Intelligent Algorithmic Trading Assignment

*Comparing indicators used in LSTM

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***Abstract*—The main scope covered in this paper is to cover what kind of impact does technical indicators have on the outcome of an long short term memory (LSTM) neural network. This is done buy having two different sets of indicators, for each stock the LSTM will be trained on each set and the combination of the sets and thus tested and compared to each other and base line figures. The style of trading that is going to be held is a Buy, short or not traded for each day (No stock is kept overnight). This is done by approximating the closing price using the LSTM of that day and then classifying the decision.**

***Index Terms*—Algorithmic Trading, long short term memory, neural network**

I. Introduction

The idea of using Artificial intelligence in the financial is predominately used in helping or automating decisions making. Having automatically making decisions frees up the financial industry in subjective decisions which may or may not improve the quality of the decision. Over the years Algorithmic trading (AT) has made remarkable impact in this sector. In the mid-1990s AT is introduced, by 2009 it been reported to cover up to 73 percent of trading volume in the United States.

What make AT so good is its diversity of application among the data rich sectors of finance. It Ranges well over portfolio management, day trading and micro trading or high frequency trading. For example Quote stuffing, a malicious tactic employed that involves entering and withdrawing large quantities of stock so to over value the market, and then taking the advantage of traders who participating in the inflation [1]. Classically, algorithms are used by institutional investors to trade large quantities of stock gradually over time but its becoming very common to automate the roll of trading to an algorithm taking advantages of the speed and accuracy that a bot can deliver on [2].

When investing the public information on that asset makes a huge impact on its value. It is important to understand that the clarity and the amount of information about the asset being bought, reflects the chances of purchasing a stock that is undervalued or inflated as the investments would move accordingly to it's objective nature. The efficient market hypothesis (EMH), referred to some times as the efficient market theory, states that the the values of a stock that reflects all the information, making it impossible to out perform the market and thus as a results of increasing profits true investing with riskier investments as a fully efficient market will have a random walk. [3]

Something more specific to this paper to keep in mind is the strong argument against using recurrent neural networks when predicting a stock price. The argument states that the neural network will create prediction that are more or less the same from the day before and that the results are just a shift away from the actual stock and thus it is not making any valuble predictions. Thus the error calculated can't be taken by face value but instead it would be idea to visually and see how the prediction are made on a chart. [4]

The main objective of this paper is to have a better understand of how dependent variables namely indicators have an affect on the results of an neural network. In the case of this paper the used of LSTM are used for there superior quality when it comes to time series problems. What will be tested is two set of dependent variables, and the third that is both of the set put together and test the profitability produced by the LSTM setup. The LSTM is set up to indicate an approximation of the closing value of that day, thus each trade will be per day and strictly keeping it for the whole day, unless the day is skipped. This inherits regression qualities but also considers time complexity issues that may occur with time series data behavior. Once the approximation is found, if the that approximation price is lower than the open price of that day the machine will short the market and if its hire it will buy the sock. Also if the approximation is not above or below a range it will not buy that day, this was done in attempt to lower the number of stocks traded in total while not missing on good opportunities. Thus as final out come it is a classification of whether to buy, short or no traded that day.

When learning about the field and AT systems a retaliation that the the majority of research focus on the system, For example to use Gated Recurrent Unit (GRU) vs LSTM or compare weaknesses in the neural network or model used rather than criticize the variables used. This creates a gap in the lecture found that gives a review on what and where indicators work best and finding an ideology when fine tuning algorithms. Its is easier to see the logic interpreted by humans, on the other hand neural networks are black boxes where the

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independent and dependent variables can mean something different. Finding what and how these react to known neural networks maybe be the way of more sophisticated models. This paper contributes it comparing dependent variables when working with LSTM in hope to shed light on perspectives on what these indicators mean to the neural network.

II. Literature Review

Under limited time of research investigating on domain of AT, LSTM has show very interesting results, feasible automation in creating liquidation and proved it self to be superior over other models in several papers. A paper covering multiple scenario with LSTM, besides showing its adaptability to work with meany stocks it also shows results that where promising. This is the fact that the neural network obtained an average of 55.9% accuracy when predicting if the price of a particular stock is going to go up or not in the near future [5]. This paper and other where an encouraging factor to use LSTMs. Additionally a papers where they tried different architectures and explains that LSTM did better then other architecture setups, comparing, GRU, other Artificial Neural Networks (ANN) and Support Vector Machines (SVM). In the results they have stated that the LSTM outperformed the other architectures returning 400% greater than the hold and wait strategy. [6]

From these findings LSTMs became a point of interest. Thus a deeper perspective on this subject is important to understand the underlying reason on why they are so good and how technical indicators may help. LSTM's are a form of recurrent neural network that deals with what data is valuable to be stored and what should be forgotten [7]. Thus is very good at dealing with vanishing gradient problems. This means that the starting data that would be train on dose not become under valued due to new training data. As a result it has be proved that LSTMs are very successful in this area where they deal well with Time series prediction problems. These tend to be difficult type of predictive modeling problem as the underlying logic may change due time [8]. Thus by this knowledge indicators play a very important role as indicators infer perspective on changes interact with the outcome of the stock. It is important to note that technical analyses is subjective and thus a challenge to frame it as scientific [9]. Interpenetrating whether an indicator is a factually superior based on the scientific method is tricky. What also adds complications is the chaotic nature of traders. Study's into behavioral economics demonstrates inefficient and irrational outcomes made by traders, finding anomalies in return reversal and incoherent volatility clustering [9].

In this paper a number of indicators are used, the following explain in brief each;

Relative Strength Index (RSI) is used to indicate whether if a stock or other asset is overbought or oversold state. RSI uses the average gain and losses from the asset to read a a value from 0 to 100. This is a oscillator that at each end shows if the stock is overbought or undervalued. This range is a percentage of popularity, thus this indicator is a popular momentum oscillator. Typically an asset is thought of oversold when it is below 30% and overbought when over 70%. In (1) shows the equation used. [10]

$$RSI = 100 - \left[\frac{100}{1 + \frac{averagegain}{averageloss}} \right] \tag{1}$$

Williams %R is also a values that lies between two values 0 and -100 that suggest that if the overbought and oversold. Developed by Larry Williams it is used in similar to Stochastic oscillator which is going to be mentioned soon. When the reading is over -20 it is overbought and when its under -80 is oversold. At taking the closest closed priced this can be calculated by equations (2) where H_{14} is the highest price in the look back window of normally 14 days, C is the closest closing day and L_{14} is the lowest price in the same look back window. [11]

$$Williams\%R = \frac{H_{14} - C}{H_{14} - L_{14}} \tag{2}$$

Stochastic oscillator as previously mention is used to suggest to show when an asset is in an overbought or oversold position. This is done by comparing the closed price and how it price ranges over a 14 day window. Stochastic oscillator is very popular among traders as it is easy to understand and is quite accurate when indicating when to sell or buy. It is extremely similar to Williams %R, equations (3) show the difference where %K is Stochastic oscillator results. (The letters represent the same values) [12]

$$\%K = \frac{C - L_{14}}{H_{14} - L_{14}} \tag{3}$$

Simple moving average (SMA) used normally by a lot of chart readers with a 0-day, 50-day, and 200-day sliding window calculating the mean to get a moving average (MA). These MAs are used for important analytical suggesting or identify current price trends and have an idea of future changes. [13]

Exponential Moving Average (EMA) on the other hand are used similarly to SMA that places more impotence to resent prices by having a greater weight on closer to the present data points.The exponential moving average is also referred to as the exponentially weighted moving average. Equations (4) shows how this is calculating where t is time step and N is number of days being calculated. [14] [15]

$$EMA = Price(t) * k + EMA(t-1) * \frac{2}{(N+1)} \quad (4)$$

A Triple Exponential Moving Average (TEMA) is a used as a traditional MA without the lag associated getting the averages. This is show in equations (6) where EMA_t is the $TEMA$ and where EMA_2s EMA of EMA_1 and EMA_3 is the EMA of EMA_2. This is done to subtract some lag from the orignal EMA. This is used to identify trend direction, signal potential short-term trend changes or pullbacks, and provide support or resistance. [16]

$$EMA_t = (3 \times EMA_1)(3 \times EMA_2) + EMA_3 \quad (5)$$

Moving Average Convergence Divergence (MACD) is a trend-following momentum indicator that uses the relationship between EMA of 12 day period and a 26 day period. By subtracting the two EMA The result calculate the MACD line. On the 9th day of the MACD is the ”signal line,” plotted on top of the MACD line its self used typically as a function to buy and sell. When crossing above its signal line a short occurs and below the signal line a buy occurs. MACD indicators has a subjective use and is used differently by investors. [17]

Bollinger Band® (BB) a very simple but effective technical analysis tool that uses SMA typically of 20 days and uses the standard deviations (SD) to create a upper bound and a lower bound. A standard deviations of 2 is normally used. The bounds are used normally to indicate a buy or sell, for example the lower bound tends to be used as a stop loss. This is an advantage as its calculated on the average rather then have a fixed price. [18]

Price Rate Of Change Indicator (ROC), a momentum-based technical indicator, calculates the percentage change in price between the current price and the price previous valued at. Useful when plotted, A line graph representing the stock is displayed starting form zero persent. As looking forwards, If moving upwards this is positive territory indicates profit from the time step being calculated and on the other hand on the downside shows loss. [19]

Commodity Channel Index (CCI) measures the difference between the current price and the historical average price where positive show above the historic average and vice versa. A Ranging between 100 and -100 is normally taken as strong indications to buy and sell accordingly. The (7) show the formal used to calculate CCI where P is the number of periods, MA is the moving average, H is the highest point, MD is mean deviation, l is the lowest and C is closed. [20]

$$CCI = \frac{TP - MA}{0.015 * MD} \quad (6)$$

$$TP = \sum_{i=1}^{P} \frac{(H + L + C)}{3} \quad (7)$$

Ichimoku Kinko Hyo seen as an all in one indicator is comprised of five lines called the tenkan-sen, kijun-sen, senkou span A, senkou span B and chikou span. These indicators are used to highlight areas of residence and calculate momentum. ”ichimoku” is a Japanese word that means ”one look”, thus it is designed to have all the indicators needed displayed on the chart, determining momentum, support, and resistance. In the following equation show how to calculate each. [21]

- Tenkan-sen calculated by adding the highest high and the highest low over the past nine insistence and then halved. This indicates a resistance level, used as well as a signal line for reversals.
- Kijun-sen sometimes referred to as base line. This is calculated by summing highest high and lowest low points in a 26 periods window and then halved, represents an other resistance level used to indicate a trend change.
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- Senkou Span B or leading span B, calculated by adding the highest high and the lowest low over the past 52 periods, halved once again, and then plotting the result 26 periods ahead. This is used similarly to Senkou Span A.
- Chikou Span or lagging span, is a lagged indicator to show areas of resistance. It is simply the current period’s closing price plotted 26 days back on the chart.

Used in this paper is Double Confirmation Momentum Strategy as a algorithmic strategy. This is a very simple strategy where it capitalizes on a continues existing trend. Momentum investing involves normally of holding assents for some time and profits occurs by staying with trend not matter how long. You can see the succes with up very successful investors in the US stock market form 2009 up trending up till the end of 2018. The main idea is that Double Confirmation Momentum Strategy works normally by having a lagged indicator having idea of the overall trend and in moments when it time to buy it is confirmed by a leading indicator. Double Confirmation Momentum Strategy is particularly used in Forex trading but it is profitable in any market that has trends favouring Momentum Strategy’s.

When viewing these technical indicators and the fact that it seem unpopular to cover a comparison of different sets of technical indicators when used with a ML algorithm seems to be a weakness that is addressed in this paper. Thus understanding the value in these indicators and specifically seeing how these variable effect certain architectures and work on a curtain market will deem to be valuable. In hope that it would lead to a more intuitive ways of fine tuning systems and getting insight to what these variables mean to neural nets. In this assignment, I thought it would be interesting to go over indicates a learn what they mean individually at the same time present how these interact with an LSTM Model by compare results form sets of indicators to see what an impact it can make to the results.

III. Method

In this paper, the method comprises of comparing the impact of what indicators may have on an LSTM, and then compare it to two AT strategies, Double Confirmation Momentum Strategy using RSI and MACD and the second strategy is using BB to place buy and sell orders. When doing the analyses on how the LSTM is effected by the indicators, three groups where established for observation. After the LSTM was design to meet the work load of the challenge, the effects of these three groups where analyses after training and testing on each stock, keeping track of how well training took place, frequency of trades, success of trades, and profits or losses.

The aim for this is to see if the most capitalization is occurring using a fixed model and then comparing it to other processes to have a bench mark. Getting the results from different assets is impotent as assets treads differ a lot even assets from the same market, so it was every impotent to get a mix of assets of the same and different markets. Thus when drawing conclusions, it is done to reflect the diversity of the market and so that strengths and weakness can be draw out of the system. Above all when comparing the set of indicators, there is no similar trend that make one set better then the other.

A period of 2000 trading day after 2020 was used out-of-sample testing is simple uses the last 5% of the period of history of the stock and the rest is used for training on in-set validation. An exception was made for Ripper (XRP) this is beacuse there are not a sufficent data set. This was done for particulare change diffrent trend that was idea for diversification of the final results. The neuron networks consist of three LSTM layers and a dense layer. A split of 95:5 for training and testing found to have optimal results amusing small array of tests and is relistic when applying this to a real scenario. For obtaining results it was also impotent to have relatable asset so others can compare to, for example it was found that testing on Tesla and Amazon where often chosen. Additionally common indexes where chosen with the same reasoning. Also these are important indexes as the are popular among the community and reflects more or less of a whole market spanning over lots of successful companies. The ones chosen are SPN500 (SPN), Nasdaq (IXIC), and DOW Jones (DJI). When trading with the LSTM model the style of trading chosen reflexes day trading this includes not keeping stocks over night. It is impotent to mention that trading in this way skips on fees that tend to be included in Commodity based ETFs options as overnight fees thus the following four are intresting to see what results are obtained; Gold (GLD) , Silver, and Oil (USO). What also would be interesting to look into is how well performing the system is with three popular currencies between each other; The American dollar, Japanese Yen and Euro (USDEUR, USDJPY, EURJPY). These tend to have low SD from one day to the next and thus have impact to the final reults. Finally to see how well the performances is to high volatile stock such as Ripple (XRP-USD) and see how abnormal trends such as the spike seen earlier on the trading days effects the system.

The way how the system is trained is that the input are the open price that day, and the information about the day before such as; the open and close price, 10, 50 and 200 day moving average, the highest and lowest price of that day, volume and the technical indicators of that group. What is aimed to be predicted is the closing price of that day given the information of the day before and the open price of that day and have a desertion on where that days is good to short of buy for profits.

The first group of indicators have; The percent of change from the day before, cumulative product of the daily return, the difference in opening and closing price, Relative Strength Index, Williams %R, an additional 7 and 21 day moving average, 26 day and 12 day Exponential Moving Average, Moving Average Convergence Divergence, Bollinger Band High and Low Indicator, and Momentum Indicators. For the seconded group there are; Stochastic technical indicator and its moving average of 3 days, Price Rate Of Change Indicator, Momentum Indicator, Commodity Channel Index, Triple Exponential Moving Average, Kijun-Sen, Tenkan-Sen and the Chikou Span indicator. Further more the out put would be the closing price of that day. For the final group a combination of all the indicator are used to see weather group these indicators have an impact of the final results or that just feed all the indicators at once just out preforms indcication that the more depended variables there are the better it will do.

When it came to pricing it became a issue as the prices differ greatly. When trading with in the foreign exchange most brokers fees would be over prices unless using one that specialise in only foreign exchanges. The same problem happens with ETF, some brokers would charge over night fees and others would have a premium on each trade. The way it should be done in real world is chosen the idea broker for each category of asset and this deemed to be out of the point of the experiment. Thus no fees where calculated as simple comparison of out comes wanted to be view and adding such complexities will skew the outcome.

Once the results of all the ten stocks are complete a t-test will be done to see if there is a statistical significance for each test. In addition the mean average comparing all three test is done to see which one make the most impact overall. Further more the results are tested against bench marking tests this so further investigation can take place to see whether each asset differ and seen if it better or worse using different and simpler method that are popular amounds traders to see if there is an advantage being taken. These bench marks are indicators to understand how well the results are in relation to that asset. A simple algorithm that trades randomly over the whole test sample is one that is use and shows an reference to an ideology that is deemed to be beaten. What also is used to compare is the results is using the BB strategy this is done by iterating true two main variable, one is the window of the rolling standard deviation and moving averages and the other is the width of the BB high and low which is controlled by the amount of standard deviation away from the moving average line. How it works is that it shorts passed the BB high and buy past the BB low. This is going to be tested on the window size of 10, 20 and 50 and the with of the BB bar of 2, 3, and 5 for the amount of standard deviation away from the moving average (the best and worse case scenario is used for comparison). Double Confirmation Momentum Strategy, slightly more sophisticated then former, using the RSI as the leading indicator by signaling the overbought or oversold conditions of that asset is used to confirm the perches of the stock. On the other hand MACD is used as the lagging indicator to indicate the trend weather its moving up words or down words. Using the MACD histogram bars, once it cross over zero into the positive area it indicates that the trend is up and uses the RSI to see if ther is the condition that the stock is bought enough to keep the trend sufficient. The value of RSI is chosen at 50, once both indicators show positive sighns to buy the stock is bought. When selling the stock an inverse is necessary this means that once the MACD cross under zero and the RSI is under 50 it will not only sell but shorts the market as this show signs of a down market. An other bench mark used is the buy and hold method where the stock is bought and never sold across the period is done additionally the buy only method is also used to see how well a stock performs only in the open period will be used to have other comparable method.

IV. Results and Evaluation

As expected the LSTM ML model performed the best across a 70 day training window overall. Unfortunately the training window need to be shorten due to unexpected batch sized problems. When it came the mean of all the results in Figure I it show that the second set of indicators did best. It started with a 1000 (USD) to trade with and ended with the column 'value' in Table I. Interesting the amount of good trade performed is almost as equal as the first set but managed to out perform buy 2.9%. There is quite a contrast in tactics used between the two while the first set of indicators traded on the model used more short trades while the second did the opposite while retaining the same days not trading. On the other hand using all the indicators used up more of the trading days having a decrease of 31.5% less unused days but only having a few day approximately 16% of less profit days but having fewer loss days overall. These results are positive as there where almost equal amount of up days and down days and over all not gain profits by buying only and random strategies.

TABLE I
Mean results of LSTM and other bench marks

set	None	Buys	Shorts	Profits	Losses	Value	Sharp Radio
1	28.5	23.75	44.75	35.83	32.66	1089.42	0.96
2	28	38.25	24.75	33.58	29.41	1122.16	0.54
3	17.5	31.91	21.5	28.5	24.91	1060.97	0.76

First 5 columns are used to show the frequency of days ('None', No trades done)

When comparing to the RSI and MACD Double Confirmation Momentum Strategy it shows much more completion. One are that it beats the LSTM is the little amount of trades done thus taking advantage of low fees when in practice. It is impotent to mention that once advantage that the RSI and MACD Double Confirmation Momentum Strategy has is the ablity to hold stocks over a period of days. Thus would have been ideal to adapt the LSTM to do so. All in all comparing these two we definitely see advantages with the ML model as it has a standard deviation of 156.99 (USD) with the highest value hitting 1778.04 (USD) and a low of 955.97 (USD), while on the other hand the RSI and MACD Strategy does low trades so may beat the LSTM over all although it has heavy losses in with the Tesla stock losing more then half its value. In Table II we see the frequency of trading done by the RSI and MACD Double Confirmation Momentum Strategy and in Table III we see a comparison made by the LSTM trained on the second set.

TABLE II
Mean results of LSTM and other bench marks

stock	None	Buys	Shorts	Value	Sharp Radio
USO	69	0	1	1358.56	1.18
XRP-USD	67	1	2	1049.81	0.22
USDJPY	70	0	0	1000	0
TSLA	69	1	0	447.92	-2.06
SPN	68	1	1	1027.59	0.30
SLV	68	1	1	1143.04	0.99
Nasdaq	68	1	1	1001.06	0.016
GLD	69	0	1	1134.56	1.09
EURUSD	70	0	0	1000	0
EURJPY	70	0	0	1000	0
AMZN	68	1	1	928.55	-0.44
DJI	68	1	1	1085.87	0.73
Mean Avg.	68.66	0.58	0.75	1014.75	0.17

First 5 columns are used to show the frequency of days ('None', No trades done)

TABLE III
MEAN RESULTS OF LSTM AND OTHER BENCH MARKS

	Vaule	
stock	RSI and MACD	LSTM 2
USO	1358.56	1368.90
XRP-USD	1049.81	1000
USDJPY	1000	998.70
TSLA	447.92	1778.03
SPN	1027.59	1058.15
SLV	1143.04	1135.78
Nasdaq	1001.06	955.97
GLD	1134.56	990.65
EURUSD	1000	994.75
EURJPY	1000	1000.57
AMZN	928.55	1285.08
DJI	1085.87	1020.94
Mean Avg.	1014.75	1132.29

Looking closer at the currencies, the profits slacked for both the LSTM and the RSI and MACD Strategy slacked severly when it came to the currencies including the cryptocurrency. This might be because of the low standard deviation among the currencies. While mean of the standard deviation of 48.13 (USD) the reset of the assets having a 867.820755956108 (USD), Using the BB trading strategy seems to work better when taking the best case scenario of range profits of 3 to 8 percent taking advantage of lowering the gap of BB highs and lows creating good trades. In Figure 2 show that the BB trading strategy have perks in these trading environments but show that on average it was not so competitive as the other two methods.

Going back to the LSTM ML model, when it came to training they all seemed to be similar. This may indicate that the different sets of indicate may not have such a great influence as expected. Although its is interesting to see large fluctuation when training with all indicators. These may show that there may be limits to how many indicators that can be put into the system and that more indicators does not help the system to get greater results.

V. CONCLUSION

When it came to see the overall picture using the ML model prove to be not only more relatable but more profitability. Before starting this experiments a lack of understanding how assets differ among each other shows that an over arching system maybe be difficult to achieve. The BB trading seemed to create more profit with the currencies while the other two strategies lost or gained very little. It seemed to be that too much importence has been placed on what indicators are used for the LSTM model and seems to be that the strategy or model used will bring more value to the system according to the assets behavour.

Following this point when comparing the results between the LSTM model and seeing the best set of indicators is to be

Fig. 1. Comparing the LSTM ML model, buy only and random results to the BB strategy

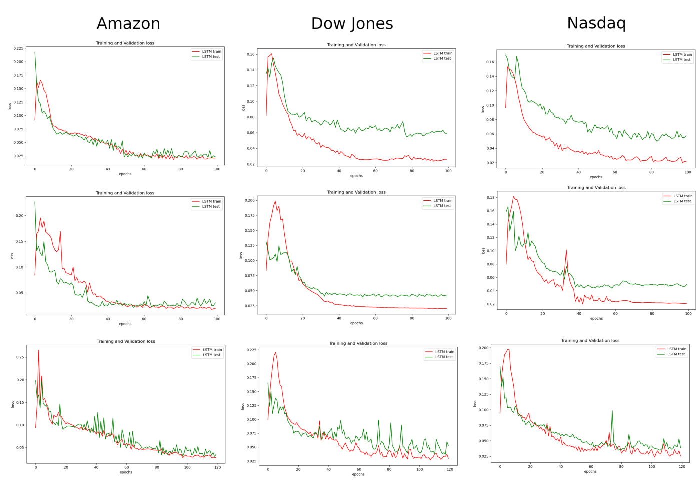

Fig. 2. The learning rates of the LSTM model. top row trained on the first set, and so forth.

used it is not as simple as compering all assets equally. Among the results of each set there where no distinctive difference to say one is better then the other. Thus looking them individually may help to achieve the peak performances is needed to lower the error rate and increase profits. Additionally the more indicators added the more fluctuation is created while training and not necessarily improving results and it showed that it does not increase profits. Thus it show that picking the indicators maybe help although jugging buy the the t-test the P-values show that there has been very little improvement and is far from significant. Having level of significance of p ¡ .05 may be low for this test the results show that there is very little improvement and is not significant enough to say that the hypothesis holds up. In Table IV show the t-test results comparing each other.

TABLE IV
T-TEST CONFUSION MATRIX

	Set 1	Set 2	All
Set 1	1	0.678	0.42
Set 2	0.67	1	0.35
All	0.42	0.35	1

A. *future works*

Despite the results it would be more valuable to understand on a deeper level what each indicators do best with different types of stocks so that fine tune can occur in a more educated manner. Expanding the the sets and making then more comprehensible to what advantages can be made from each ones a system is traded on can help navigate the fine tuning of a system.

Anther area that can be beneficial is how the indicators are prepossessed having so sort of layer that makes the data view differently that may have benefits such as a convolution layer to the test out where this help the LSTM to view the results better rather then keeping the values strictly to by them selves.

Additionally using the LSTM a lot has been learn from the traning window relating to the outcome. Having a sliding window of where its learning and performing on a small amount of days could be key in creating better outcomes. Having re update its self ever few days keeping the model up to day and not run into issues such as concept drift.

A further investigation on AT is also needed as there maybe competitive strategies based outside the ML area. These having less to posses and getting the end goal done is idea for a real world solutions.

The final comment is that the LSTM was used strictly used and other models where not compare with. That and it was on used for day trading and this did not do justice in observing how indicators play out in different scenarios. Comparing the buy only strategy and the buy and hold method show that since the buy only strategy lost value there is profits in the after market that was not tapped into and indicator with different set up can show advantages in this retrospect.

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