5_1_RNN_based_strategy

September 24, 2023

0.0.1 Recurrent Neural Network (LSTM) Based Strategy Implementation

Implement RNN based strategy and optimize it on all symbols in the avarage ETFs amd Stocks set

[1]:
```python
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib
import seaborn as sns
import os
import pickle
import itertools
from backtesting import Backtest
from backtesting import Strategy

from sklearn.metrics import mean_squared_error, roc_auc_score
from sklearn.preprocessing import MinMaxScaler
from keras.callbacks import ModelCheckpoint, EarlyStopping, TensorBoard
from keras.models import Sequential
from keras.layers import Dense, LSTM
import keras
```

```
/home/kraken/Desktop/work/UoL/uol_final_tmp/venv/lib/python3.8/site-
packages/tqdm/auto.py:21: TqdmWarning: IProgress not found. Please update
jupyter and ipywidgets. See
https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
/home/kraken/Desktop/work/UoL/uol_final_tmp/venv/lib/python3.8/site-
packages/backtesting/_plotting.py:50: UserWarning: Jupyter Notebook detected.
Setting Bokeh output to notebook. This may not work in Jupyter clients without
JavaScript support (e.g. PyCharm, Spyder IDE). Reset with
`backtesting.set_bokeh_output(notebook=False)`.
  warnings.warn('Jupyter Notebook detected. '
```

```
2023-09-24 08:53:26.109783: I tensorflow/tsl/cuda/cudart_stub.cc:28] Could not
find cuda drivers on your machine, GPU will not be used.
2023-09-24 08:53:26.130037: I tensorflow/tsl/cuda/cudart_stub.cc:28] Could not
find cuda drivers on your machine, GPU will not be used.
```

```
2023-09-24 08:53:26.130442: I tensorflow/core/platform/cpu_feature_guard.cc:182]
This TensorFlow binary is optimized to use available CPU instructions in
performance-critical operations.
To enable the following instructions: AVX2 FMA, in other operations, rebuild
TensorFlow with the appropriate compiler flags.
2023-09-24 08:53:26.598046: W
tensorflow/compiler/tf2tensorrt/utils/py_utils.cc:38] TF-TRT Warning: Could not
find TensorRT
```

[2]:

```
# change into Dataset't directory
os.chdir("../dataset")
```

[3]:

```
with open("3_1_avg_stocks.pckl", "rb") as f:
    %time avg_Stocks = pickle.load(f)
```

```
CPU times: user 276 µs, sys: 219 µs, total: 495 µs
Wall time: 438 µs
```

[4]:

```
with open("3_1_avg_etfs.pckl", "rb") as f:
    %time avg_ETFs = pickle.load(f)
```

```
CPU times: user 200 µs, sys: 159 µs, total: 359 µs
Wall time: 307 µs
```

[5]:

```
with open("3_1_stock.pckl", "rb") as f:
    %time Stocks = pickle.load(f)
```

```
CPU times: user 734 ms, sys: 355 ms, total: 1.09 s
Wall time: 1.09 s
```

[6]:

```
with open("3_1_etfs.pckl", "rb") as f:
    %time ETFs = pickle.load(f)
```

```
CPU times: user 16.1 ms, sys: 49 µs, total: 16.1 ms
Wall time: 16 ms
```

[7]:

```
# Get symbol real names
ndt_reference = pd.read_csv("ndt_reference.csv")
```

[8]:

```
avg_ETFs = pd.merge(avg_ETFs, ndt_reference[["Symbol", "Security Name"]],␣
 ↪on="Symbol")
avg_Stocks = pd.merge(avg_Stocks, ndt_reference[["Symbol", "Security Name"]],␣
 ↪on="Symbol")
```

0.0.2 Preprocessing SPY’s data

[9]:
```
# Prepare first work on SPY
SPY = ETFs["SPY"].copy()
SPY = SPY[["Adj Close"]]
SPY["ret_pct"] = SPY["Adj Close"].pct_change()
# to introduce log normality.
SPY["log_ret_pct"] = np.log(1 + SPY["ret_pct"])
SPY.dropna(inplace=True)
```

[10]:
```
SPY
```

[10]:
```
             Adj Close   ret_pct  log_ret_pct
Date
2000-01-04   93.693573 -0.039106    -0.039891
2000-01-05   93.861176  0.001789     0.001787
2000-01-06   92.352676 -0.016072    -0.016202
2000-01-07   97.716209  0.058077     0.056453
2000-01-10   98.051422  0.003430     0.003425
…                  …        …          …
2023-08-28  442.760010  0.006341     0.006321
2023-08-29  449.160004  0.014455     0.014351
2023-08-30  451.010010  0.004119     0.004110
2023-08-31  450.350006 -0.001463    -0.001464
2023-09-01  451.190002  0.001865     0.001863

[5954 rows x 3 columns]
```

[11]:
```
SPY.describe()
```

[11]:
```
         Adj Close      ret_pct  log_ret_pct
count  5954.000000  5954.000000  5954.000000
mean    171.338935     0.000334     0.000257
std     112.609567     0.012417     0.012426
min      53.155308    -0.109424    -0.115887
25%      88.294670    -0.004804    -0.004815
50%     112.451721     0.000651     0.000650
75%     233.685982     0.006019     0.006001
max     477.709991     0.145198     0.135577
```

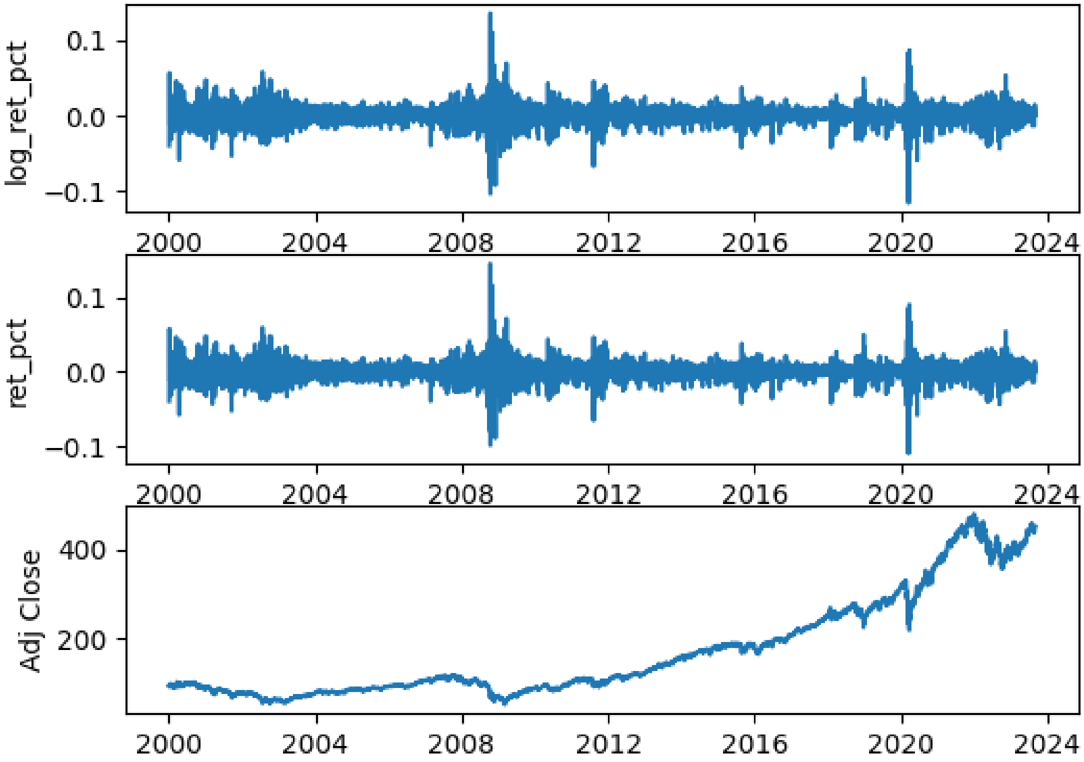
[12]:
```
# Plot the column to show log normality and why the training will happen on␣
 ↪log_ret_pct
# Ajd Close is very chaotic with big changes it would be hard for a model to␣
 ↪understand even with scalingon its own.
#
# Both ret_pct and log_ret_pct mean is around zero
# log_ret_pct tracks better the smaller changes due to assumed log normality
# more info about that could be read here: https://quantivity.wordpress.com/
↪2011/02/21/why-log-returns/
plt.figure(figsize=(40, 10))
fig, axis = plt.subplots(3, 1)

axis[2].plot(SPY.index, SPY["Adj Close"], label="Adj Close")
axis[2].set_ylabel("Adj Close")

axis[1].plot(SPY.index, SPY["ret_pct"], label="ret_pct")
axis[1].set_ylabel("ret_pct")

axis[0].plot(SPY.index, SPY["log_ret_pct"], label="log_ret_pct")
axis[0].set_ylabel("log_ret_pct")
plt.show()
```

```
<Figure size 4000x1000 with 0 Axes>
```



[13]:
```
# Scale SPY values
SPY_ = SPY[["Adj Close", "log_ret_pct"]].values
scaler = MinMaxScaler(feature_range=(0, 1)).fit(SPY_)
SPY_scaled = scaler.transform(SPY_)
```

[14]:

```
SPY_scaled[0]
```

[14]:

```
array([0.0954842 , 0.30221228])
```

[15]:

```
# Set the number of observation that will be used to traing the LSTM
# use 63 based on 3 months or avaraged working day
time_step = 63
```

[16]:

```
y = SPY_scaled[time_step: ,0]
```

[17]:

```
X = []
for i in range(time_step, len(SPY_scaled)):
    X.append(SPY_scaled[i - time_step: i])

X = np.array(X)
```

[18]:

```
X.shape
```

[18]:

```
(5891, 63, 2)
```

[19]:

```
# make sure that X and y len is matching
assert len(X) == len(y)
```

[20]:

```
# split data into train, val and test sets

p_85 = int(len(X) * 0.85)
p_90 = int(len(X) * 0.90)

X_train, y_train = X[:p_90], y[:p_90]
X_val, y_val = X[p_85:p_90], y[p_85:p_90]
X_test, y_test = X[p_90:], y[p_90:]

print(X_train.shape, y_train.shape)
print(X_val.shape, y_val.shape)
print(X_test.shape, y_test.shape)
```

```
(5301, 63, 2) (5301,)
(294, 63, 2) (294,)
(590, 63, 2) (590,)
```

0.0.3 Build RNN

[21]:

```
observation, step, features = X.shape
```

[22]:

```
rnn = Sequential([
    LSTM(units=32,
         input_shape=(step, features),
        name="LSTM_1",
        dropout=0.2,
        recurrent_dropout=0.2,
        return_sequences=True),
    LSTM(units=16,
        name="LSTM_2",
        dropout=0.2,
        recurrent_dropout=0.2),
    Dense(10, name="DENSE_1"),
    Dense(10, name="DENSE_2"),
    Dense(1, name="Output")
])
```

```
2023-09-24 08:53:28.594720: I
tensorflow/compiler/xla/stream_executor/cuda/cuda_gpu_executor.cc:995]
successful NUMA node read from SysFS had negative value (-1), but there must be
at least one NUMA node, so returning NUMA node zero. See more at
https://github.com/torvalds/linux/blob/v6.0/Documentation/ABI/testing/sysfs-bus-
pci#L344-L355
2023-09-24 08:53:28.596442: W
tensorflow/core/common_runtime/gpu/gpu_device.cc:1960] Cannot dlopen some GPU
libraries. Please make sure the missing libraries mentioned above are installed
properly if you would like to use GPU. Follow the guide at
https://www.tensorflow.org/install/gpu for how to download and setup the
required libraries for your platform.
Skipping registering GPU devices…
```

[23]:

```
rnn.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 LSTM_1 (LSTM)               (None, 63, 32)            4480

 LSTM_2 (LSTM)               (None, 16)                3136

 DENSE_1 (Dense)             (None, 10)                170

 DENSE_2 (Dense)             (None, 10)                110

 Output (Dense)              (None, 1)                 11

=================================================================
Total params: 7907 (30.89 KB)
Trainable params: 7907 (30.89 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[24]:

```python
rnn_1 = keras.models.clone_model(rnn)
rnn_2 = keras.models.clone_model(rnn)

rnn_1.compile(loss='mean_squared_error', optimizer="adam")
rnn_2.compile(loss='mae', optimizer="RMSProp")
```

0.0.4 Train RNN 1

[25]:

```python
metric = 'val_loss'
rnn_path = "../models/rnn_1_spy_2.weights.best"
tb_path = "../tensorboard/rnn_1_spy"
```

[26]:

```python
tensorboard = TensorBoard(log_dir=tb_path,
                          histogram_freq=0,
                          write_graph=True,
                          write_images=True)
```

[27]:

```python
early_stopping = EarlyStopping(monitor=metric,
                               patience=5,
                               restore_best_weights=True)
```

[28]:

```python
checkpointer = ModelCheckpoint(filepath=rnn_path,
                               monitor=metric,
                               save_best_only=True,
                               save_weights_only=True,
                               save_freq="epoch")
```

[29]:

```python
result_1 = rnn_1.fit(X_train,
                 y_train,
                 epochs=100,
                 batch_size=32,
                 validation_data=(X_val, y_val),
                 callbacks=[checkpointer, early_stopping, tensorboard],
                 verbose=1)
```

```
Epoch 1/100
166/166 [==============================] - 6s 26ms/step - loss: 0.0031 -
val_loss: 0.0013
Epoch 2/100
166/166 [==============================] - 4s 24ms/step - loss: 0.0014 -
val_loss: 0.0016
Epoch 3/100
166/166 [==============================] - 4s 24ms/step - loss: 0.0011 -
val_loss: 0.0032
Epoch 4/100
166/166 [==============================] - 4s 24ms/step - loss: 9.3095e-04 -
val_loss: 0.0020
```

```
Epoch 5/100
166/166 [==============================] - 4s 24ms/step - loss: 0.0011 -
val_loss: 0.0017
Epoch 6/100
166/166 [==============================] - 4s 24ms/step - loss: 8.0455e-04 -
val_loss: 0.0021
```

0.0.5 Train RNN 2

[30]:

```
metric = 'val_loss'
rnn_path = "../models/rnn_2_spy_2.weights.best"
tb_path = "../tensorboard/rnn_2_spy"
```

[31]:

```
tensorboard = TensorBoard(log_dir=tb_path,
                          histogram_freq=0,
                          write_graph=True,
                          write_images=True)
```

[32]:

```
early_stopping = EarlyStopping(monitor=metric,
                              patience=5,
                              restore_best_weights=True)
```

[33]:

```
checkpointer = ModelCheckpoint(filepath=rnn_path,
                              monitor=metric,
                              save_best_only=True,
                              save_weights_only=True,
                              save_freq="epoch")
```

[34]:

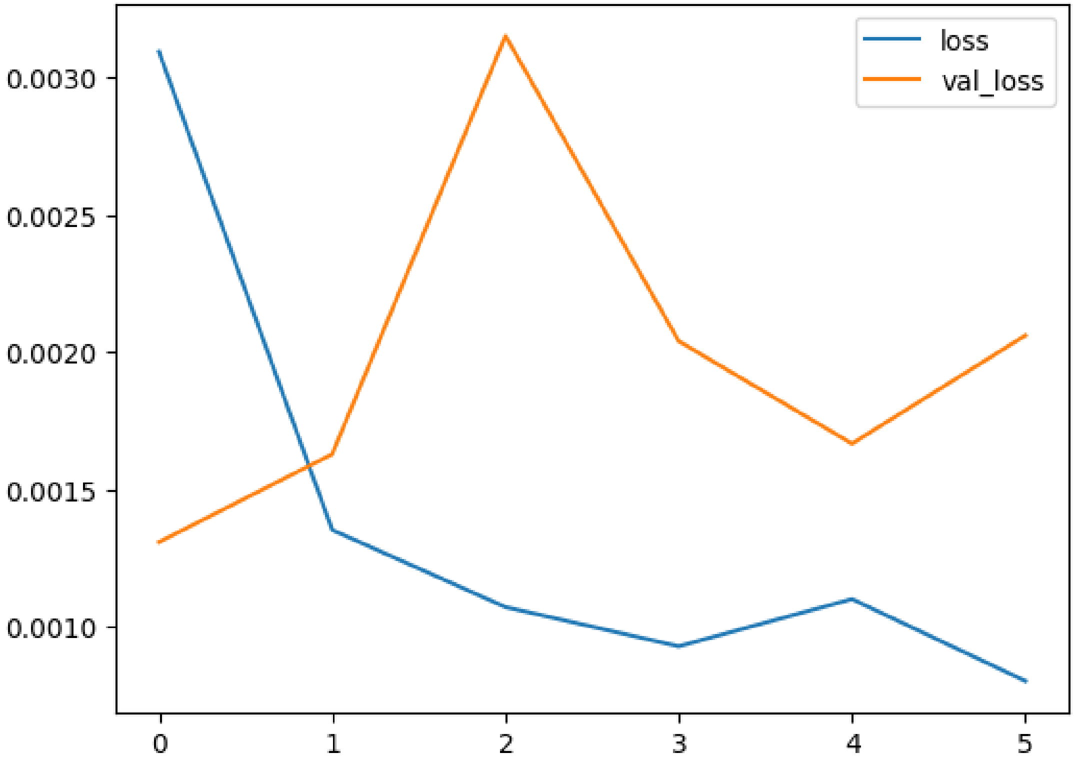
```
result_2 = rnn_2.fit(X_train,
                  y_train,
                  epochs=100,
                  batch_size=32,
                  validation_data=(X_val, y_val),
                  callbacks=[checkpointer, early_stopping, tensorboard],
                  verbose=1)
```

```
Epoch 1/100
166/166 [==============================] - 6s 26ms/step - loss: 0.0379 -
val_loss: 0.0304
Epoch 2/100
166/166 [==============================] - 4s 24ms/step - loss: 0.0282 -
val_loss: 0.0783
Epoch 3/100
166/166 [==============================] - 4s 25ms/step - loss: 0.0262 -
val_loss: 0.0458
Epoch 4/100
166/166 [==============================] - 4s 24ms/step - loss: 0.0257 -
val_loss: 0.0824
```

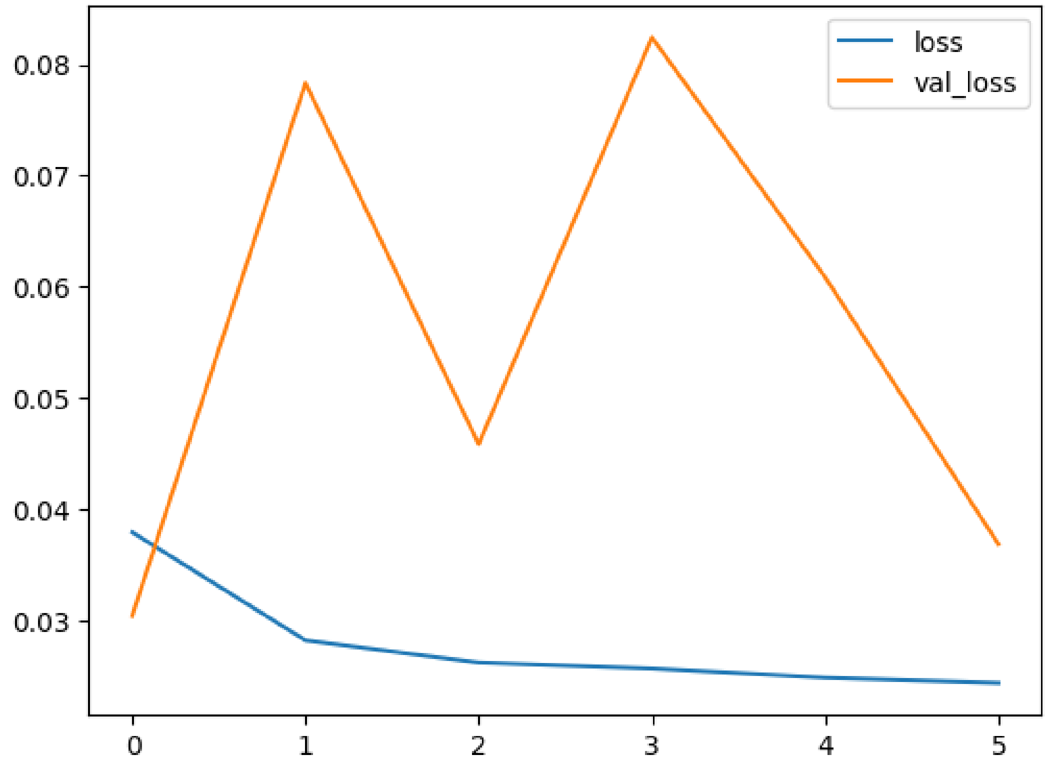
```
Epoch 5/100
166/166 [==============================] - 4s 25ms/step - loss: 0.0249 -
val_loss: 0.0609
Epoch 6/100
166/166 [==============================] - 4s 24ms/step - loss: 0.0244 -
val_loss: 0.0369
```

0.0.6 Compare train results

[35]:
```
pd.DataFrame(result_1.history).plot();
```



[36]:
```
pd.DataFrame(result_2.history).plot();
```



[37]:

```
# Create predictions
y_pred_1 = rnn_1.predict(X_test)
y_pred_2 = rnn_2.predict(X_test)
y_pred_full_1 = rnn_1.predict(X)
y_pred_full_2 = rnn_2.predict(X)
```

```
19/19 [==============================] - 0s 6ms/step
19/19 [==============================] - 0s 6ms/step
185/185 [==============================] - 1s 6ms/step
185/185 [==============================] - 1s 6ms/step
```

[38]:

```
# Scale back predictions with scaler object
y_pred_1 = np.c_[y_pred_1, np.zeros(y_pred_1.shape)]
y_pred_1 = scaler.inverse_transform(y_pred_1)
y_pred_1 = [x[0] for x in y_pred_1]

y_pred_2 = np.c_[y_pred_2, np.zeros(y_pred_2.shape)]
y_pred_2 = scaler.inverse_transform(y_pred_2)
y_pred_2 = [x[0] for x in y_pred_2]

y_pred_full_1 = np.c_[y_pred_full_1, np.zeros(y_pred_full_1.shape)]
y_pred_full_1 = scaler.inverse_transform(y_pred_full_1)
```

```
y_pred_full_1 = [x[0] for x in y_pred_full_1]

y_pred_full_2 = np.c_[y_pred_full_2, np.zeros(y_pred_full_2.shape)]
y_pred_full_2 = scaler.inverse_transform(y_pred_full_2)
y_pred_full_2 = [x[0] for x in y_pred_full_2]
```

[39]:

```
# check only the data rows that have predictions
SPY = SPY.iloc[time_step:].copy()
```

[40]:

```
SPY["RNN 1 Full"] = y_pred_full_1
SPY["RNN 2 Full"] = y_pred_full_2
SPY.loc[SPY.index[len(SPY) - len(y_pred_1):], "RNN 1 Test"] = y_pred_1
SPY.loc[SPY.index[len(SPY) - len(y_pred_2):], "RNN 2 Test"] = y_pred_2
```

[41]:

```
SPY
```

[41]:

```
             Adj Close   ret_pct  log_ret_pct  RNN 1 Full  RNN 2 Full  \
Date
2000-04-04  100.905151 -0.007438    -0.007466  101.927509  100.424515
2000-04-05  100.275024 -0.006245    -0.006264  102.201598  100.714983
2000-04-06  101.146713  0.008693     0.008655  102.434921  100.929226
2000-04-07  101.787308  0.006333     0.006313  102.676366  101.237629
2000-04-10  101.388298 -0.003920    -0.003928  102.926235  101.575558
…                  …         …          …           …           …
2023-08-28  442.760010  0.006341     0.006321  418.419265  418.663640
2023-08-29  449.160004  0.014455     0.014351  418.254881  418.577652
2023-08-30  451.010010  0.004119     0.004110  418.381029  418.772984
2023-08-31  450.350006 -0.001463    -0.001464  418.620291  418.922236
2023-09-01  451.190002  0.001865     0.001863  418.907280  419.056152

            RNN 1 Test  RNN 2 Test
Date
2000-04-04         NaN         NaN
2000-04-05         NaN         NaN
2000-04-06         NaN         NaN
2000-04-07         NaN         NaN
2000-04-10         NaN         NaN
…                  …           …
2023-08-28  418.419215  418.663614
2023-08-29  418.254881  418.577702
2023-08-30  418.381003  418.772984
2023-08-31  418.620241  418.922236
2023-09-01  418.907255  419.056127

[5891 rows x 7 columns]
```

[42]:

```
training_error_1 = np.sqrt(rnn_1.evaluate(X_train, y_train, verbose=0))
testing_error_1 = np.sqrt(rnn_1.evaluate(X_test, y_test, verbose=0))
print('Training Error 1: {:.4f} | Test Error 1: {:.4f}'.
 ↪format(training_error_1, testing_error_1))
```

```
Training Error 1: 0.0170 | Test Error 1: 0.0536
```

[43]:

```
training_error_2 = np.sqrt(rnn_2.evaluate(X_train, y_train, verbose=0))
testing_error_2 = np.sqrt(rnn_2.evaluate(X_test, y_test, verbose=0))
print('Training Error 2: {:.4f} | Test Error 2: {:.4f}'.
 ↪format(training_error_2, testing_error_2))
```

```
Training Error 2: 0.1275 | Test Error 2: 0.2090
```

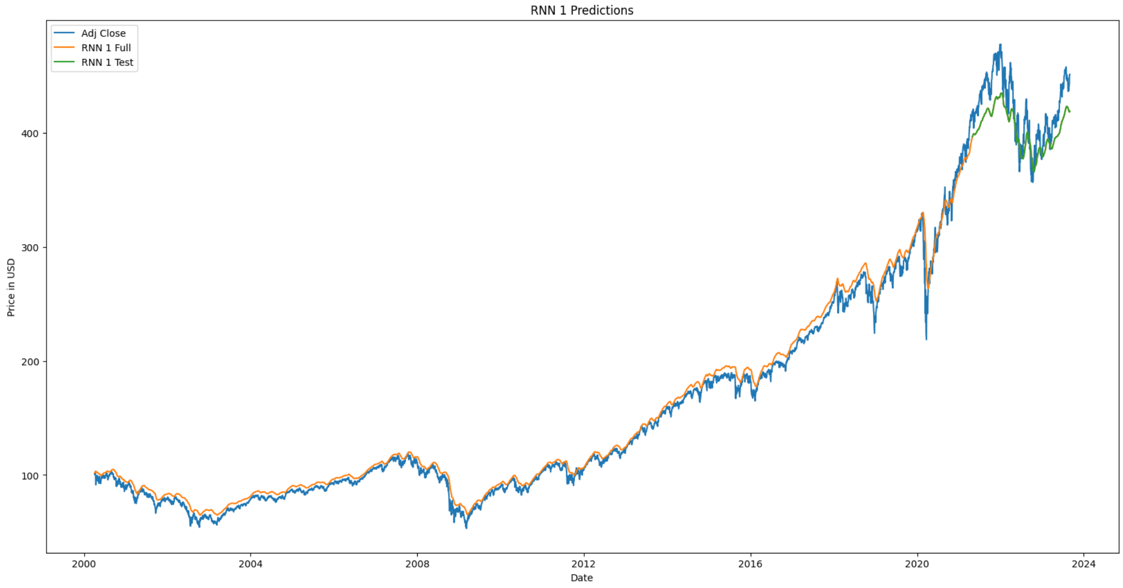
1 Plot the two RNNs predictions

[44]:

```
# Plot RNN 1 reslts
plt.figure(figsize=(20,10))

plt.plot(SPY.index, SPY["Adj Close"], label="Adj Close")
plt.plot(SPY.index, SPY["RNN 1 Full"], label="RNN 1 Full")
plt.plot(SPY.index, SPY["RNN 1 Test"], label="RNN 1 Test")

plt.xlabel("Date")
plt.ylabel("Price in USD")
plt.legend()
plt.title("RNN 1 Predictions")
plt.show()
```

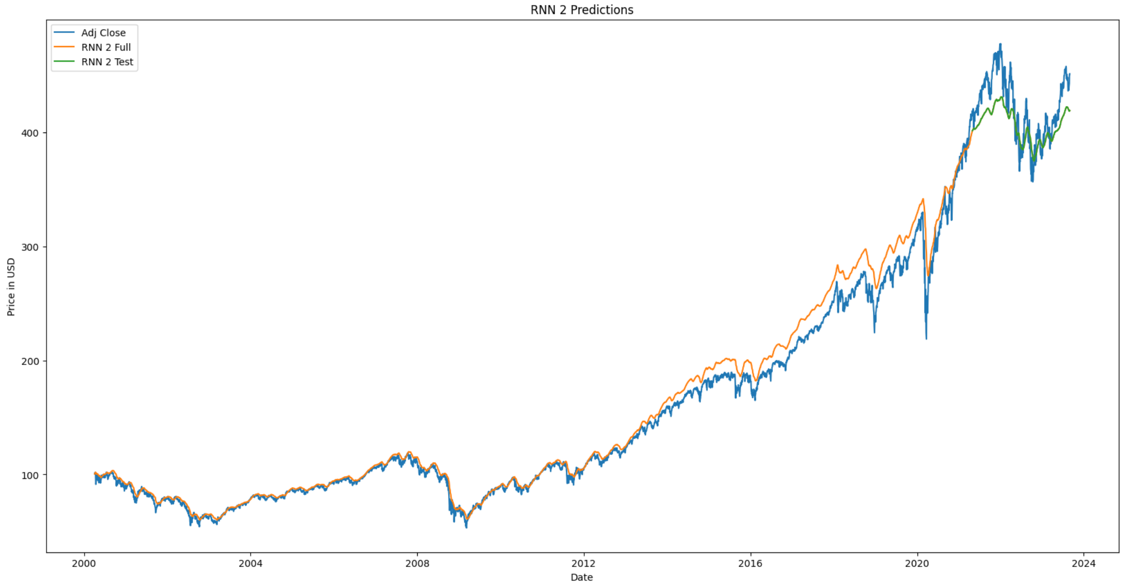


[45]:

```
# Plot RNN 2 reslts
plt.figure(figsize=(20,10))

plt.plot(SPY.index, SPY["Adj Close"], label="Adj Close")
plt.plot(SPY.index, SPY["RNN 2 Full"], label="RNN 2 Full")
plt.plot(SPY.index, SPY["RNN 2 Test"], label="RNN 2 Test")

plt.xlabel("Date")
plt.ylabel("Price in USD")
plt.legend()
plt.title("RNN 2 Predictions")
plt.show()
```



[46]:

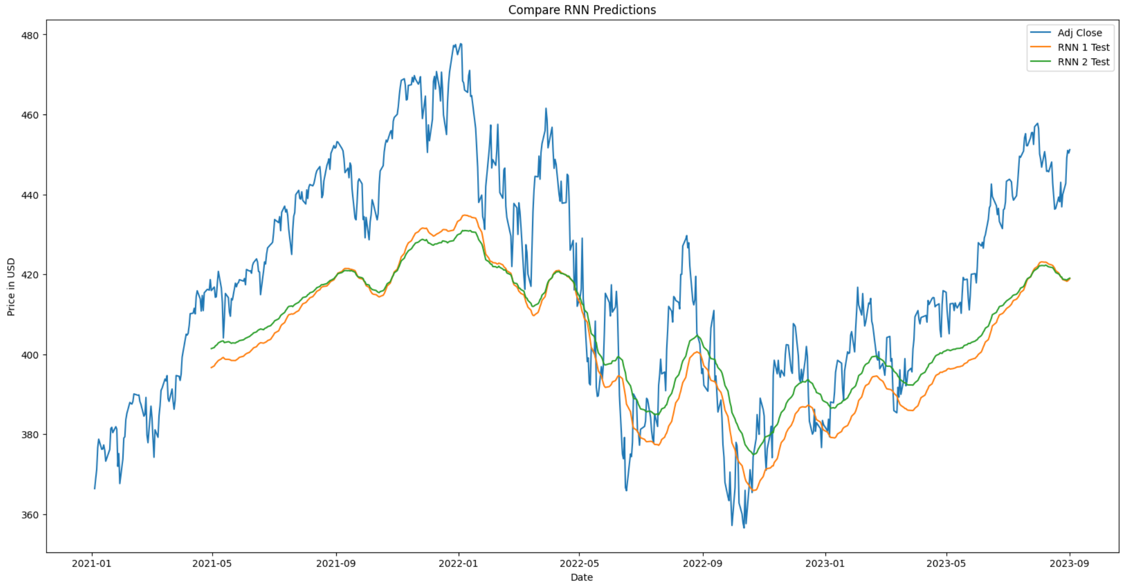
```
# Compare only the test predictions

SPY_ = SPY.loc["2021-01-03":]

# Plot RNN 2 reslts
plt.figure(figsize=(20,10))

plt.plot(SPY_.index, SPY_["Adj Close"], label="Adj Close")
plt.plot(SPY_.index, SPY_["RNN 1 Test"], label="RNN 1 Test")
plt.plot(SPY_.index, SPY_["RNN 2 Test"], label="RNN 2 Test")

plt.xlabel("Date")
plt.ylabel("Price in USD")
plt.legend()
plt.title("Compare RNN Predictions")
plt.show()
```



[ ]:

```
```