CS971: AI for Finance Assignment 2

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11-04-2025

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), ]
```

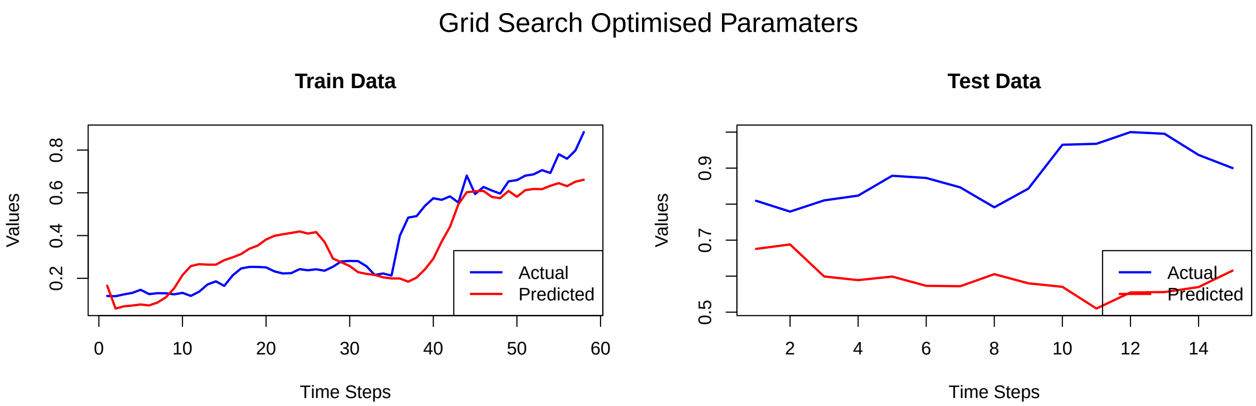
Genetic Algorithm

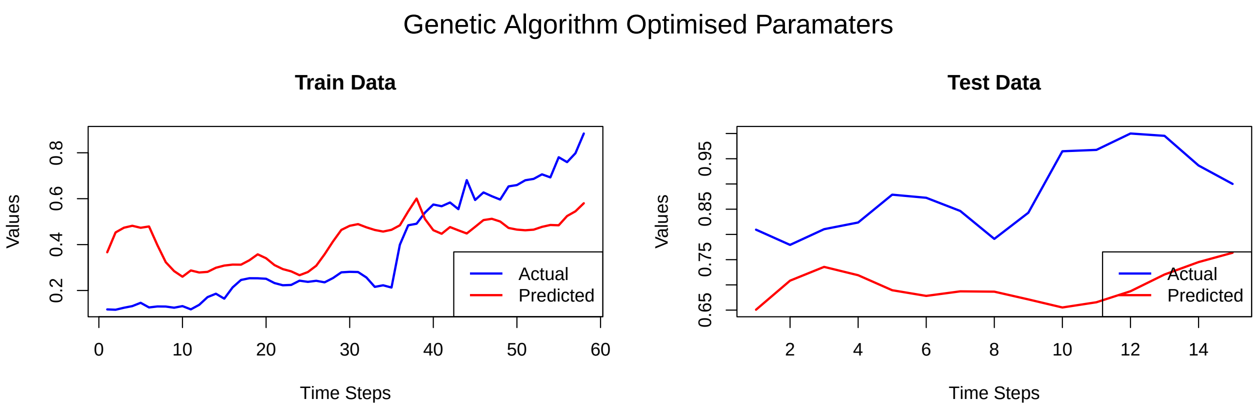
A genetic algorithm is an evolutionary process that mimics natural selection and genetics. This algorithm has been used to identify optimal hyperparameters within specified ranges (lower and upper). This implementation has a maximum of 100 iterations and will stop executing if the fitness does not improve 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, for this reason, the LSTM trained with optimised parameters from grid search will be used for algorithmic trading.





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.

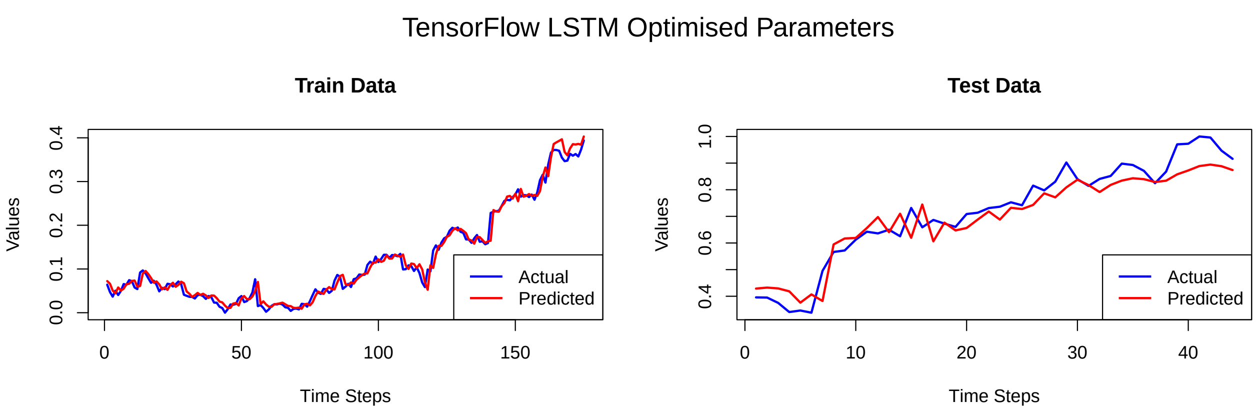
This was done in order to mitigate the problems that would arise during trading due to poor predictions. Namely, no “BUY” or “SELL” actions will take place given the significant discrepencies between the predicted and actual prices.

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 - 548ms/epoch - 91ms/step
```

```
## 2/2 - 0s - 14ms/epoch - 7ms/step
```



Trading

A trading strategy is a systematic plan for making trading decisions in the financial markets. Based on the price predictions made using the Grid Search (GS) and Genetic Algorithm (GA) LSTM models, 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

```r
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 - 15ms/epoch - 7ms/step
```

```r
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 GA 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.

```r
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
```

```r
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
      action = "SELL"
    }
  }
  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_thre
      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
```

```r
  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
cat("\nFinal Asset Value: $", round(final_asset_value, 2), "\n")
```

```
##
## Final Asset Value: $ 13833.16
```

```r
cat("Profit/Loss: $", round(profit_loss, 2), "\n")
```

```
## Profit/Loss: $ 3833.16
```

```r
cat("Return on Investment (ROI): ", round(roi, 2), "%\n")
```

```
## Return on Investment (ROI):  38.33 %
```

```r
print(trading_rule)
```

```
##          Date actual_price predicted_price action asset_value shares_held
## 1  2024-10-28        44.97        47.01913    BUY   10000.000         222
## 2  2024-10-29        44.93        47.24749   HOLD    9991.120         222
## 3  2024-10-30        43.69        47.05579   HOLD    9715.839         222
## 4  2024-10-31        41.56        46.38199   HOLD    9242.980         222
## 5  2024-11-01        41.92        43.74469   HOLD    9322.899         222
## 6  2024-11-04        41.41        45.66875   HOLD    9209.680         222
## 7  2024-11-05        51.13        44.12522   SELL   11367.520           0
## 8  2024-11-06        55.53        57.28683    BUY   11367.520         204
## 9  2024-11-07        55.88        58.66763   HOLD   11438.920         204
## 10 2024-11-08        58.39        58.78885   HOLD   11950.960         204
## 11 2024-11-11        60.24        61.09233   HOLD   12328.361         204
## 12 2024-11-12        59.85        63.65119   HOLD   12248.800         204
## 13 2024-11-13        60.70        60.12133   HOLD   12422.200         204
## 14 2024-11-14        59.18        64.42734   HOLD   12112.120         204
## 15 2024-11-15        65.77        58.81952   SELL   13456.480           0
## 16 2024-11-18        61.26        66.57191    BUY   13456.480         219
## 17 2024-11-19        62.98        58.00428   SELL   13833.160           0
## 18 2024-11-20        62.12        62.35580   HOLD   13833.160           0
## 19 2024-11-21        61.36        60.54299   HOLD   13833.160           0
## 20 2024-11-22        64.35        61.10736   HOLD   13833.160           0
## 21 2024-11-25        64.65        63.05785   HOLD   13833.160           0
## 22 2024-11-26        65.74        64.93962   HOLD   13833.160           0
```

```
## 23 2024-11-27        66.05        63.06273   HOLD   13833.160            0
## 24 2024-11-29        67.08        65.79993   HOLD   13833.160            0
## 25 2024-12-02        66.39        65.51249   HOLD   13833.160            0
## 26 2024-12-03        70.96        66.46480   HOLD   13833.160            0
## 27 2024-12-04        69.85        69.16815   HOLD   13833.160            0
## 28 2024-12-05        71.87        68.22824   HOLD   13833.160            0
## 29 2024-12-06        76.34        70.55065   HOLD   13833.160            0
## 30 2024-12-09        72.46        72.32747   HOLD   13833.160            0
## 31 2024-12-10        70.89        71.09394   HOLD   13833.160            0
## 32 2024-12-11        72.51        69.45679   HOLD   13833.160            0
## 33 2024-12-12        73.20        71.12399   HOLD   13833.160            0
## 34 2024-12-13        76.07        72.12299   HOLD   13833.160            0
## 35 2024-12-16        75.75        72.66921   HOLD   13833.160            0
## 36 2024-12-17        74.39        72.45251   HOLD   13833.160            0
## 37 2024-12-18        71.51        71.79705   HOLD   13833.160            0
## 38 2024-12-19        74.21        72.10196   HOLD   13833.160            0
## 39 2024-12-20        80.55        73.57722   HOLD   13833.160            0
## 40 2024-12-23        80.69        74.48263   HOLD   13833.160            0
## 41 2024-12-24        82.38        75.50291   HOLD   13833.160            0
## 42 2024-12-26        82.14        75.84655   HOLD   13833.160            0
## 43 2024-12-27        79.08        75.46748   HOLD   13833.160            0
## 44 2024-12-30        77.18        74.57321   HOLD   13833.160            0
##       cash_held daily_profit_loss
## 1      16.65973          0.000000
## 2      16.65973         -8.880203
## 3      16.65973       -275.280373
## 4      16.65973       -472.859390
## 5      16.65973         79.919289
## 6      16.65973       -113.219627
## 7   11367.51997       2157.840271
## 8      39.40022          0.000000
## 9      39.40022         71.400467
## 10     39.40022        512.039658
## 11     39.40022        377.400467
## 12     39.40022        -79.560654
## 13     39.40022        173.400467
## 14     39.40022       -310.080093
## 15 13456.47953       1344.359253
## 16     40.53990          0.000000
## 17 13833.15980        376.680267
## 18 13833.15980          0.000000
## 19 13833.15980          0.000000
## 20 13833.15980          0.000000
## 21 13833.15980          0.000000
## 22 13833.15980          0.000000
## 23 13833.15980          0.000000
## 24 13833.15980          0.000000
## 25 13833.15980          0.000000
## 26 13833.15980          0.000000
## 27 13833.15980          0.000000
## 28 13833.15980          0.000000
## 29 13833.15980          0.000000
## 30 13833.15980          0.000000
## 31 13833.15980          0.000000
```

```
## 32 13833.15980          0.000000
## 33 13833.15980          0.000000
## 34 13833.15980          0.000000
## 35 13833.15980          0.000000
## 36 13833.15980          0.000000
## 37 13833.15980          0.000000
## 38 13833.15980          0.000000
## 39 13833.15980          0.000000
## 40 13833.15980          0.000000
## 41 13833.15980          0.000000
## 42 13833.15980          0.000000
## 43 13833.15980          0.000000
## 44 13833.15980          0.000000
```

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 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.

```r
#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

# 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_unscaled
```

```r
# 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 && sha
      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
  }
```

```r
  # 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
cat("\nFinal Asset Value: $", round(final_asset_value, 2), "\n")
```

```
##
## Final Asset Value: $ 17635.72
```

```r
cat("Profit/Loss: $", round(profit_loss, 2), "\n")
```

```
## Profit/Loss: $ 7635.72
```

```r
cat("Return on Investment (ROI): ", round(roi, 2), "%\n")
```

```
## Return on Investment (ROI):  76.36 %
```

```r
print(trading_rule_dual)
```

```
##          Date actual_price predicted_price      RSI action asset_value
## 1  2024-10-28        44.97        47.01913 74.48528   HOLD   10000.000
## 2  2024-10-29        44.93        47.24749 74.13794   HOLD   10000.000
## 3  2024-10-30        43.69        47.05579 64.15137    BUY   10000.000
## 4  2024-10-31        41.56        46.38199 51.35469   HOLD    9514.361
## 5  2024-11-01        41.92        43.74469 53.05900   HOLD    9596.440
## 6  2024-11-04        41.41        45.66875 50.36680   HOLD    9480.160
## 7  2024-11-05        51.13        44.12522 75.68703   HOLD   11696.321
## 8  2024-11-06        55.53        57.28683 80.52929   HOLD   12699.520
## 9  2024-11-07        55.88        58.66763 80.85591   HOLD   12779.321
## 10 2024-11-08        58.39        58.78885 83.05165   HOLD   13351.600
## 11 2024-11-11        60.24        61.09233 84.46587   HOLD   13773.401
## 12 2024-11-12        59.85        63.65119 82.89550   HOLD   13684.480
## 13 2024-11-13        60.70        60.12133 83.61069   HOLD   13878.280
## 14 2024-11-14        59.18        64.42734 77.37990   HOLD   13531.720
## 15 2024-11-15        65.77        58.81952 83.21879   HOLD   15034.240
## 16 2024-11-18        61.26        66.57191 69.91740   HOLD   14005.960
## 17 2024-11-19        62.98        58.00428 71.77057   HOLD   14398.120
## 18 2024-11-20        62.12        62.35580 69.46632   HOLD   14202.040
## 19 2024-11-21        61.36        60.54299 67.40672   HOLD   14028.760
## 20 2024-11-22        64.35        61.10736 71.04411   HOLD   14710.480
```

```
## 21 2024-11-25        64.65        63.05785 71.38912   HOLD   14778.881
## 22 2024-11-26        65.74        64.93962 72.66356   HOLD   15027.400
## 23 2024-11-27        66.05        63.06273 73.03150   HOLD   15098.081
## 24 2024-11-29        67.08        65.79993 74.27062   HOLD   15332.921
## 25 2024-12-02        66.39        65.51249 71.88769   HOLD   15175.600
## 26 2024-12-03        70.96        66.46480 77.12301   HOLD   16217.560
## 27 2024-12-04        69.85        69.16815 73.54068   HOLD   15964.480
## 28 2024-12-05        71.87        68.22824 75.74836   HOLD   16425.041
## 29 2024-12-06        76.34        70.55065 79.77070   HOLD   17444.199
## 30 2024-12-09        72.46        72.32747 69.06309   HOLD   16559.560
## 31 2024-12-10        70.89        71.09394 65.24663   HOLD   16201.600
## 32 2024-12-11        72.51        69.45679 67.25726   HOLD   16570.961
## 33 2024-12-12        73.20        71.12399 68.10368   HOLD   16728.280
## 34 2024-12-13        76.07        72.12299 71.41385   HOLD   17382.640
## 35 2024-12-16        75.75        72.66921 70.53490   HOLD   17309.680
## 36 2024-12-17        74.39        72.45251 66.77340   HOLD   16999.600
## 37 2024-12-18        71.51        71.79705 59.53315   HOLD   16342.961
## 38 2024-12-19        74.21        72.10196 63.52605   HOLD   16958.560
## 39 2024-12-20        80.55        73.57722 70.80956   HOLD   18404.081
## 40 2024-12-23        80.69        74.48263 70.94753   HOLD   18436.001
## 41 2024-12-24        82.38        75.50291 72.62924   HOLD   18821.320
## 42 2024-12-26        82.14        75.84655 71.99192   HOLD   18766.600
## 43 2024-12-27        79.08        75.46748 64.25046   HOLD   18068.921
## 44 2024-12-30        77.18        74.57321 59.94046   SELL   17635.720
##    shares_held   cash_held daily_profit_loss
## 1            0 10000.00000           0.00000
## 2            0 10000.00000           0.00000
## 3          228    38.68031           0.00000
## 4          228    38.68031        -485.63937
## 5          228    38.68031          82.07927
## 6          228    38.68031        -116.27962
## 7          228    38.68031        2216.16028
## 8          228    38.68031        1003.19948
## 9          228    38.68031          79.80052
## 10         228    38.68031         572.27962
## 11         228    38.68031         421.80052
## 12         228    38.68031         -88.92073
## 13         228    38.68031         193.80052
## 14         228    38.68031        -346.56010
## 15         228    38.68031        1502.51917
## 16         228    38.68031       -1028.27962
## 17         228    38.68031         392.16028
## 18         228    38.68031        -196.08014
## 19         228    38.68031        -173.27962
## 20         228    38.68031         681.71951
## 21         228    38.68031          68.40070
## 22         228    38.68031         248.51917
## 23         228    38.68031          70.68118
## 24         228    38.68031         234.83972
## 25         228    38.68031        -157.32056
## 26         228    38.68031        1041.95993
## 27         228    38.68031        -253.08014
## 28         228    38.68031         460.56097
## 29         228    38.68031        1019.15854
```

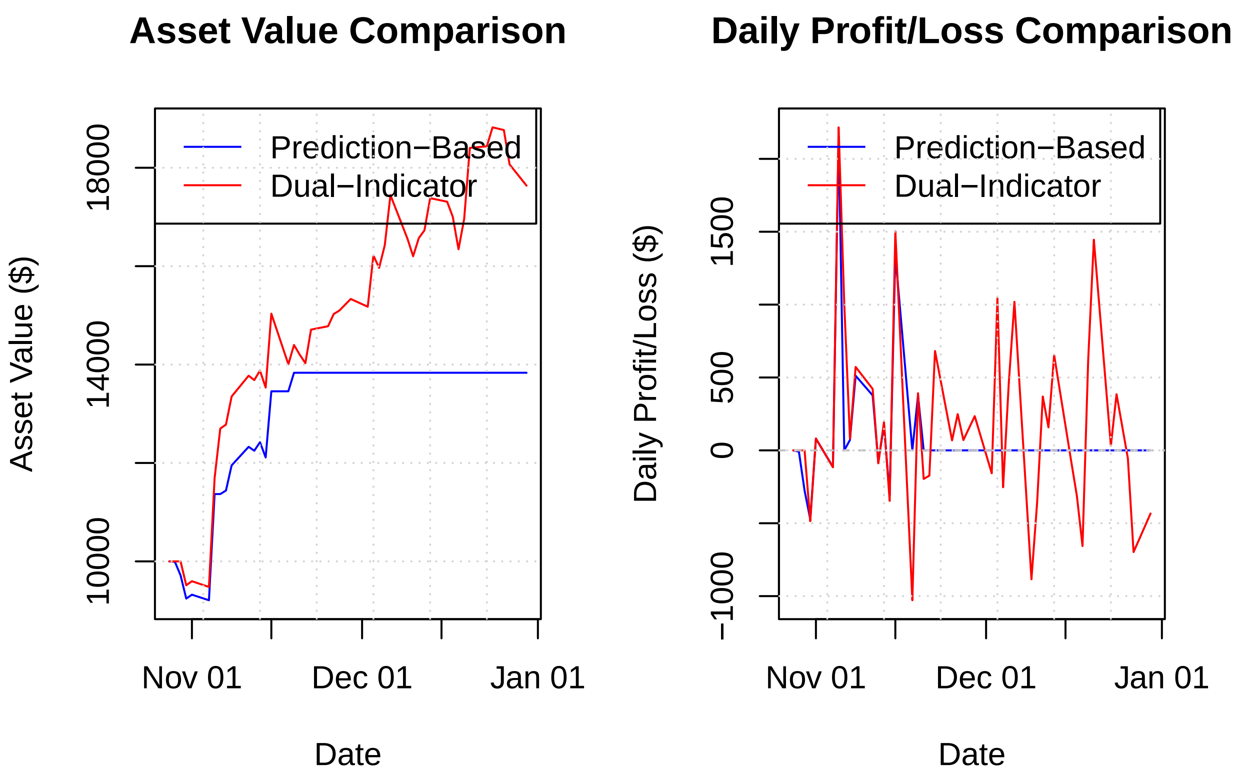
```
## 30          228    38.68031        -884.63937
## 31          228    38.68031        -357.95993
## 32          228    38.68031         369.36063
## 33          228    38.68031         157.31882
## 34          228    38.68031         654.36063
## 35          228    38.68031         -72.95993
## 36          228    38.68031        -310.08014
## 37          228    38.68031        -656.63937
## 38          228    38.68031         615.59930
## 39          228    38.68031        1445.52090
## 40          228    38.68031          31.91986
## 41          228    38.68031         385.31882
## 42          228    38.68031         -54.71951
## 43          228    38.68031        -697.67944
## 44            0 17635.72038        -433.20035
```

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.

```r
par(mfrow = c(1, 2))
plot(trading_rule$Date, trading_rule$asset_value, type = "l", col = "blue",
     xlab = "Date", ylab = "Asset Value ($)",
     main = "Asset Value Comparison", ylim = range(c(trading_rule$asset_value, trading_rule_dual$asset_v
lines(trading_rule_dual$Date, trading_rule_dual$asset_value, type = "l", col = "red")
legend("topleft", legend = c("Prediction-Based", "Dual-Indicator"), col = c("blue", "red"), lty = 1)
grid()

plot(trading_rule$Date, trading_rule$daily_profit_loss, type = "l", col = "blue",
     xlab = "Date", ylab = "Daily Profit/Loss ($)",
     main = "Daily Profit/Loss Comparison", ylim = range(c(trading_rule$daily_profit_loss, trading_rule_
lines(trading_rule_dual$Date, trading_rule_dual$daily_profit_loss, type = "l", col = "red")
legend("topleft", legend = c("Prediction-Based", "Dual-Indicator"), col = c("blue", "red"), lty = 1)
abline(h = 0, lty = "dashed", col = "gray")
grid()
```




```
par(mfrow = c(1, 1))
```

References

[1] A. Dangi, "Optimizing LSTM Network using Genetic Algorithm for Stock Market Price Prediction," 24 April 2023. [Online]. Available: https://www.linkedin.com/pulse/optimizing-lstm-network-using-genetic-algorithm-stock-akash-dangi/. [Accessed 10 April 2025].

[2] R. M. Dhokane and S. Agarwal, "LSTM Deep Learning Based Stock Price Prediction with Bollinger Band, RSI, MACD, and OHLC Features," International Journal of Intelligent Systems and Applications in Engineering, vol. 12, no. 3, p. 1169–1176, 2024.