TRADING & QUANTITATVE RESEARCH REPORT

TRADING THROUGH ARTIFICIAL EYES

Time Series Classifications Using Deep Neural Networks

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THESIS, TRADING STRATEGY AND METHOD

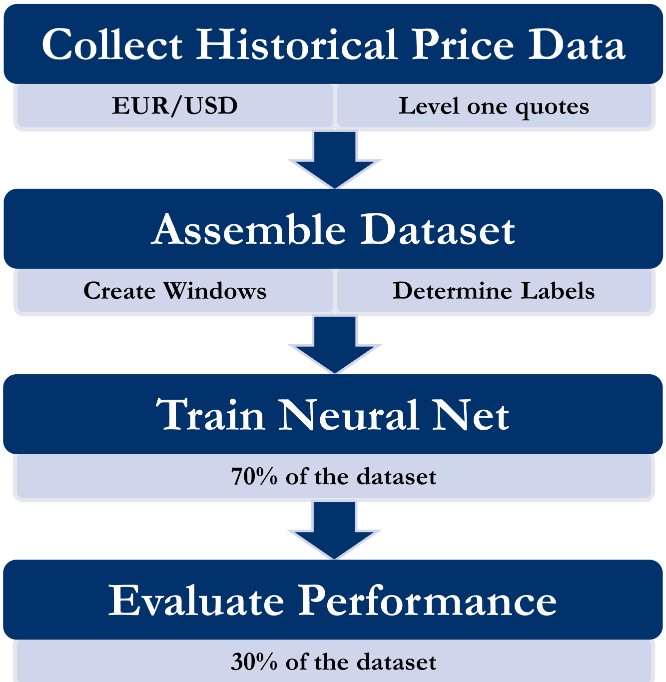

Exhibit A: Schematic overview of the preparation phase. The historical price data is assembled into a dataset, that is then used to train and evaluate the networks classification performance.

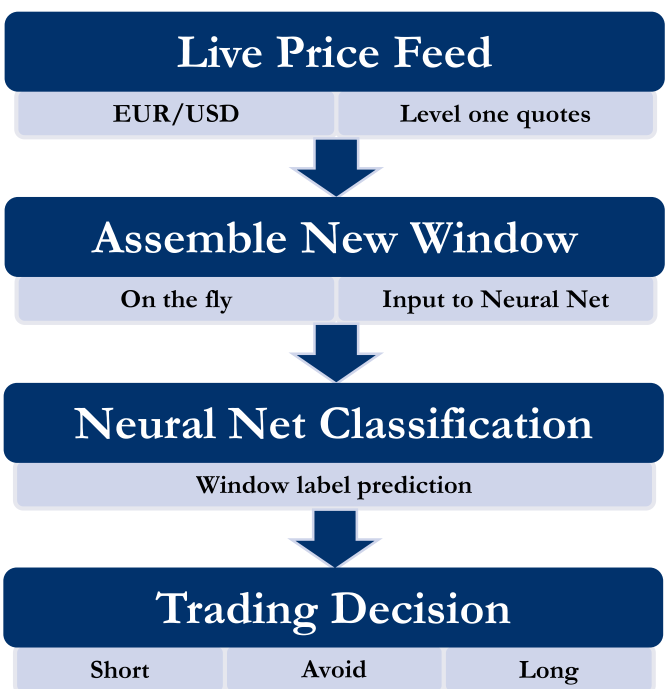

Exhibit B: Schematic overview of a trading phase. Price data is collected through a live feed and assembled into window samples for the network to predict the nature of. Trades are then placed based on the history of predictions.

Investment Thesis

While making a trade is not uncommon to rely on visual queues, simply the look of previous price history contains lots of information, such as current trends and volatility. If it was possible to construct an algorithm that could see the financial data in a similar way to us humans, maybe it is also possible to automate trading through its artificial eyes. These types of algorithms are indeed possible to construct, as advancements in deep learning has made computer vision powerful and yet relatively easy to implement. A type of neural network called a Convolutional Neural Network (CNN) is a state of the art image processing algorithm that borrow similarities to the workings of human vision. These networks can be taught to identify objects within an image by giving them labeled images and training them through a process called back-propagation. They function by scanning the image with filters that they have learned to find edges and particular shapes that belong to the objects it is asked to identify. The output of such a neural net is a probability distribution over all the classes of objects that it has been trained on.

By assembling windows of historical price data and labelling them given their overall bullish, bearish and noisy nature, one can train these neural networks to pick up on characteristic visual queues that can distinguish these three classes of windows.

A schematic overview of the neural net preparation phase can be seen in Exhibit A.

Trading Strategy

With these visual queues as inputs, the next question would be what trading strategy could exploit them. It is possible to add another network that takes the outputs of the CNN and is trained by reinforcement learning to make it find its own strategy. But instead of going down that long road, one could play around with the simple strategy of going long or going short after the network makes label predictions, based on some pre-determined criteria. It was found that treating the neural net classifications as indicating local high or low price levels could be made significantly profitable. The strategy is to open positions if a given number of bearish or bullish windows have previously been predicted and satisfies a set of criteria, that is to be introduced later. This works by placing many positions at the peaks and troughs of price movements, maximizing the likelihood of profits. This approach accompanied with a collective take profit and stop loss, as well as a dynamic take profit level made a successful strategy.

Method

Historical level one quotes are collected from the most liquid currency pair, the EUR/USD, which span most working days between August 2018 to March 2019, and consists of best bid and best ask values with millisecond granularity. This data is then sampled into 20 minute windows, and labelled depending their bullish, bearish or noisy nature, through a calculation of the average profit or loss by buying and selling in these windows. The dataset is then split 70% into a training dataset, and 30% as a test dataset to evaluate the classification performance.

All trading is simulated trough code written in Python, where trading conditions are made realistic by accounting for spreads, execution fees, roll over fees and slippage. Additionally, trading on margin is added, where one can leverage an investment up to 30 times. The system keeps track of usable margin and will produce a margin call if necessary. The training dataset is also used to optimize the trading strategy while its trading performance is evaluated on the test dataset.

As is displayed in Exhibit B, during the trading process, a continuous feed of price data is to be assembled into windows every minute. New trades are then made on the fly as the network predicts new labels and checks the criteria. Trades are then closed once they reach the take profit or stop loss levels.

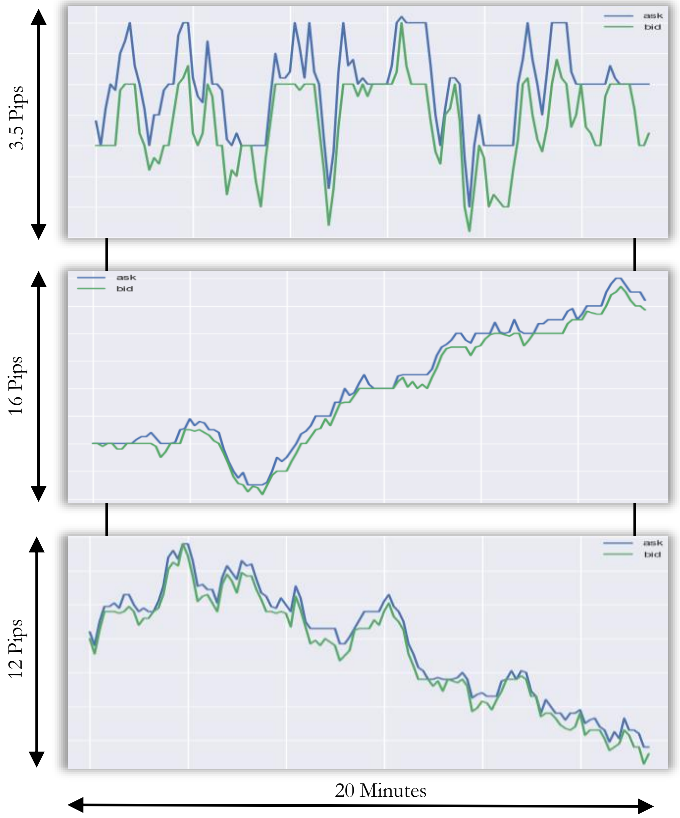

Exhibit C: Three examples of typical noisy, bullish and bearish windows.

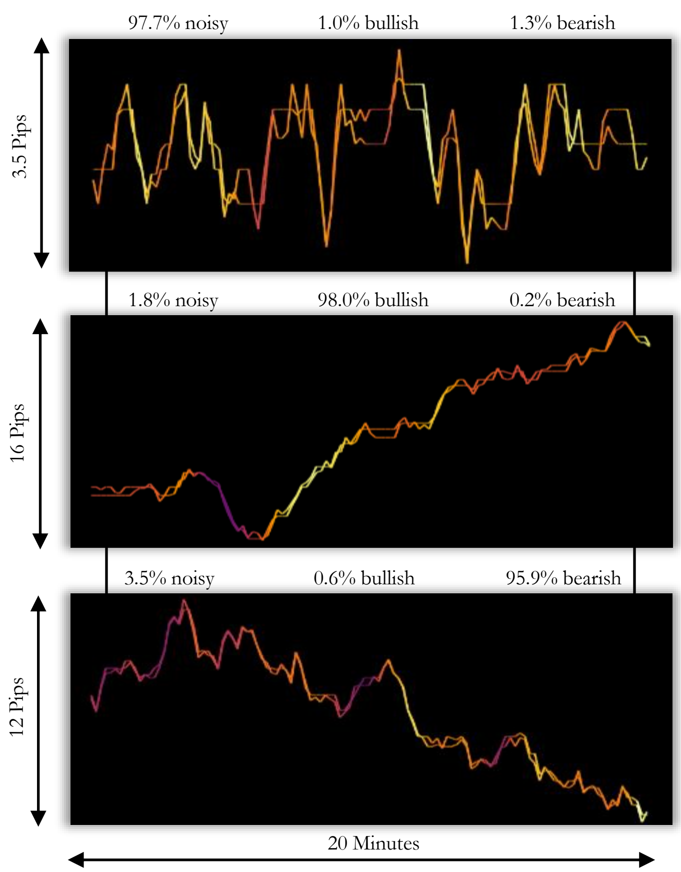

Exhibit D: The neural nets view of the windows shown in Exhibit C. The numeric output of the network is displayed above the subfigues, that is the probability distribution over the labels of the window below.

Typical Windows

A typical window of each label is presented in Exhibit C. The top window shows a clear noisy nature, as it contains little information of where the price might be moving next. The middle window shows a clear bullish nature, and the bottom window a clear bearish nature. These bottom two should certainly be more connected to future price movement than the top one.

All windows have been zeroed around their starting value, then averaged over intervals of 10 seconds, and normalized to units of pip, which are increements on the fourth decimal of the price. This is done to aid the network during training and to reduce computation time. The zeroing removes any dependance on the actual price, which mean that windows at the end of the dataset are treated the same as those in the beginning. Averaging the windows over intervals of 10 seconds reduces the size of the input, which in turn reduces computation time significantly. The normalization to units of pip was mainly done for convenience.

Classification Performance

The assembled dataset contains 96826 windows of which 11443 are labelled as bullish, 12189 are labelled as bearish, and the rest noisy. As can be seen, there are many more noisy windows than bullish and bearish ones, which is to be expected if it would capture useful information. The slight imbalance between the amount of bearish and bullish windows does indicate an overall drop in average price over the whole dataset, which can be confirmed.

Training the network for just one hour achieves above 90% accuracy on both the training and test part of the dataset. This means that very little overfitting was done and that it managed to find general visual queues that is able to distinguish these classes well. An interesting note is that no misclassifications between bullish and bearish labels was made. Additionally, those windows that were misclassified acutally looks mislabelled instead, demonstrating the neural nets ability to improve upon the coarse labelling function.

Network Visualization

A common problem with neural networks is that they hide their decision making, and in most cases there is no way of knowing why they make the choices they make. It could be beneficial to see what they have learned in order to more easily make improvements on them. For Convolutional Neural Networks (CNN's) some visualization methods have been developed, and one of these methods is called a Class Activation Map (CAM) which requires the network to have a specific architecture, which is precisely the architecture used in this project. This method takes a window along with the neural net and colors the price history in different intensities, with high intensities corresponding to the places the network is mainly focusing its eyes.

A CAM of the previously displayed noisy, bullish and bearish windows can be seen in Exhibit D. The network classifies the noisy window corretly as containing mainly noise, with a little bit of bullish and bearish nature. According to the intensities, it does look at most of this window during classification, which could be some sort of internal moving average calculation. It also classifies the bullish window correctly, but here it is interesting to note that it focuses mainly on the middle of the upswings while ignoring the middle of downswings, which is quite a reasonable way to identify bullish movements. The bearish window is also classified correctly, and interestingly it is determined to have a bit more noisy nature than the bullish one, which does seem reasonable when comparing the appearence of the two. It can also be seen that it focuses on the opposite for bearish windows than what it does for bullish windows, and that is the middle of downswings, which again seems reasonable. Both the bullish and bearish window has focus at the endpoints, which is likely there as the endpoint value is a way step to differentiate between many bullish and bearish windows.

PARAMETERS AND OPTIMIZATION

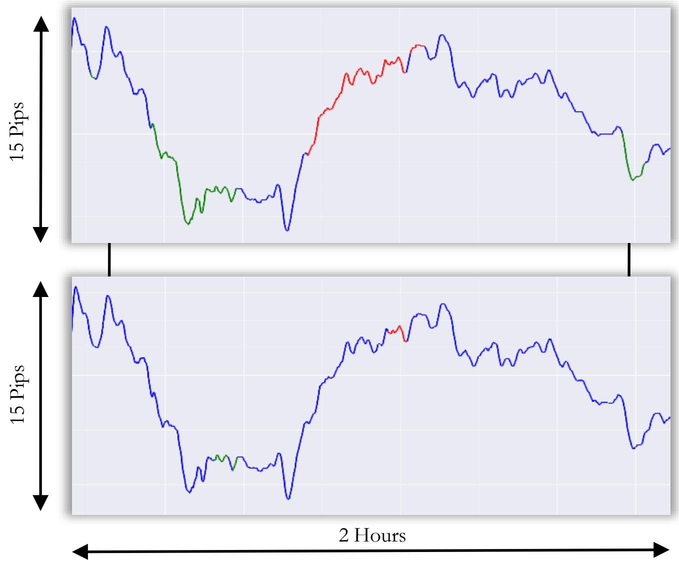

Exhibit E: The running predictions of the naive approach can be seen in the top subfigure, while the running predictions of the more cautious approach can be seen in the bottom subfigure. Blue signals avoid, green signals to go long and red signals to go short.

Exhibit F: Simulated trades placed by the strategy. The green dots represents opening points of long positions, and red dots representst opening points of short positions.

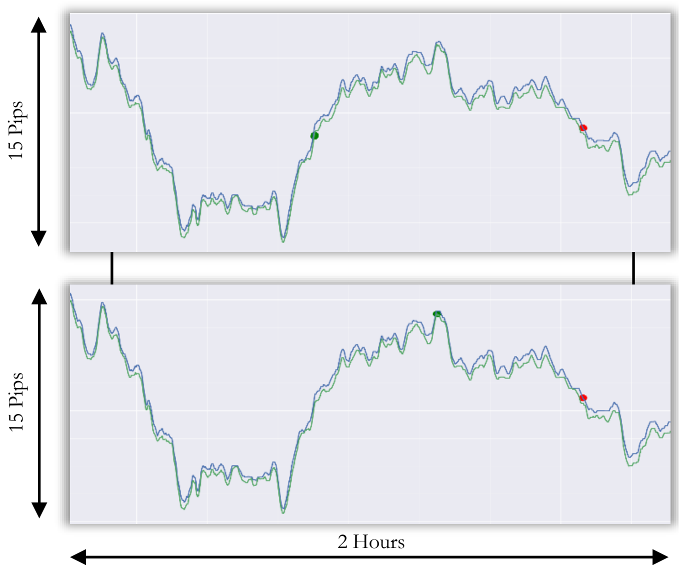

Exhibit G: The closing points of the trades opened in Exhibit F. The top subfigure represents the closing points for the strategy with a static take profit of 5 pips, while the bottom subfigure represents the closing points with the dynamic take profit applied with a trigger also at 5 pips.

Trading Parameters

One trading parameter to optimize is how to trade on the predictions made by the network, i.e. given what criteria should a new position be placed. A naive approach would be to simply go short after a bullish window, and go long after a bearish window. In the top subfigure in Exhibit E, one can see the running predictions made by this naive strategy over a 2 hour period. During this period there would be many positions opened, as a new window is assembled every minute. Many of these positions could be closed at a profit, however, it is unfavourable to place positions in the start of the, say, prediction lines (green and red), as these positions should have less probability of getting covered within the first couple of hours. A more cautious approach would be to track the previous predictions and only place positions given an additional set of criteria, for example, one only opens a long position if the current window has much less bearish nature than, say, all the previous ten, given that these ten were fully predicted as bearish. These modified predictions can be seen in the bottom subfigure of Exhibit E. It is clear that this approach makes the strategy more precise.

A collective take profit is also to be used, which means that all open positions of a certain type are closed simultaneously after their average value reaches a profit of 10 pips. This is not a large amount, and is set small to increase the probability of profits. This also makes sure to close unfavourably placed positions, making the collective take profit act as a type of stop loss. Additionally, a rather large collective stop loss is set to close all positions of a certain type if the average loss does exceed 500 pips. This makes sure to allow for daily and weekly swings while setting an upper bound on possible losses. The initial balance is chosen to be 100000$, as it is large but not unreasonable. This is then leveraged 30 times as possible by many brokers. A stop trading condition is also put in place to make sure that the free margin stays close to about 50% of the current account value, in order to stay far from devastating margin calls.

The overall theory behind the strategy is that most unfavourably placed positions should be able to get covered by the collective of all new favourably placed positions. Thus, the strategy rides on daily and sometimes weekly fluxuations while placing most positions at local and global extrema that collectively should be able to generate a profit.

To additionally increase the probability of profits, the daily trading period is set at the later half of the London market open, as this period sees the largest price movements.

Dynamic Take Profit

An interesting possibility that follows from having a probability distribution over the bullish, bearish and noisy nature of the current price window, is that you can construct a dynamic take profit level, that follows the trend and closes at a hopefully higher level than if only a static take profit were to be used. This can be done by first chosing a profit level that triggers a tracking of the probability distribution as it changes with the live feed, for example, when the long positions are up about 5 pips, a tracking of the bullish probability is initiated, and if the network continues to find that the new window has a bullish probability of above, say, 50%, then the position is held further, but once it drops below 50% the position is closed.

A simulated trading example by the strategy is demonstrated in Exhibit F and G. In the top subfigure of Exhibit G are the closing points of the previously opened positions due to an applied static take profit level. It is not unreasonable to assume that a normal trader would have held the long position further given the appearence of the price movement. The bottom subfigure in Exhibit G are the closing points if the dynamic take profit level is instead applied. It is clear that the long positions are now closed at the best possible place that maximize its profits. Interestingly, the short positions are closed at the same point, as there was not enough signal to take it further. Having the dynamic take profit activated tends to generate on average 20% more profit from trades.

Exhibit H: The trading period equity and balance curves. The balance curve represents the initial value of the account plus the realized profits, while equity curve represents the balance plus the unrealized profit or loss. The trading period spans 41 working days from 17th of October to 13th of December.

Performance Summary

Common Metrics

Average Daily Return	3.7%
Standard Deviation	4.9%
Max Drawdown	15.6%
Daily Value at Risk	7.6%
Sharpe Ratio	12.1

Trading Details

	All	Long	Short
Total Net Profit	44790$	29070$	15720$
Gross Profit	52970$	35710$	17260$
Gross Loss	-8180$	-6640$	-1540$
Profit Factor	6.5	5.4	11.2
Total Number of Trades	322	184	138
Percent Profitable	86.3%	84.2%	89.1%
Winning Trades	278	155	123
Losing Trades	41	27	14
Even Trades	3	2	1
Transaction Fees	-646$	-368$	-278$
Roll Over Fees	1575$	2013$	-438$
Avg. Trade Net Profit	140$	159$	113$
Avg. Trade Net Loss	191$	232$	140$
Largest Winning Trade	1370$	1370$	590$
Largest Losing Trade	-770$	-770$	670$
Return on Initial Capital	45.7%	30.7%	15.0%
Annual Rate of Return	291.7%	196%	95.7%

Performance

As can be seen by the balance and equity curves in Exhibit H, the strategy managed to consistenly collect a rather large profit in just about 41 working days. This resuls in a return on initial capital of 45.7%, which amounts to 45700$, which includes the profit of about 1575$ made from roll over fees minus 650$ from transaction fees. This amount of profit was possible due to the large leverage that was used, which does increase risk, however, the strategy was at no time close to a margin call, as the usable margin was always stayed above 40000$. Over the trading period the average price had shifted downwards by about 160 pips from 1.1530$ to 1.1370$. Therefore, any investment in short position placed in the beginning of this period and closed at the end would have made a solid return of about 1.4%. One could thus expect that short positions should generate more profits, however, as can be seen in the performance summary below, it is interesting to note that this strategy made about 70% of its profits from long positions, going against the major trend of the price. The strategy detected more signals to go long than it did to go short. This could mean that when the price does swing against the current major trend, it tends to do so more distinctly than when the price moving with it. But as expected, and can be seen in the performance summary, the placed short positions were more likely to be profitable, having a profit factor of 11.2, while placed long positions had of profit factor of 5.4, which is still significant.

Statistics

As can also be seen in the performance summary, the average daily return is quite substantial at 3.7%, also the standard deviation is substantial, this could be expected as the strategy does carry some positions over to the next day, even the weekend, therefore, if there is a price gap it would get quite affected, either posititevly or negatively. Of all long positions 50% were closed within the first day, while for all short positions it was a significant 80%. The average holding time for all positions is a little more than one day, with about two weeks being the maximum and one minute the minimum. The maximum drawdown is 15.6%, this is large but should be acceptable as the strategy produces a high return. Two of these sizeable drawdowns happened late October and mid November, afterwards all drawdowns were significantly smaller. This is likely due to the shift in average price during this period. In the beginning the shift is rather sharp and then later levels out, which seems to happen after 20th of November. This means that unfavourably placed long positions is even more unfavourable, as a stop trading condition is set at 50% free margin, the strategy might not have enough capital to place more favourable positions, with more capital this should be less of a problem. As seen in the equity curve of Exhibit H, flat parts are weekends, and significant drawdowns tend to happen afterwards, one could therefore try and limit some risk by closing as many positions at the end of the week as possible. The daily value at risk is 7.6%, which means that an investment of 1000$ could expect to lose 76$ every 20th day. This is also not an unreasonable risk given the return. A quite common measure of risk adjusted returns is the sharpe ratio, which for this strategy is calculated to be 12.1, which is considered very high. For this calculation a 90 day T-bill at 2% was used. Additional trading details can also be found under the performance summary, of which the most relevant column should be [All] as that takes into account both long and short positions.

Conclusion

It was certainly possible to make a successful trading strategy that trades by the use of computer vision, i.e. through artificial eyes. The strategy indentifies shifts in prices and places positions at peaks and troughs, maximizing the probability of profits. It managed to generated a significant return, which comes with some but manageable risk. There are many ways of trying to reduce the risk, for example, tracking the monthly nature of price monvements and only trading long or short positions according to it. Additionally, the strategy does not take news events into account, a reduction in risk could also be made by making sure to close positions before certain news events are scheduled to occur. But regardless it seems like this strategy can be considered quite successful.

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