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Investment Strategy: A low-volatility and momentum strategy with LSTM neural network 1-day predictions

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ABSTRACT In the dynamic landscape of stock market prediction, the intricate nature of non-linear patterns and temporal dependencies poses a challenge for accurate forecasting. This paper explores the utilization of advanced machine learning techniques, specifically Long Short-Term Memory (LSTM) networks, to enhance the precision and reliability of stock value prediction for investment strategies. Combining the use of this type of neural network with pre-selection based on the analysis of asset volatility and momentum is capable of providing a favorable outcome for portfolio construction.

INDEX TERMS finance, lstm, momentum, portfolio, quantitative, returns, strategy, volatility, wallet

I. INTRODUCTION

THE prediction of stock values may not be as straightforward due to the dependence on non-linear patterns and temporal dependencies. Therefore, the use of more advanced machine learning techniques can facilitate a more accurate and reliable prediction compared to models with linear dependencies. Thus, the use of LSTM (Long Short-Term Memory) networks can be advantageous due to their capacity for learning and retaining patterns identified in extensive time series data, as opposed to regression methods or typical recurrent neural networks where issues of vanishing or exploding gradients may arise.

In traditional approaches, problems such as vanishing or exploding gradients can lead to long-term memory terms, corresponding to inputs from distant past, being minimized to the extent that they have little influence on learning or growing excessively large compared to the current input, giving unwanted weight to the network's long-term memory at the expense of the current input.

Additionally, an initial step of pre-selecting assets was adopted based on a 'Low-Volatility-Momentum' strategy, which aims to identify whether the asset's volatility is high. According to academic literature, a momentum strategy involves buying past winners and selling past losers, relying on the ability of past returns to predict future returns. Evidence indicates that momentum profits are significantly positive and widespread across multiple time periods.

II. METHODOLOGY

A. LOW-VOLATILITY-MOMENTUM

The first stage of the asset selection strategy involves a pre-selection of available assets in the database based on their volatilities and momentum scores over periods of 21, 63 and 126 days - 1 working month time, 3 working months and 6 working months time, respectively.

Volatility is defined from the log-return of an asset compared to the previous day, and those with high volatility do not pass the test. The volatility threshold is determined through visual inspection of the data and can be adjusted as needed in the case of changes in the index or database.

Momentum score is defined as the log-returns of assets over a period (comparing the current date with the date from the defined period), which can be short, medium, or long term. In this strategy, three periods were chosen, one for the medium term and two for the long term, with weights assigned to form a weighted average. Thus, momentum for 21 days (weight 4), 63 days (weight 3) and 126 days (weight 3) were established. Then, from the analysis of the momentum frequencies of assets in the database, it was decided that all assets with an average momentum below $log(1.1)$ (average appreciation of 10% over the historical medium and long term) would be disqualified in the pre-selection.

Finally, from the assets not disqualified in the tests above, the top 10 scores (this value can be easily changed if more assets are necessary) of the weighted average of momentum were filtered to proceed to the next stage.

B. LSTM NETWORK

The LSTM stage involves using data from the assets selected in the Low-Volatility-Momentum stage to predict the returns for the next day. Subsequently, the selected assets and their respective weights are determined based on these predicted returns.

Initially, the dataset is prepared for model training. Tables are constructed with log-returns' values up to $n = 60$ days prior for each available date, along with the log-return target (next date compared to the current). The data related to the 60-day log-returns will be used to predict the target value.

As for the architecture of the LSTM network, the decision was made to predict each asset using the others as exogenous variables. To select the best configuration of hidden layers, an iteration was set up to find the optimal combination of the number of *Dense* layers and the number of neurons in each *Dense* layer based on the lowest mean square error, although the number of LSTM neurons was fixed in 96, which may hereafter be altered in order to also be included in the optimization iteration. This theoretically allows the model to provide a reliable prediction of the return for the next date.

Finally, from the predicted returns, only the positive ones are chosen, and the weights of the assets in the portfolio are determined based on the following expression:

$$w_A = \frac{ret_A}{\sum_i^n ret_i} \tag{1}$$

where ret_a is the return of asset A e w_s is the weight of asset A.

III. RESULTS AND DISCUSSION

It was chosen to select the S&P 500 index to test the defined strategy.

A. LOW VOLATILITY AND HIGH MOMENTUM

In-depth visual analysis was performed on the dataset, specifically focusing on the log returns of the index's assets. The examination led to the determination that setting the volatility limit at 0.02 would be an appropriate choice.

Following the pre-selection phase, a detailed exploration of momentum frequencies was undertaken. This analysis covered stocks both within the selected set and those outside it. In Fig. 1 (representing not selected stocks) and Fig. 2 (representing selected stocks), two illustrative frequency histograms of weighted momentum showcase the distinct patterns.

It's worth noting that the selected asset KR (KROGER COMPANY) exhibits a more evenly distributed histogram, implying a broader occurrence of positive momentum across various timeframes. Conversely, for the not-selected asset TSLA (TESLA), the histogram suggests a more concentrated occurrence of positive momentum within specific intervals.

These insights highlight the effectiveness of the pre-selection strategy in capturing assets with favorable momentum characteristics, as illustrated by the distinctive patterns in the frequency histograms.

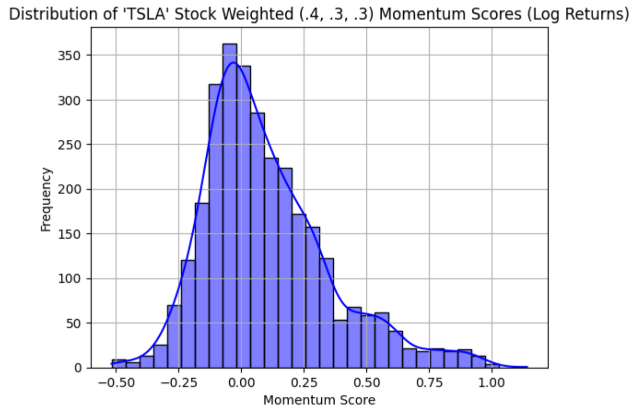

FIGURE 1. Weighted Momentum Score for TSLA Stock

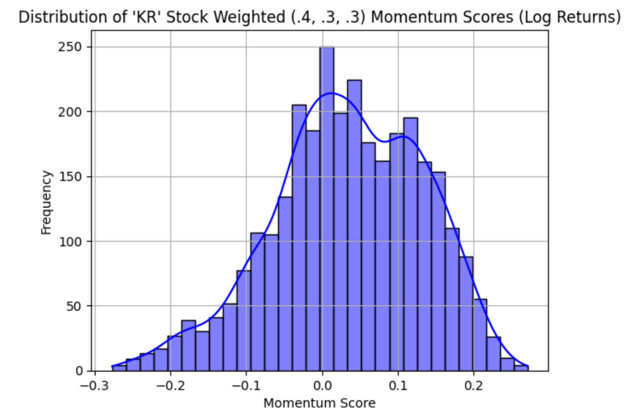

FIGURE 2. Weighted Momentum Score for KR Stock

B. LSTM NETWORK

After training and forecasting with the model, the prediction charts for each pre-selected stock were generated. Two examples can be observed in Fig. 3 and Fig .4.

Upon examining the validation and test data, it becomes apparent that the constructed neural networks were not able to accurately predict the values of asset log returns. Nevertheless, they exhibited a noteworthy ability to accurately capture the upward or downward trend of stock prices. This suggests their potential to assemble a portfolio with profitable assets in the short term.

The Table 1 presents the final outcome of the strategy. All assets forecasted with negative returns had their weights assigned as 0. Furthermore, among the portfolio constituents, only one asset realized a negative actual return, with a minimal depreciation. The asset with the highest actual appreciation received the highest weight. Therefore, it is possible to assess that the forecast obtained a satisfactory result, with 8

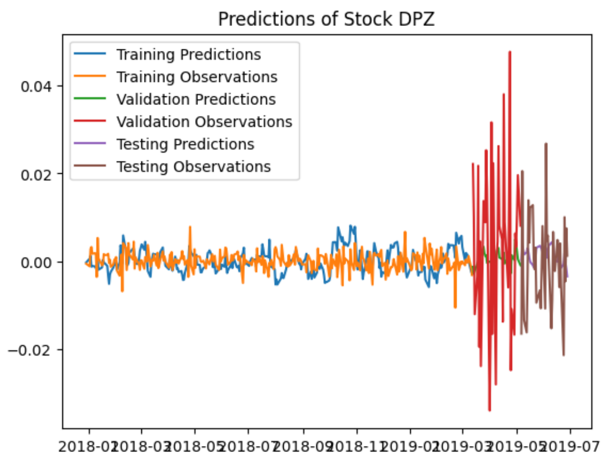

FIGURE 3. Predicted data for DPZ Stock (last score in pre-selection), in returns

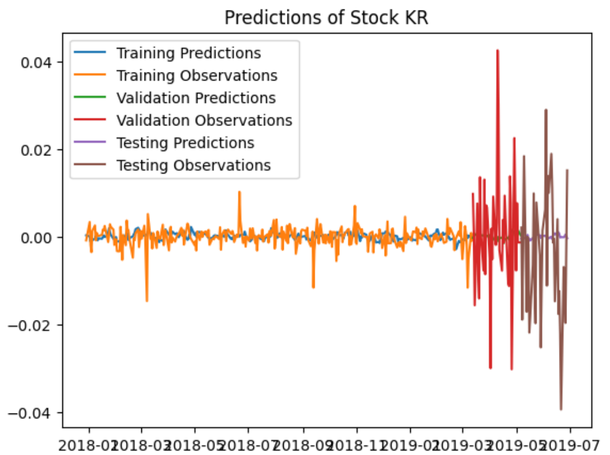

FIGURE 4. Predicted data for KR Stock (best score in pre-selection), in returns

stocks comprising the portfolio. In most instances, the exclusions were associated with cases of minimal appreciation or depreciation of the stocks:

TABLE 1. Wallet with weights and returns comparison between predicted and real data

Stock	Weights	Predicted Returns	Real Returns
DPZ	0.0000	-0.030969	0.001238
WST	0.2947	0.009545	0.012684
ODFL	0.1419	0.004596	0.013652
MKTX	0.0358	0.001161	0.016032
TYL	0.0519	0.001683	0.013417
AAPL	0.1684	0.005456	-0.009082
CPRT	0.0000	-0.012798	0.018811
MSCI	0.3071	0.009948	0.020016
EXR	0.0000	-0.002078	0.004654
KR	0.0000	-0.002860	0.015275

C. BACKTESTING

In order to conduct the backtesting, a period from 2013-05-30 to 2015-07-14 was chosen to allow for a detailed analysis of the strategy, which was performed by generating a tearsheet. A longer time frame couldn't be utilized due to the lack of computational capacity required to run the tests, as an LSTM neural network demands substantial machine processing. For the strategy, a 5-day period takes an average of 30 minutes to execute.

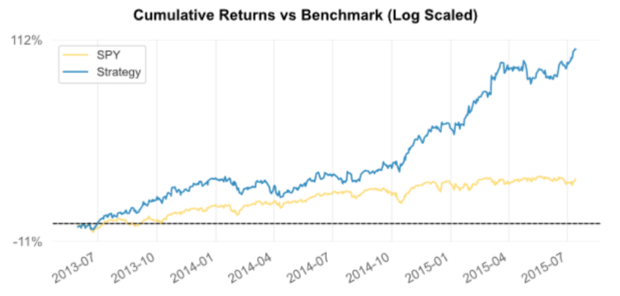

FIGURE 5. Cumulative returns of the portfolio compared to SP&500

In Figure 5, a superior performance of the portfolio defined by the algorithm compared to the S&P 500 index can be observed. There are few sharp declines, indicating a strong performance of the chosen portfolio. Additionally, the long-term cumulative return is significantly higher, reaching up to 5 times that of the index in the selected period of the back-testing. Note, in Figure 6, that the portfolio's performance remains superior even when both the portfolio and the index are adjusted to the same level of volatility.

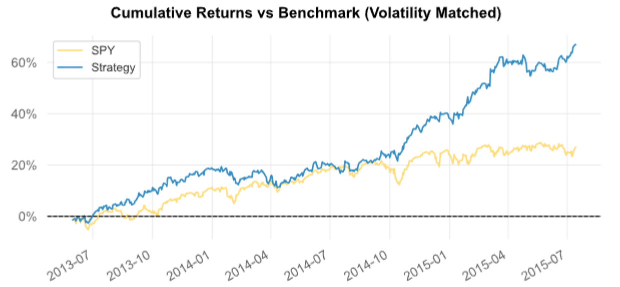

FIGURE 6. Cumulative returns of the portfolio compared to SP&500 (Volatility Matched)

In Figure 7, the daily active returns are presented. It is notable that the returns generated by the strategy demonstrate a commendable performance, given that the variation remains largely within the range of -5% to 5%. Furthermore, it is evident that the negative returns, on average, are considerably smaller than the positive returns, indicating potential profitability.

In Figure 8, the end-of-year returns for the strategy and the index are depicted. A significantly higher annual return is evident, well above that provided by the S&P 500. Over the selected backtesting years (2013 to 2015), the annual return

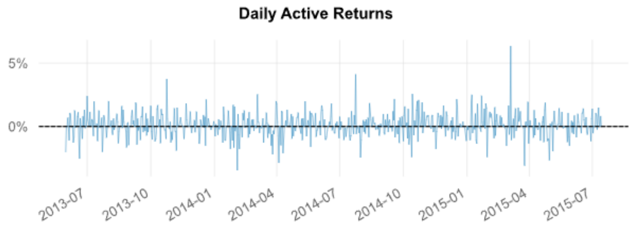

FIGURE 7. Daily returns comparison

ranged between 24% and 30%, demonstrating excellent profit potential, as it remained consistently high with minimal variation throughout the period. The standout year was 2015, during which the return generated by the S&P 500 drastically decreased, whereas the portfolio achieved its record return.

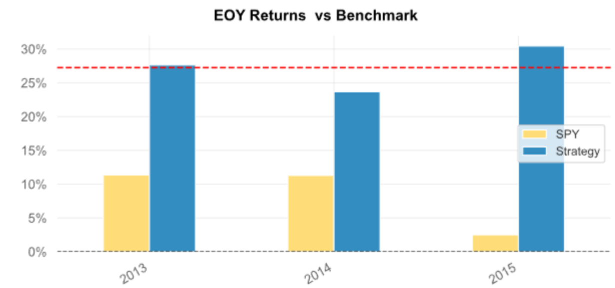

FIGURE 8. End of year returns comparison

TABLE 2. EOY Returns vs Benchmark

Year	SP&500	Strategy	Multiplier	Won
2013	11.37	27.64	2.43	+
2014	11.29	23.67	2.10	+
2015	2.50	30.45	12.18	+

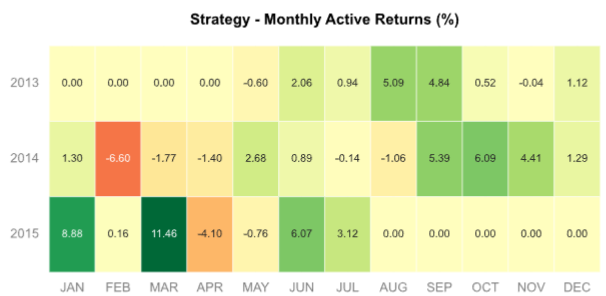

FIGURE 9. Monthly active returns comparison

In Figure 9, the values of monthly returns within the analyzed period through backtesting are presented. It is observed that, overall, the quantity of negative returns is low, and when they occur, their values are not notably low compared to positive returns. Furthermore, the maximum return is 11.46%, and the minimum is -6.46%. Hence, these metrics support the strategy's commendable performance. Moving to Figure 10, it shows the histogram displaying the distribution of monthly

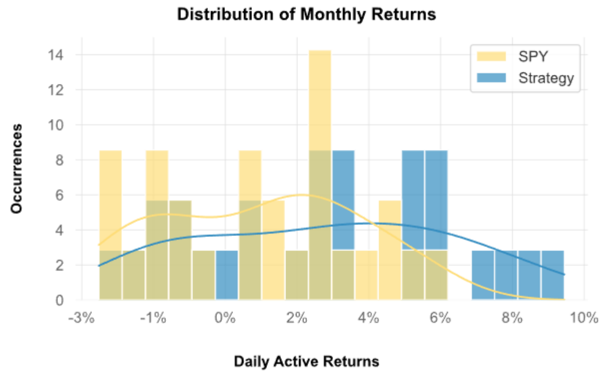

FIGURE 10. Monthly active returns comparison

returns. Note that the majority of returns are concentrated in the central region, ranging from 4% to 6%. Although there is left skewness in the histogram, it is evident that the occurrences are not significant enough to detrimentally affect the strategy's performance.

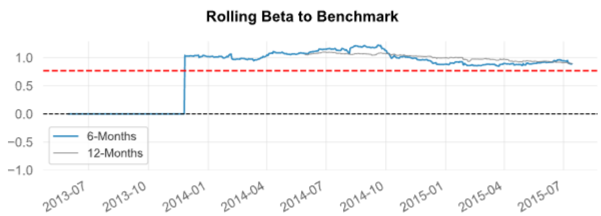

FIGURE 11. Rolling Beta

During the period from July 2013 to July 2015, the analysis of the rolling beta chart for 6-month and 12-month periods, as shown in Figure 11, reveals consistent insights into the strategy's relationship compared to the market. The asset's beta remained relatively stable around 1 throughout this timeframe. This stability around 1 indicates a volatility relationship similar to that of the overall market. In other words, the asset appeared to closely track the market's fluctuations and movements during these two years, suggesting a strong correlation with market behavior.

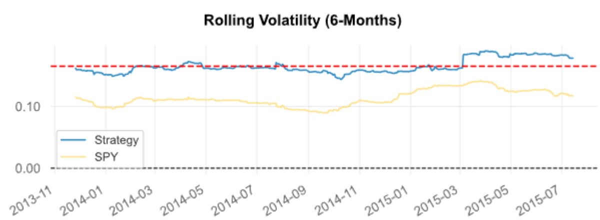

FIGURE 12. Rolling volatility for 6 months

Figure 12 indicates that the strategy maintains a volatility around 0.18, while the S&P 500 exhibits lower volatility fluctuating between 0.1 and 0.13, several insights can be derived. This shows that the asset exhibits slightly more pronounced price swings. The disparity in volatility between the asset and the S&P 500 implies the asset's heightened sensitivity to market fluctuations. Its slightly higher volatility might offer increased profit potential due to broader price swings, but correspondingly, poses higher risks for investors. Thus, this scenario suggests that its slight deviation from the S&P 500's volatility may present opportunities for investors seeking higher potential returns amid increased risk.

FIGURE 13. Rolling Sharpe for 6 months

During the analyzed period, the Sharpe ratio exhibited considerable variation, fluctuating between 0 and 4, with an average stabilized around 2. This average indicates a generally robust performance of the investment concerning the assumed risk throughout the period. However, the range between the extremes of 0 and 4 indicates periods of varied performance. Instances where the Sharpe ratio reaches its maximum values (4) may signify exceptional periods of strong performance relative to the assumed risk, while the minimums (0) could denote phases of relatively lower performance. These fluctuations may be associated with specific events or changes in market conditions, as they display a certain regularity within the presented timeframe, as observed in the curve's pattern depicted in Figure 13.

FIGURE 14. Rolling Sortino for 6 months

The Sortino ratio chart shows variations between 4 and 8, with an average around 5. This considerable range indicates a significant fluctuation in the investment's effectiveness in generating returns concerning negative risk. These peaks and valleys may represent periods of exceptionally strong performance, indicated by the maximum values, and phases of relatively lower performance, reflected in the minimum values. Moreover, the pattern of oscillation, as shown in Figure 14, suggests a regularity in the movements of the Sortino ratio, which could indicate a cyclical or seasonal trend in the investment's performance concerning negative risk.

FIGURE 15. Worst 5 Drawdown periods

TABLE 3. Worst 5 Drawdowns

Started	Recovered	Drawdown	Days
2014-01-16	2014-06-04	-9.74%	140
2015-04-27	2015-07-06	-7.09%	71
2014-06-10	2014-07-23	-5.22%	44
2014-07-25	2014-08-18	-4.71%	25
2014-10-09	2014-10-20	-4.62%	12

Regarding the drawdowns verified within the backtesting period, none of them were above 10%. The maximum drawdown was of -9.74%, which took about 5 months to recover (the longest recovery time), as one may see in Figure 15 and Table 3. These values indicate that the strategy developed is likely to shelter the invested amount, but could be further developed with stop-loss mechanisms to alleviate the drawdown amounts for the more conservative investor. Overall, the strategy did not present any alarming peak-to-trough declines, nor any excessively long periods of drawdown, which therefore points to an interesting downside-volatility stock filtering capacity.

Similarly, Figure 16 that follows shows the underwater plot as another way to see the drawdowns and their momentary losses - it is worthy of noting that the average drawdown was of -1.95%, close to the -1.6% of the benchmark alternative, but with considerably more EOY (End of Year) returns, as one may note from Figure 17.

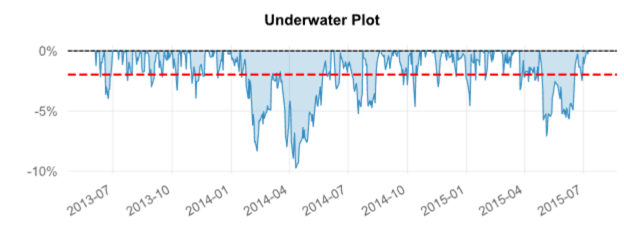

FIGURE 16. Underwater plot

The following return quantiles, comparatively to the S&P500 benchmark, also show a superior performance. The expected returns within each specified timeframe on these quantiles outperform the benchmark as we can see in Table 4, with emphasis to the yearly quantiles, whose returns range from 21% to 30%.

FIGURE 17. Returns distributions by timeframe

TABLE 4. Expected returns by timeframe

Strategy	Expected Daily	Expected Monthly	Expected Yearly
SPY	0.04%	0.89%	8.31%
LSTM Strategy	0.14%	2.71%	27.22%

IV. CONCLUSION

In summary, this study introduced and implemented a strategy for asset selection that relied on volatility and momentum analysis, coupled with an LSTM network approach. Through meticulous data analysis, the model demonstrated proficiency in recognizing trends of appreciation and decline, although it had limitations in precisely predicting specific log-return values. Furthermore, when applied to construct a portfolio using a defined strategy, the returns exhibited great performance, surpassing the benchmark index (S&P500) and showcasing significantly higher results over extended periods.

Despite persistent challenges in achieving heightened precision in predictions, this study highlights the practicality and efficacy of the proposed approach in building portfolios based on time series forecasts utilizing Machine Learning techniques. Future iterations of this model could benefit from further enhancements and the inclusion of more comprehensive datasets and variables, thereby augmenting its capacity to discern lucrative investment opportunities within the financial market.

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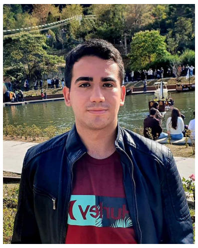

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