CS971: AI for Finance Assignment 2

Stewart Macfarlane, Vladimir Lenkov, Alvee Kabir

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Background and Project Overview

Background and Description of the Problem

The goal of this project is to build a trading system that leverages advanced machine learning techniques to forecast asset prices and execute trading decisions. The system first selects an optimal asset from the S&P 500 by evaluating risk-adjusted historical performance using daily returns and Sharpe ratios. Once the asset is chosen, its price data are pre-processed with technical indicators such as the RSI, MACD, and volume moving averages to capture market dynamics. An LSTM neural network which is well-known for its ability to model temporal dependencies is then employed to predict next-day prices. The model's hyperparameters are then finely tuned using both grid search and genetic algorithms. Finally, trading rules are applied to convert predictions (alone or in combination with RSI signals) into buy, sell, or hold actions in a simulated trading environment.

Related Work

Recent work on machine learning-based trading strategies spans deep neural models, technical analysis, and evolutionary optimization. Recurrent architectures like LSTM networks have been widely applied to stock price prediction and trading signal generation, leveraging their ability to capture temporal patterns and often outperforming traditional statistical models [1]. Many studies enhance such models by incorporating popular technical indicators such as RSI and MACD as input features, effectively fusing signals with data-driven learning to improve predictive accuracy [2]. In addition, optimization techniques like genetic algorithms have been used to fine-tune both model hyperparameters and strategy parameters. For example, GAs optimizing LSTM settings have achieved better forecasting performance than untuned benchmarks and similarly have been applied to calibrate indicator-based trading rules to maximize metrics like the Sharpe ratio [1]. These combined approaches demonstrate that integrating LSTM-driven prediction with technical indicators and applying evolutionary optimization can yield more robust, profitable trading strategies in practice which is precisely what our project aims to do.

Asset Selection

The initial assets were gathered using the S&P 500 index, a stock market index that tracks the performance of 500 of the largest trading companies in the United States. In addition to having an extensive collection of assets, this index represents a wide range of sectors including but not limited to technology, healthcare and finance. This serves as a solid foundation for selecting a significant asset for the project.

```
assets <- tq_index("SP500") # Load 500 assets from S&P
```

Furthermore, the daily returns for each asset are retrieved to calculate the Sharpe ratio.

```
load_daily_returns <- function(asset_symbols, startDate, endDate) { removed_assets <- c()
  assets_train <- lapply(asset_symbols, function(sym) {
    tryCatch(dailyReturn(getSymbols(sym, from = startDate, to = endDate, auto.assign = FALSE)),
      error = function(e) {removed_assets <<- append(removed_assets, sym); NULL})})
  asset_symbols <- setdiff(asset_symbols, removed_assets)
  df <- setNames(do.call(merge, c(assets_train, all = T)), asset_symbols)
  df <- na.omit(df); df <- df[, colSums(is.na(df)) < nrow(df)]
  return(df)}
```

The start and end date for the period to be used to make next-day predictions has been set to two months. This is so that enough data is present to reflect vital patterns to make predictions, however, not a long enough time period whereby the large quantity of historic data will negatively skew results.

```
asset_symbols <- assets$symbol; startDate <- "2024-08-01"; endDate <- "2024-12-31"
df <- load_daily_returns(asset_symbols, startDate, endDate)
```

```
calc_sharpe_ratio <- function(returns, rf_rate) {mean_return <- mean(returns); risk <- sd(returns)
  sharpe_ratio <- ((mean_return - rf_rate) / risk) * sqrt(252)
  return(sharpe_ratio)}
```

The performance of all 500 assets is evaluated and compared to one another based on their Sharpe ratios. The Sharpe ratio serves as a valuable tool for measuring investment prospects for a specific asset as it enables the comparison of the expected return for the level of risk being taken (risk-adjusted return). In this case, a risk-free rate is dynamically retrieved and used within the Sharpe ratio calculation for each asset.

$$S_a = \frac{E[R_a - R_b]}{\sigma_a}$$

$$Where: S_a = \text{Sharpe Ratio } E = \text{Expected Return}$$

$$R_a = \text{Asset Return } R_b = \text{Risk Free Rate } \sigma_a = \text{Asset Risk}$$

```
rf_rate <- as.numeric(last(getSymbols("DGS3MO", src = "FRED", auto.assign = FALSE)))/100 /252
best_res <- calc_sharpe_ratio(df[, 1], rf_rate); best_asset <- NULL
for (col in colnames(df)) { curr_sharpe <- calc_sharpe_ratio(df[, col], rf_rate)
  if (curr_sharpe > best_res) { best_res <- curr_sharpe; best_asset <- col}}
```

Once all assets have been compared, the best-performing asset is selected to be used to make next-day predictions in alignment with a comprehensive trading rule. All relevant data is then retrieved, this includes opening, high, low and closing prices.

```
best_asset_data <- getSymbols(best_asset, from = startDate, to = endDate, auto.assign = FALSE)
```

Data Preprocessing

Before training the LSTM-based model, we first enrich our data with technical indicators (RSI, MACD, and others), then remove any missing values and normalize each feature. Normalization helps ensure that the ranges of different variables do not negatively impact model training. Afterwards, we structure the data as sequences for the network by selecting the features of interest, choosing an appropriate sequence length and splitting into training and test sets.

We then add these new indicators as columns in our main dataset and remove any rows with missing values.

```
best_asset_data$RSI = rsi; best_asset_data$MACD = macd
best_asset_data$Volume_MA = volume_ma; best_asset_data = na.omit(best_asset_data)
```

Next, we normalize each column to the range [0,1] using a simple min-max scaling function to help the model converge more reliably during training.

```
data <- data.frame(best_asset_data[,1:9])
min_max_normalize <- function(x) {(x - min(x)) / (max(x) - min(x))}
data_scaled <- as.data.frame(lapply(data, min_max_normalize))
```

We now define a custom splitting function for time-series data. The idea is to convert our continuous dataset into overlapping sequences of length `seq_length`.

```
train_test_split <- function(asset, seq_length, target_feature, test_size = 0.2) {
  asset_matrix <- as.matrix(asset)
  num_seq <- nrow(asset_matrix) - seq_length + 1; num_features <- ncol(asset_matrix)
  seq_data <- array(dim = c(num_seq, seq_length, num_features))
  for (index in 1:(nrow(asset_matrix) - seq_length +1)) {
    seq_data[index, , ] <- asset_matrix[index:(index + seq_length - 1), ]}
  test_set_size <- round(test_size * nrow(seq_data)); train_set_size <- nrow(seq_data) - test_set_size
  x_train <- seq_data[1:train_set_size, 1:(seq_length - 1), , drop = FALSE]
  y_train <- seq_data[1:train_set_size, seq_length, target_feature, drop = FALSE]
  x_test  <- seq_data[(train_set_size + 1):nrow(seq_data), 1:(seq_length - 1), , drop = FALSE]
  y_test  <- seq_data[(train_set_size + 1):nrow(seq_data), seq_length, target_feature, drop = FALSE]
  return(list(x_train = x_train,y_train = y_train,x_test = x_test,y_test = y_test))}
```

With all preprocessing steps established, we can now select the columns to include and specify which feature to treat as our target for prediction. Below, we choose a sequence length of 8, meaning 7 steps for model inputs plus 1 step for the label.

```
open <- paste(best_asset, "Open", sep = ".");close <- paste(best_asset, "Close", sep = ".")
high <- paste(best_asset, "High", sep = ".");low <- paste(best_asset, "Low", sep = ".")
rsi = "RSI"; macd = "MACD"; volume_ma = "Volume_MA"; seq_length <- 8
features <- data_scaled[, c(open, high, low, close, macd, volume_ma)]
split_data <- train_test_split(features, seq_length, target_feature=4)
x_train <- split_data$x_train; y_train <- split_data$y_train
x_test <- split_data$x_test; y_test <- split_data$y_test
```

Finally, we split part of the training set again for validation. This secondary split is helpful for hyperparameter tuning without contaminating our final test set.

```
split_validation <- function(x, y, valid_prop = 0.2) { total <- dim(x)[1]
  valid_size <- round(valid_prop * total);train_size <- total - valid_size
  x_train_tune <- x[1:train_size, , , drop = FALSE]
  x_val <- x[(train_size + 1):total, , , drop = FALSE]; y <- as.matrix(y)
  y_train_tune <- y[1:train_size, , drop = FALSE]
  y_val <- y[(train_size + 1):total, , drop = FALSE]
  return(list(x_train_tune = x_train_tune,y_train_tune = y_train_tune,
    x_val = x_val,y_val = y_val))}
split_data <- split_validation(x_train, y_train, valid_prop = 0.2)
x_train_tune <- split_data$x_train_tune; y_train_tune <- split_data$y_train_tune
x_val <- split_data$x_val; y_val <- split_data$y_val
```

Optimising LSTM Parameters

The LSTM parameters are optimised using two techniques: grid search and genetic algorithms. This was done to compare the results from utilising traditional versus evolutionary approaches and conclude the pros and cons of each. Furthermore, the optimised parameters identified from this process are used by the LSTM to make predictions in conjunction with the proposed trading rule.

```
tune_lstm <- function(learningrate, hidden_dim, num_layers, numepochs, batch_size) {
  model <- trainr( Y = y_train_tune, X = x_train_tune, learningrate = learningrate,
    hidden_dim = hidden_dim, num_layers = num_layers, numepochs = numepochs,
    network_type = "lstm", seq_to_seq_unsync = TRUE,batch_size = batch_size)
  predictions <- predictr(model, x_val)
  mse <- mean((predictions - y_val)^2, na.rm = TRUE)
  return(mse)}
```

Grid Search

Grid search is a traditional approach to identifying optimal hyperparameter values for machine learning models. In this approach, the key hyperparameters to be tested are listed inside a vector, which the algorithm then systematically iterates over each combination and records the result. In this case, the mean squared error (MSE) is used on validation data to determine the current performance.

```
lr_vals <- c(0.001, 0.005, 0.01); hd_vals <- c(8, 16, 32, 64, 128) # Grid parameters
nl_vals <- c(1, 2, 3); ne_vals <- c(50, 100, 150, 200); bs_vals <- c(8, 16, 32, 64)
```

```
run_grid_search <- function(lr_vals, hd_vals, nl_vals, ne_vals, bs_vals){
  for (lr in lr_vals) {for (hd in hd_vals) {for (nl in nl_vals) {
    for (ne in ne_vals) {for (bs in bs_vals) { current_mse <- tune_lstm(lr,hd,nl,ne,bs)
          log_results(lr, hd, nl, ne, bs, current_mse)}}}}}}
#run_grid_search(lr_vals, hd_vals, nl_vals, ne_vals, bs_vals)
#best_params_GS <- results[which.min(results$mse), ]
```

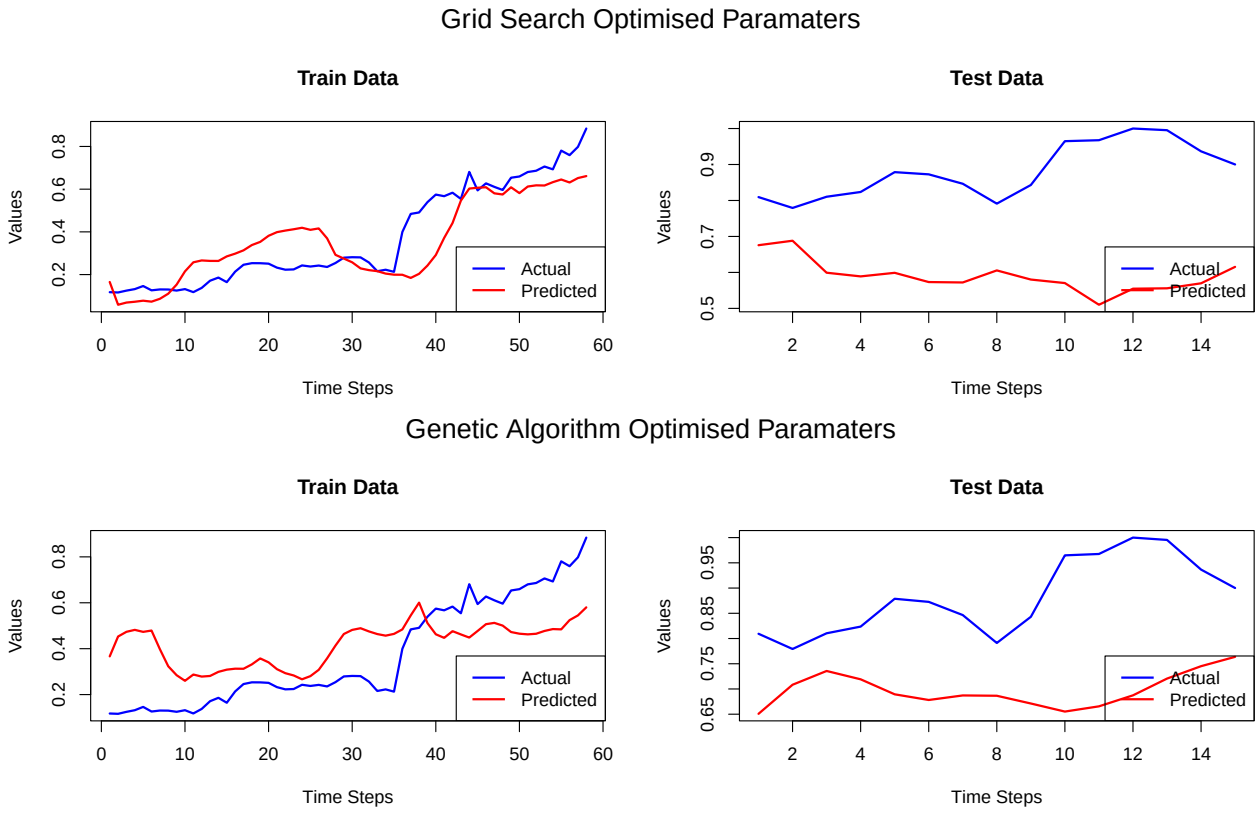
Genetic Algorithm

A genetic algorithm is an evolutionary process that mimics natural selection and genetics. This algorithm has been used to identify optimal hyperparameters within specified ranges (lower and upper). This implementation has a maximum of 100 iterations and will stop executing if the fitness does not improve after 20 iterations. The fitness is determined using the fitness function which evaluates performance against the MSE value.

```
fitness_function <- function(params) {
  lr <- params[1]; hd <- round(params[2]); nl <- round(params[3])
  ne <- round(params[4]); bs <- round(params[5])
  mse <- tune_lstm(lr, hd, nl, ne, bs)
  return(-mse)}
run_ga <- function(){ ga_result <- ga(type = "real-valued",fitness = fitness_function,
    lower = c(0.0001, 8, 1, 50, 8),upper = c(0.01, 128, 3, 200, 64),
    popSize = 20,maxiter = 100,run = 20)
    return(ga_result)}
#ga_result <- run_ga(); best_params_GA <- ga_result@solution
```

Optimisation Comparisons

Through experimenting with both of the above approaches key benefits and downfalls of each have been identified. First, Grid search is strictly limited to searching the specified hyperparameters whereas the GA solution can navigate the search space more effectively only being restricted to lower and upper bounds. Furthermore, both algorithms are computationally expensive, although, genetic algorithms have an edge as they can effectively terminate execution if the performance has not improved over a specified number of iterations, whereas grid search must evaluate all combinations. Finally, this difference between the two approaches is what sets them apart as a GA can get stuck in a local maximum and never converge to the optimal solution, on the other hand, grid search will evaluate all provided combinations guaranteeing the most optimal from the provided is found. Overall, both methods gain a similar performance using MSE. However, grid search slightly outperforms the GA result with an MSE score of 0.0161161 compared to 0.03577853 on the test (unseen) data.



TensorFlow LSTM

After observing suboptimal performance with our initial approach, we decided to utilise the TensorFlow framework to build and train a deeper LSTM network. The R interface to TensorFlow provides a higher-level API and greater flexibility in model design, allowing us to stack multiple LSTM layers and customise hyperparameters such as the hidden units and learning rate. Additionally, this setup supports advanced optimisations and GPU acceleration, which can significantly improve training speed and predictive performance. As a result, the deeper LSTM architecture built with TensorFlow was able to capture more complex temporal dynamics in the data and deliver significantly more accurate predictions.

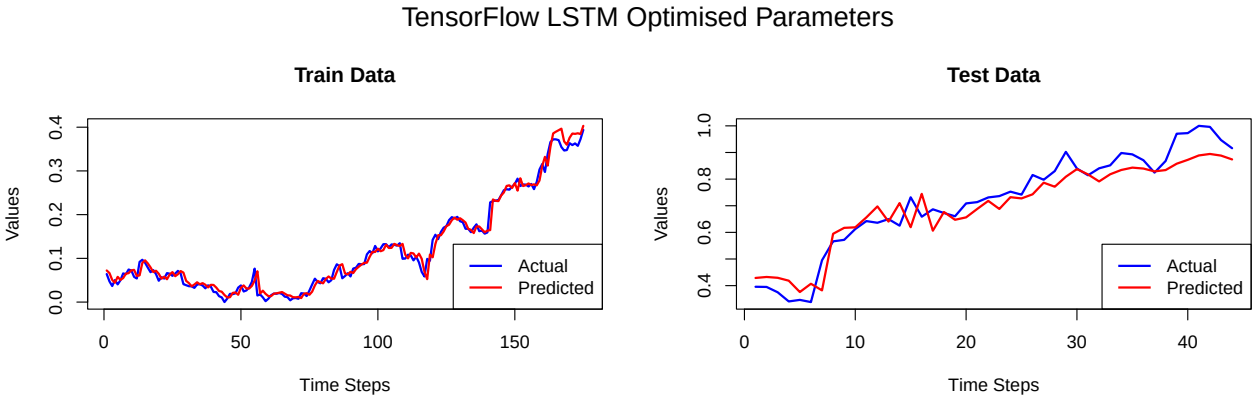
This was done in order to mitigate the problems that would arise during trading due to poor predictions. Namely, no "BUY" or "SELL" actions will take place given the significant discrepencies between the predicted and actual prices.

Below, we define a deeper LSTM architecture using TensorFlow. The network consists of three LSTM layers stacked on top of each other, this is then followed by a dense layer that outputs a single value. Stacking multiple LSTM layers helps the model capture more complex temporal patterns in our time series data. We compile the model with the Adam optimiser and use MSE as the primary loss function. Finally, we train the model for 200 epochs while feeding samples in batches of size 32 at each iteration. Given the success of grid search on the previous LSTM, this method has been employed again to optimise the following parameters: learning rate, hidden dimensions, number of epochs and batch size.

```
#lr <- best_params$learningrate; hd <- best_params$hidden_dim
#ne <- best_params$numepochs; bs <- best_params$batch_size
train_model <- function(lr, hd, ne, bs){
  model <- keras_model_sequential() %>%
  layer_lstm(units = hd, input_shape = c(7, 6), return_sequences = TRUE) %>%
  layer_lstm(units = hd, return_sequences = TRUE) %>%
  layer_lstm(units = hd) %>%
  layer_dense(units = 1, activation = "tanh")
  model %>% compile( optimizer = optimizer_adam(learning_rate = lr),
    loss = "mse", metrics = c("mse"))
  history <- model %>% fit( x_train, y_train, epochs = ne, batch_size = bs,
    validation_split = 0.2, verbose = 0)
    return(model)}
#model <- train_model(lr, hd, ne, bs)
#save_model_hdf5(model, "tensorflow_lstm.keras")
model <- load_model_hdf5("tensorflow_lstm.keras")
```

```
## 6/6 - 1s - 544ms/epoch - 91ms/step
```

```
## 2/2 - 0s - 16ms/epoch - 8ms/step
```



Algorithmic Trading

A trading strategy is a systematic plan for making trading decisions in the financial markets. Based on the price predictions made using tensorflow LSTM model, two different trading strategies have been utilised: 1. Prediction-Based strategy 2. Dual-Indicator strategy

Before the strategies can be implemented, the data for backtesting is prepared. Backtesting refers to testing the trading strategies using historical data of the asset to assess the performance of the strategy. The predicted and actual closing prices are inverse scaled

```
inverse_scale <- function(scaled_value, unscaled_min, unscaled_max) {
  scaled_value * (unscaled_max - unscaled_min) + unscaled_min}
predictions_scaled = model %>% predict(x_test)
```

```
## 2/2 - 0s - 17ms/epoch - 8ms/step
```

```
unscaled_min_close = min(data[, paste(best_asset, "Close", sep = ".")])
unscaled_max_close = max(data[, paste(best_asset, "Close", sep = ".")])
predictions_unscaled = inverse_scale(predictions_scaled, unscaled_min_close, unscaled_max_close)
actual_unscaled = inverse_scale(y_test, unscaled_min_close, unscaled_max_close)
```

Prediction-Based strategy

This strategy relies on the pre-trained TensorFlow LSTM model to predict the closing price of the asset for the next day. Based on the predictions, a "BUY" action is triggered and shares are bought when the predicted price for the next day is greater than the current price by a threshold of 1% (0.01) and if there is sufficient cash on hand to execute the purchase. If both conditions are satisfied, then the maximum number of shares affordable is bought. Otherwise, no shares will be purchased. On the other hand, a "SELL" action is triggered and shares are sold off when the predicted price for the next day is less than the current price by a threshold of -1% (-0.01) and if shares are currently held. If both conditions are satisfied, then shares can be sold. Additionally, a sub-action "SELL OUT" is triggered when the current price drops below the last buying price by more than a loss minimisation threshold of 5% (-0.05). This action is taken to minimise losses. If neither a buy or sell condition is met, then the "HOLD" action is triggered. Finally on the last day, all of the remaining shares are sold off which acts as the final day liquidation.

```
starting_funds = 10000; investment = starting_funds
cash_on_hand = starting_funds; shares = 0
trading_rule = data.frame(
  Date = index(tail(best_asset_data, nrow(y_test))), actual_price = rep(NA, nrow(y_test)),
  predicted_price = rep(NA, nrow(y_test)), action = character(nrow(y_test)),
  asset_value = numeric(nrow(y_test)), shares_held = numeric(nrow(y_test)),
  cash_held = numeric(nrow(y_test)), daily_profit_loss = numeric(nrow(y_test)))
trading_rule$asset_value[1] = starting_funds; trading_rule$shares_held[1] = shares
trading_rule$cash_held[1] = cash_on_hand; trading_rule$daily_profit_loss[1] = 0
trading_rule$actual_price = actual_unscaled; trading_rule$predicted_price = predictions_unscaled
threshold_buy = 0.01; threshold_sell = -0.01
loss_minimisation_threshold = -0.05; last_buy_price = 0
for(i in 1:nrow(trading_rule)){
  current_price = trading_rule$actual_price[i]
  predicted_price = trading_rule$predicted_price[i]
  action = "HOLD"
  if(!is.na(predicted_price) && !is.na(current_price)){
    predicted_change_percentage = (predicted_price - current_price) / current_price
    if(predicted_change_percentage > threshold_buy && cash_on_hand > current_price){
      action = "BUY"
    } else if(predicted_change_percentage < threshold_sell && cash_on_hand < current_price && shares > 0
  trading_rule$action[i] = action
  previous_asset_value = trading_rule$asset_value[i]
  if(i > 1){
    cash_on_hand = trading_rule$cash_held[i-1]
    shares = trading_rule$shares_held[i-1]
    previous_asset_value = trading_rule$asset_value[i-1]}
```

```
  if(trading_rule$action[i] == "BUY" && cash_on_hand > 0){
    buy_quantity = floor(cash_on_hand / current_price)
    if(buy_quantity > 0){
      shares = shares + buy_quantity
      cash_on_hand = cash_on_hand - (buy_quantity * current_price)
      last_buy_price = current_price}
  } else if(trading_rule$action[i] == "SELL" && shares > 0){
    sell_value = shares * current_price
    if (last_buy_price > 0 && (current_price - last_buy_price) / last_buy_price < loss_minimisation_thr
      cash_on_hand = cash_on_hand + sell_value
      shares = 0
      last_buy_price = 0
      trading_rule$action[i] = "SELL OUT"
    } else {
      cash_on_hand = cash_on_hand + sell_value
      shares = 0
      last_buy_price = 0}}
  trading_rule$asset_value[i] = cash_on_hand + (shares * current_price)
  trading_rule$shares_held[i] = shares
  trading_rule$cash_held[i] = cash_on_hand
  # Calculate daily profit/loss
  if (i > 1) {
    trading_rule$daily_profit_loss[i] = trading_rule$asset_value[i] - previous_asset_value}
  # Sell all on the final day
  if (i == nrow(trading_rule) && trading_rule$shares_held[i] > 0) {
    final_sell_value = trading_rule$shares_held[i] * current_price
    trading_rule$asset_value[i] = trading_rule$cash_held[i] + final_sell_value
    trading_rule$cash_held[i] = trading_rule$cash_held[i] + final_sell_value
    trading_rule$shares_held[i] = 0
    trading_rule$action[i] = "SELL"}}
final_asset_value = tail(trading_rule$asset_value, 1)
initial_investment = starting_funds
profit_loss = final_asset_value - initial_investment
roi = (profit_loss / initial_investment) * 100
```

```
##   Final_Asset_Value Profit_Loss ROI_Percentage
## 1          13833.16     3833.16         38.33%
```

Dual-Indicator strategy

The Dual-Indicator strategy is similar to the Prediction-Based strategy, but utlises Relative Strength Index (RSI), a momentum indicator, alongside the LSTM predicted price movements. The conditions for "BUY" action to trigger is similar (with minor changes in the threshold buy value) with the addition of checking whether the oversold threshold is below 70. Consequently for "SELL", the overbought threshold needs to be above 30 along with the other conditions (with minor changes in the threshold sell value).

```
#Revised Dual-Indicator Trading Strategy
threshold_buy <- 0.03; threshold_sell <- -0.2
oversold_threshold <- 70; overbought_threshold <- 30
loss_minimisation_threshold <- -0.05; last_buy_price <- 0
# Reinitialize simulation variables
investment_dual <- 10000; cash_on_hand <- investment_dual; shares_dual <- 0
```

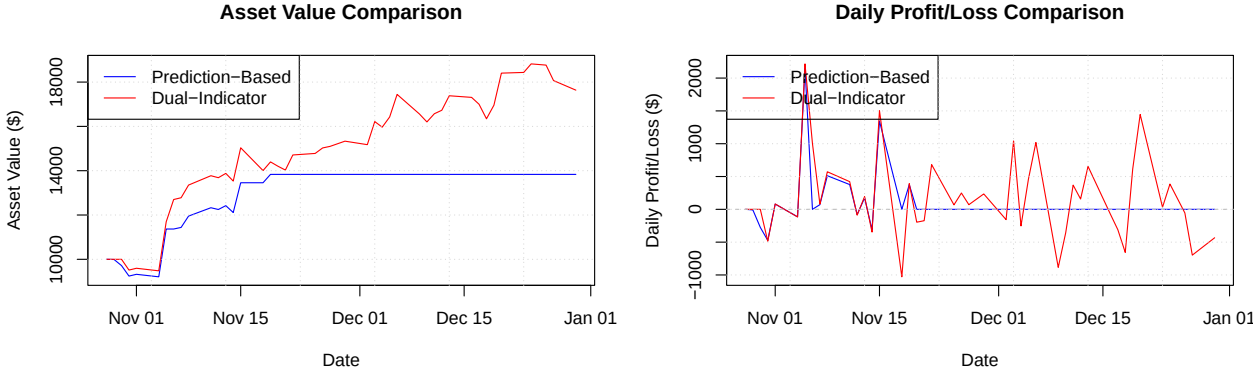
```r
# Build the trading log for the dual-indicator strategy
trading_rule_dual <- data.frame(
  Date = index(tail(best_asset_data, nrow(y_test))), actual_price = rep(NA, nrow(y_test)),
  predicted_price = rep(NA, nrow(y_test)), RSI = as.numeric(tail(best_asset_data$RSI, nrow(y_test))),
  action = character(nrow(y_test)), asset_value = numeric(nrow(y_test)),
  shares_held = numeric(nrow(y_test)), cash_held = numeric(nrow(y_test)),
  daily_profit_loss = numeric(nrow(y_test)))
trading_rule_dual$asset_value[1] <- investment_dual; trading_rule_dual$shares_held[1] <- shares_dual
trading_rule_dual$cash_held[1] <- cash_on_hand; trading_rule_dual$daily_profit_loss[1] <- 0
trading_rule_dual$actual_price <- actual_unscaled; trading_rule_dual$predicted_price <- predictions_unsc
# Simulation loop with debug prints for the first few iterations
for(i in 1:nrow(trading_rule_dual)){
  current_price = trading_rule_dual$actual_price[i]
  predicted_price = trading_rule_dual$predicted_price[i]
  current_rsi = trading_rule_dual$RSI[i]
  action = "HOLD"
  if(!is.na(predicted_price) && !is.na(current_price) && !is.na(current_rsi)){
    predicted_change_percentage = (predicted_price - current_price) / current_price
    if(predicted_change_percentage > threshold_buy && current_rsi < oversold_threshold && cash_on_hand >
      action = "BUY"
    } else if(predicted_change_percentage < threshold_sell && current_rsi > overbought_threshold && shar
      action = "SELL"}}
  trading_rule_dual$action[i] = action
  previous_asset_value = trading_rule_dual$asset_value[i]
  if(i > 1){
    cash_on_hand = trading_rule_dual$cash_held[i-1]
    shares_dual = trading_rule_dual$shares_held[i-1]
    previous_asset_value = trading_rule_dual$asset_value[i-1]}
  if(trading_rule_dual$action[i] == "BUY" && cash_on_hand > 0){
    buy_quantity = floor(cash_on_hand / current_price)
    if(buy_quantity > 0){
      shares_dual = shares_dual + buy_quantity
      cash_on_hand = cash_on_hand - (buy_quantity * current_price)
      last_buy_price = current_price}
  } else if(trading_rule_dual$action[i] == "SELL" && shares_dual > 0){
    sell_value = shares_dual * current_price
    if (last_buy_price > 0 && (current_price - last_buy_price) / last_buy_price < loss_minimisation_thre
      cash_on_hand = cash_on_hand + sell_value
      shares_dual = 0
      last_buy_price = 0
      trading_rule_dual$action[i] = "SELL OUT"
    } else {
      cash_on_hand = cash_on_hand + sell_value
      shares_dual = 0
      last_buy_price = 0}}
  trading_rule_dual$asset_value[i] = cash_on_hand + (shares_dual * current_price)
  trading_rule_dual$shares_held[i] = shares_dual
  trading_rule_dual$cash_held[i] = cash_on_hand
  # Calculate daily profit/loss
  if (i > 1) {
    trading_rule_dual$daily_profit_loss[i] = trading_rule_dual$asset_value[i] - previous_asset_value}
  # Sell all on the final day
  if (i == nrow(trading_rule_dual) && trading_rule_dual$shares_held[i] > 0) {
```

```
    final_sell_value = trading_rule_dual$shares_held[i] * current_price
    trading_rule_dual$asset_value[i] = trading_rule_dual$cash_held[i] + final_sell_value
    trading_rule_dual$cash_held[i] = trading_rule_dual$cash_held[i] + final_sell_value
    trading_rule_dual$shares_held[i] = 0
    trading_rule_dual$action[i] = "SELL"}}
final_asset_value = tail(trading_rule_dual$asset_value, 1)
initial_investment = investment_dual
profit_loss = final_asset_value - initial_investment
roi = (profit_loss / initial_investment) * 100
```

```
##   Final_Asset_Value Profit_Loss ROI_Percentage
## 1          17635.72     7635.72         76.36%
```

Comparison

The profit is calculated based on the final asset value subtracted by the initial investment in trading. Daily profits and losses are tracked based on the changes in the asset value each day. In the end, the trading strategy performance (based on the value of the asset) and daily profit/loss are plotted to get a visual representation of the strategy. These are then compared for both strategies to gain a visual understanding of their performance. It can be observed that the Dual-Indicator trading strategy outperforms the Prediction-Based strategy. This can be attributed to RSI acting as another filter to add momentum to the trades and filter out less reliable prediction-based signals.



References

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