loss)
#   focal_loss = (alpha * (1-pt)**gamma * ce_loss).mean()
#   return focal_loss
```

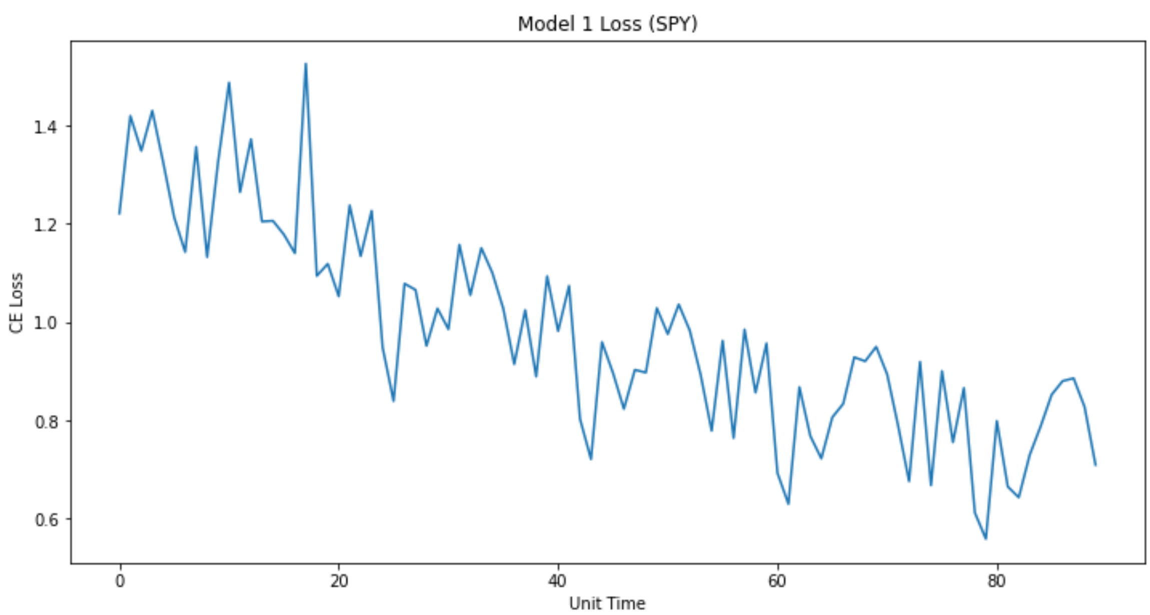
Model 1

In [ ]:
```
class Model1(torch.nn.Module):
  def __init__(self, d1, d2, ll):
    super(Model1, self).__init__()
    # ACT FUNC
    self.relu = torch.nn.ReLU()
    self.sig = torch.nn.Sigmoid()
    self.softmax = torch.nn.Softmax(dim=1)
    # LAYER IN ORDER
    self.conv1 = torch.nn.Conv2d(1, 32, 3, padding=1)
    torch.nn.init.xavier_uniform_(self.conv1.weight, gain=torch.nn.init.ca
    self.conv2 = torch.nn.Conv2d(32, 64, 3, padding=1)
    torch.nn.init.xavier_uniform_(self.conv2.weight, gain=torch.nn.init.ca
    self.maxPool = torch.nn.MaxPool2d(2, stride=2)
    self.dropout1 = torch.nn.Dropout(p=d1)
    torch.manual_seed(10)
    self.flatten = torch.nn.Flatten()
    self.fc1 = torch.nn.Linear(64*7*7, ll)
    torch.nn.init.xavier_uniform_(self.fc1.weight, gain=torch.nn.init.cal
    self.dropout2 = torch.nn.Dropout(p=d2)
    torch.manual_seed(10)
    self.fc2 = torch.nn.Linear(ll, 3)
    torch.nn.init.xavier_uniform_(self.fc2.weight)
  def forward(self, x):
    # n, 1, 15, 15
    # print(x)
    x = self.relu(self.conv1(x)) # n, 32, 15, 15
    # print(x)
    x = self.relu(self.conv2(x)) # n, 64, 15, 15
    # print(x)
    x = self.maxPool(x) # n, 64, 7, 7
    # print(x)
    x = self.dropout1(x)
    torch.manual_seed(10)
    x = self.flatten(x) # n, 64 * 7 * 7
    x = self.relu(self.fc1(x)) # n, ll
    x = self.dropout2(x)
    torch.manual_seed(10)
    x = self.fc2(x)# n, 3, no softmax because using CEL
    return x
```

Train

In [ ]:

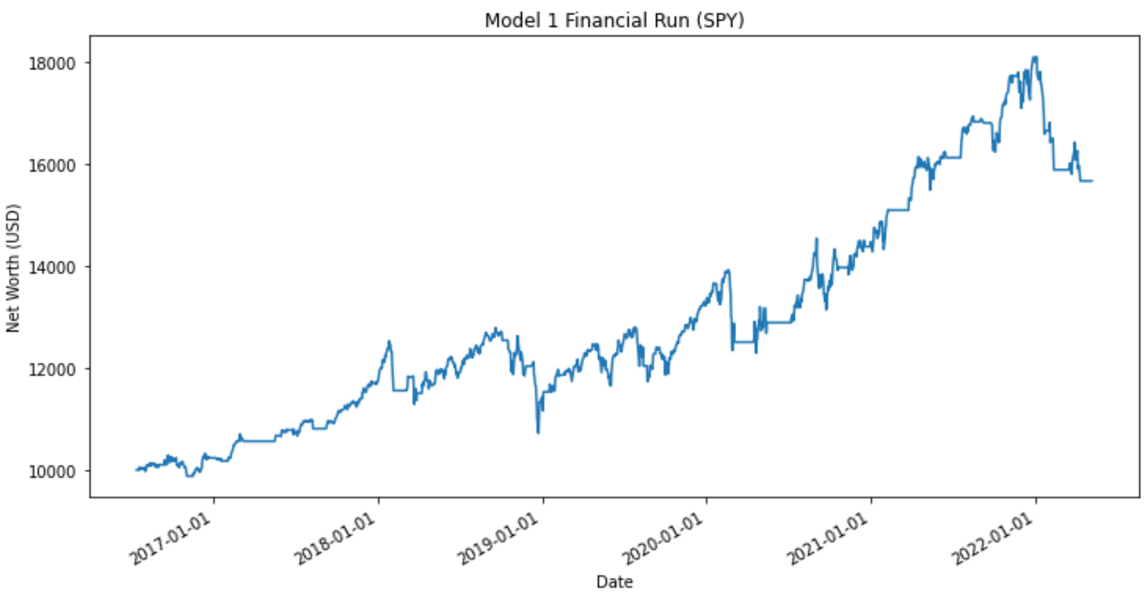
```
m1= Model1(0.25, 0.5, 64)
xlogger, ylogger = np.array([]), np.array([])
counter = 0
epoch = 5
batch_size = 32
optimizer = torch.optim.SGD(m1.parameters(), lr=1e-5)
criterion = torch.nn.CrossEntropyLoss()
for e in range(epoch):
  n_data = in_train.shape[0]
  perm = torch.randperm(n_data)
  for i in range(0, n_data, batch_size):
    optimizer.zero_grad()
    indices = perm[i:i+batch_size]
    batch_x, batch_y = in_train[indices], out_train[indices]
    out = m1.forward(batch_x)
    loss = criterion(out, batch_y)
    loss.backward()
    optimizer.step()
    # Logger
    if ((i//batch_size)+1) % 10 == 0:
      with torch.no_grad():
        xlogger = np.append(xlogger, counter)
        ylogger = np.append(ylogger, loss.item())
        counter += 1
# PLT SHOW
plt.figure(figsize=(12, 6))
plt.title(f"Model 1 Loss ({STOCKNAME})")
plt.figure(1).patch.set_facecolor("white")
plt.xlabel("Unit Time")
plt.ylabel("CE Loss")
plt.plot(xlogger, ylogger)
plt.show()
```



Evaluation Metrics

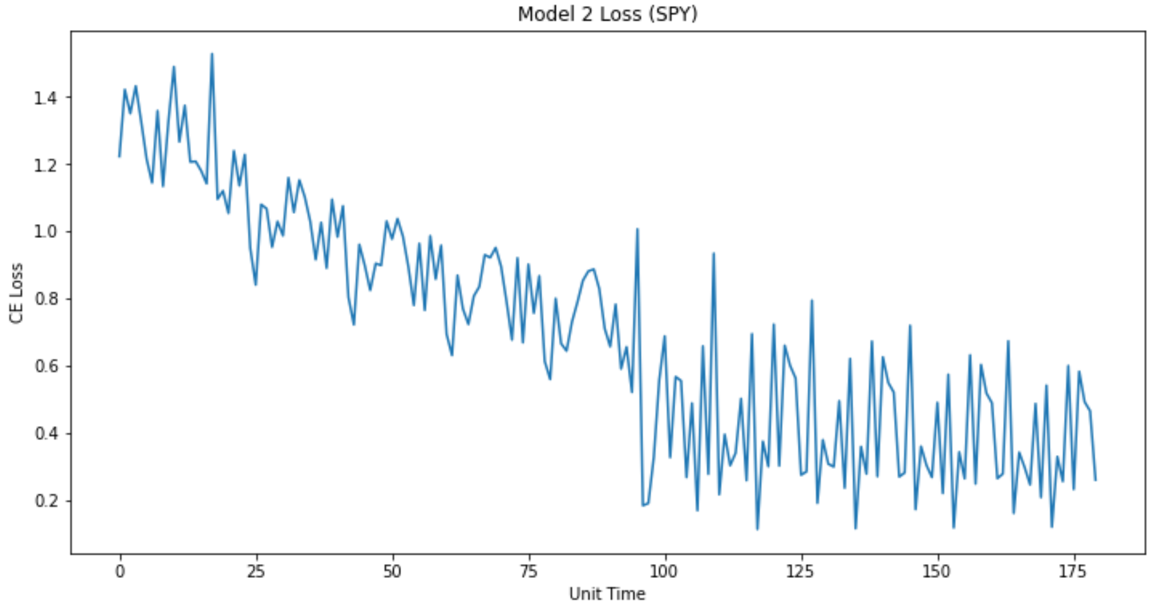
In [ ]:
```
with torch.no_grad():
  classes = ["HOLD", "SELL", "BUY"]
  out = m1.forward(in_test)
  _, outenc = torch.max(out, 1)
  cf_matrix = sklearn.metrics.confusion_matrix(out_test, outenc)
  df_cm = pd.DataFrame(cf_matrix, index = [i+" (A)" for i in classes], co
  print(df_cm)
  print_eval(cf_matrix, classes)
  do_financial_run(outenc, test_data["Date"], test_data["Close"], 10000, 
```

```
          HOLD (P)  SELL (P)  BUY (P)
HOLD (A)      1142        58      131
SELL (A)        60         0        5
BUY (A)         60         4        5

Total Accuracy: 0.7829
               HOLD  SELL       BUY
Recall     0.858002   0.0  0.072464
Precision  0.904913   0.0  0.035461
F1 Score   0.880833   0.0  0.047619

Initial Net Worth: $10000, At The End: $15663.87
```



Model 2

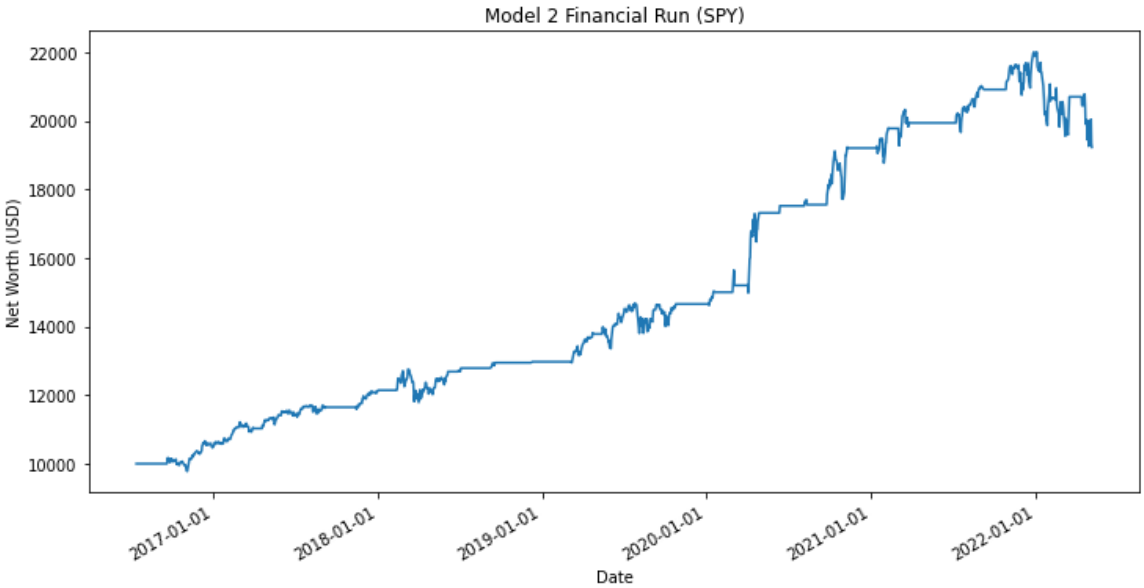
In [ ]:
```
m2 = Model1(0.5, 0.5, 64)
epoch = 5
batch_size = 32
optimizer = torch.optim.RMSprop(m2.parameters(), lr=1e-5)
criterion = torch.nn.CrossEntropyLoss()
for e in range(epoch):
  n_data = in_train.shape[0]
  perm = torch.randperm(n_data)
  for i in range(0, n_data, batch_size):
    optimizer.zero_grad()
    indices = perm[i:i+batch_size]
    batch_x, batch_y = in_train[indices], out_train[indices]
    out = m2.forward(batch_x)
    loss = criterion(out, batch_y)
    loss.backward()
    optimizer.step()
    if ((i//batch_size)+1) % 10 == 0:
      with torch.no_grad():
        xlogger = np.append(xlogger, counter)
        ylogger = np.append(ylogger, loss.item())
        counter += 1
# PLT SHOW
plt.figure(figsize=(12, 6))
plt.title(f"Model 2 Loss ({STOCKNAME})")
plt.xlabel("Unit Time")
plt.ylabel("CE Loss")
plt.figure(1).patch.set_facecolor("white")
plt.plot(xlogger, ylogger)
plt.show()
```



Evaluation Metrics

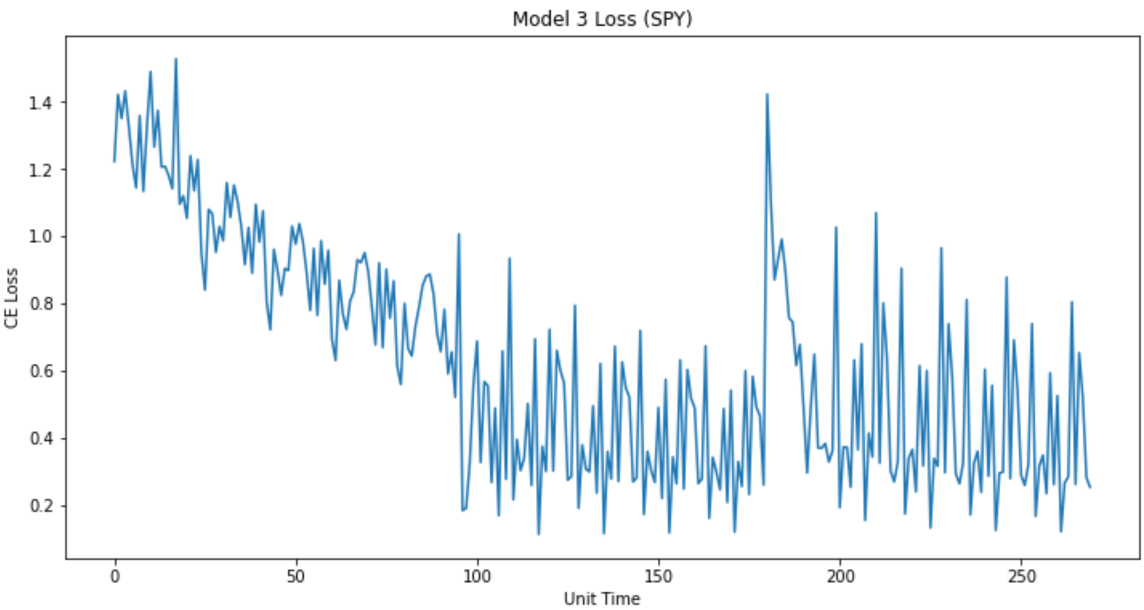
In [ ]:
```
with torch.no_grad():
  classes = ["HOLD", "SELL", "BUY"]
  out = m2.forward(in_test)
  _, outenc = torch.max(out, 1)
  cf_matrix = sklearn.metrics.confusion_matrix(out_test, outenc)
  df_cm = pd.DataFrame(cf_matrix, index = [i+" (A)" for i in classes], co
  print(df_cm)
  print_eval(cf_matrix, classes)
  do_financial_run(outenc, test_data["Date"], test_data["Close"], 10000, 
```

```
           HOLD (P)  SELL (P)  BUY (P)
HOLD (A)       1262        33       36
SELL (A)         64         1        0
BUY (A)          65         0        4

Total Accuracy: 0.8648
                HOLD      SELL       BUY
Recall      0.948159  0.015385  0.057971
Precision   0.907261  0.029412  0.100000
F1 Score    0.927259  0.020202  0.073394

Initial Net Worth: $10000, At The End: $19228.10
```



Model 3

In [ ]:
```
m3 = Model1(0.5, 0.75, 128)
epoch = 5
batch_size = 32
optimizer = torch.optim.NAdam(m3.parameters(), lr=1e-5)
criterion = torch.nn.CrossEntropyLoss()
for e in range(epoch):
  n_data = in_train.shape[0]
  perm = torch.randperm(n_data)
  for i in range(0, n_data, batch_size):
    optimizer.zero_grad()
    indices = perm[i:i+batch_size]
    batch_x, batch_y = in_train[indices], out_train[indices]
    out = m3.forward(batch_x)
    loss = criterion(out, batch_y)
    loss.backward()
    optimizer.step()
    if ((i//batch_size)+1) % 10 == 0:
      with torch.no_grad():
        xlogger = np.append(xlogger, counter)
        ylogger = np.append(ylogger, loss.item())
        counter += 1
# PLT SHOW
plt.figure(figsize=(12, 6))
plt.title(f"Model 3 Loss ({STOCKNAME})")
plt.xlabel("Unit Time")
plt.ylabel("CE Loss")
plt.figure(1).patch.set_facecolor("white")
plt.plot(xlogger, ylogger)
plt.show()
```



Evaluation Metrics

In [ ]:
```
with torch.no_grad():
  classes = ["HOLD", "SELL", "BUY"]
  out = m3.forward(in_test)
  _, outenc = torch.max(out, 1)
  cf_matrix = sklearn.metrics.confusion_matrix(out_test, outenc)
  df_cm = pd.DataFrame(cf_matrix, index = [i+" (A)" for i in classes], co
  print(df_cm)
  print_eval(cf_matrix, classes)
  do_financial_run(outenc, test_data["Date"], test_data["Close"], 10000,
```

	HOLD (P)	SELL (P)	BUY (P)
HOLD (A)	1076	125	130
SELL (A)	54	7	4
BUY (A)	52	8	9

Total Accuracy: 0.7454

	HOLD	SELL	BUY
Recall	0.808415	0.107692	0.130435
Precision	0.910321	0.050000	0.062937
F1 Score	0.856347	0.068293	0.084906

Initial Net Worth: $10000, At The End: $15963.28