Technical Analysis with imaging price trend and other indicators

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Abstract

During the independent project, we successfully build up the imaging price trend model with CNN and test it with our back testing scheme. Although the performance of 20-days and 60-days model are not satisfying, we find 5-days model indeed can generate consistent profit and quite robust compared with other indicators. Besides, we do some research on other indicators and find some potential indicators in the China A share stocks market.

1 Introduction

Technical analysis in stocks market has been a heated topic in the cross field of finance, mathematics and computer science. With the rapid development of economy in China, technical analysis on China A share stocks market is broadly studied nowadays. Therefore, during the independent research, I conduct some research on Chinese A share stock market with the CNN-imaging price trend method and other traditional indicators. We are glad to see that the signals generated by the CNN-imaging price trend method do help us build up profitable trading strategy. Although there are some other alpha indicators have good performance on the testing period, strategy with CNN indicator is more robust with lower volatility, which is important and meaningful for a trading system.

2 CNN-based Imaging Price trend Method

2.1 Intuition and principle

A large literature investigate the ability of past prices to forecast future returns, producing a handful of famous indicators including momentum and reversal. However, as these indicators become more and more popular and are widely used in the market, their marginal effect become very limited. With the vigorous development of computer science and statistics, we can design and produce more complicated and efficient indicators using machine learning techniques. Recently, many researchers are taking an interesting direction into consideration. They are trying to employ the power of CNN to detect the price-based predictive patterns.

The input to a CNN is simply an image, and we represent it as a 2D matrix in computer. It is a plot of the past market information containing open price, lowest price, highest price and close price and trading volume. CNN can automate the feature extraction process in different layers of its construction. In a given layer, CNN spatially smooths image content to reduce noise and accelerate shape configurations that correlate with future returns. This smoothing operation is applied recursively by stacking multiple layers together. Therefore, we do not need to decide the features of the price trend but let the CNN automates the whole process. Because CNN is learning the similarities of profitable price trend patterns and profitless price trend, CNN is actually learning the human behaviors in the stocks market.

2.2 Image the price data

We describe the process of imaging the price trend as the input of CNN model in this section. There are many price charts of wide stocks range from Yahoo Finance and other financial websites. For example, we show the price chart of APPLE from yahoo finance.

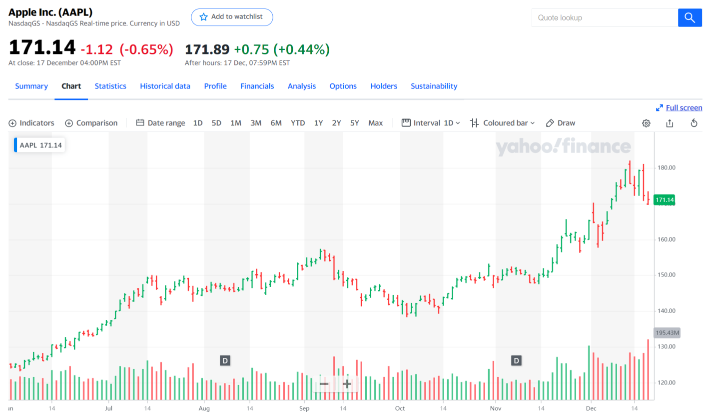

Figure 1: Price Chart of APPL.

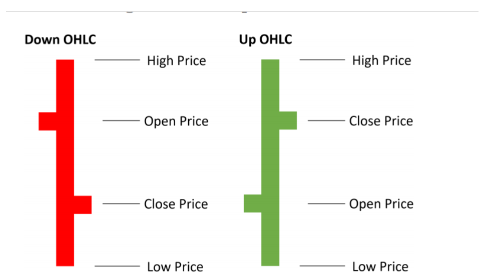

Figure 2: OHLC chart.

The images we generate follow the format of OHLC chart, which represents four elementary elements of the price trend. High and low prices are represented by the top and bottom of the middle vertical bar, while open price and close price are represented by the small horizontal lines on the left and right of the bar, respectively. In our processed images, we let one day's price occupies a three-pixel-wide area. To be specific, the center bar, open mark and close mark occupies each one pixel wide. Furthermore, the main component of our image is a concatenation of daily OHLC chart over consecutive 5, 20, and 60 days intervals. Therefore, the width of a n-day image is 3n pixels. What's more, we also replace the prices by CRSP adjusted returns to scale the open, close, highest and lowest prices and abstract the prices effect of price splits and dividend payments. For instance, once days are concatenated, we will impose a constant height for all images by scaling the vertical axis so that the maximum and minimum of the OHLC chart path coincides with the top and bottom of the image.

Here we show some examples of our OHLC images:

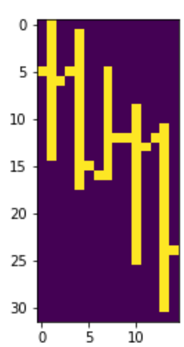

Figure 3: 5days OHLC 1

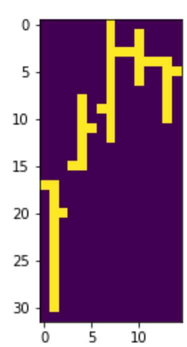

Figure 4: 5days OHLC 2

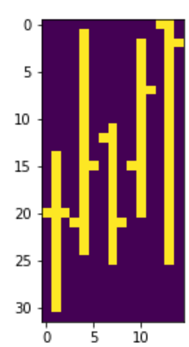

Figure 5: 5days OHLC 3

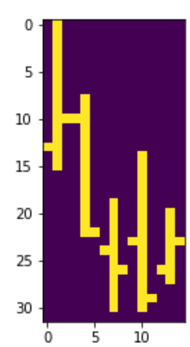

Figure 6: 5days OHLC 4

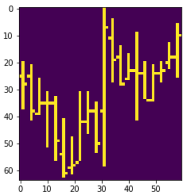

Figure 7: 20days OHLC 1

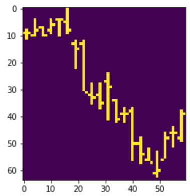

Figure 8: 20days OHLC 2

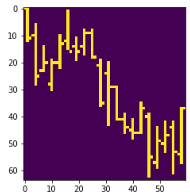

Figure 9: 20days OHLC 3

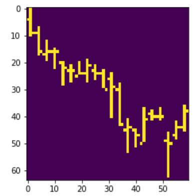

Figure 10: 20days OHLC 4

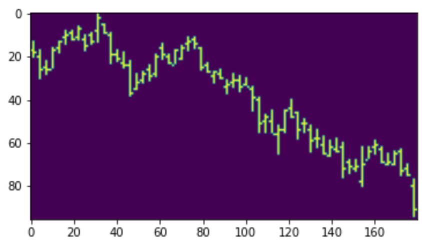

Figure 11: 60days OHLC 1

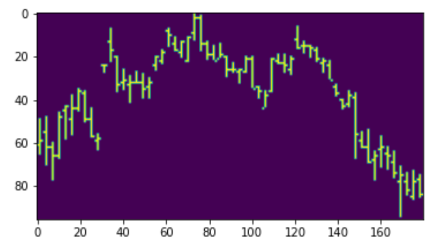

Figure 12: 60days OHLC 2

Then we consider adding the additional volume bars into our images so that they can reveal more information of the market. To be specific, we let the volume be shown in the bottom one-fifth of the image while the top four-fifths of the image is the OHLC plot mentioned above. Similar to the previous OHLC chart, the maximum volume in a given image is set equal to the upper limit of the volume bar section and the remaining volume bars are scaled accordingly. Here we show some examples of our images with volume. We will discuss the effect of adding the volume bar in the later part.

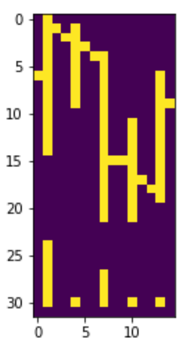

Figure 13: 5days OHLC 1

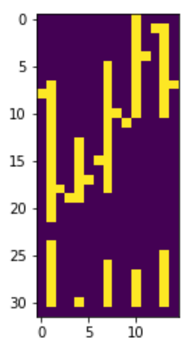

Figure 14: 5days OHLC 2

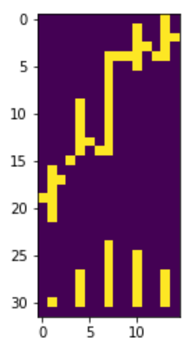

Figure 15: 5days OHLC 3

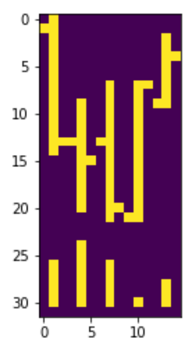

Figure 16: 5days OHLC 4

2.3 Architecture of the CNN

In the part we will describe the details and some components of our CNN models. A CNN is a modeling scheme that stacks a sequence of operations together to transform a image into a set of predictive features and finally a indicator we will use to predict the market or generate returns. A CNN contains several operations and we will use layers to realize these operations. The first operation is 'convolution' which serves as filters to filter features of the images. Second operation is the 'activation' which is a non-linear transformation applied element-wise to the output of the result of the convolution filter. For example, we use 'Leaky ReLU' which takes the max of the filter output and value and zero to sharpens the resolution of the filter output in our model. The last operation is 'pooling', where we use a small filter that scans over the input matrix and returns the maximum value(for max-pooling). It acts as a dimension reduction device because in graphs, nearby neurons output from the convolution

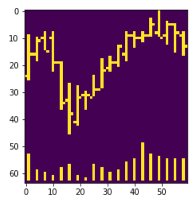

Figure 17: 20days OHLC 1

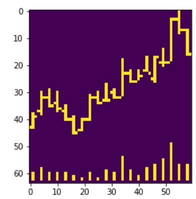

Figure 18: 20days OHLC 2

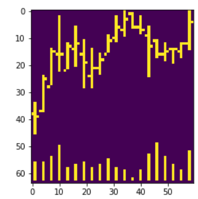

Figure 19: 20days OHLC 3

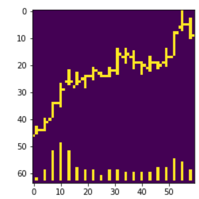

Figure 20: 20days OHLC 4

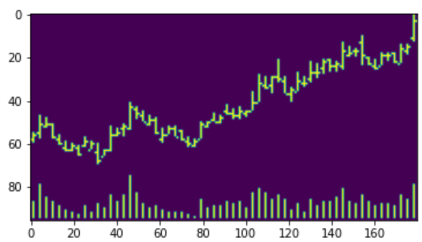

Figure 21: 60days OHLC 1

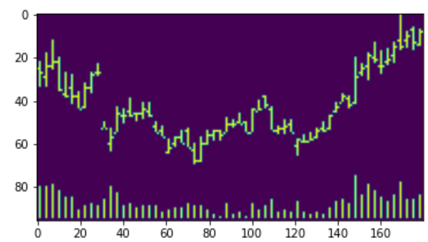

Figure 22: 60days OHLC 2

operation often carry similar information. If any of the neurons in the filter region are stimulated, max-pooling can detect it. Besides, it helps us discard locally redundant information.

Now we present the specific choices for our models. Since the images are largely sparse in the vertical dimension, we can use 5×3 convolution filters and 2×1 max-pooling filters. For convenience, we use the same parameters for convolution filters in different layers. Besides, in the first block, we use horizontal and vertical strides of 1 and 3, with vertical dilation rates of 2 and 3 for 20-day and 60-day images respectively. What's more, we use different numbers of building blocks for different sizes of images. We use 2 blocks for 5-day images, 3 blocks for 20-day images and 4 blocks for 60-day images. In total, we have 15360, 46080 and 184320 neurons for 5-day, 20-day and 60-day cnn models.

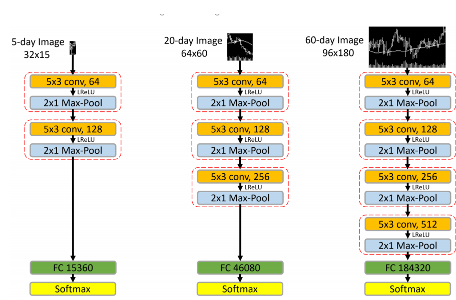

Figure 23: components and structure of CNN.

Finally, we describe the training part of the CNN model. As other common machine learning models, we divide the sample data into training, validation and testing samples. Then we treat the prediction analysis as a classification problem, which means we will classify the images into 2 categories. If the stock's return after responsive days are positive, we label this image as 1 and vice versa. The training step is set to minimize the cross-entropy loss, which is quite standard objective function for classification problems, which is defined as:

$$L(y, \hat{y}) = -ylog(\hat{y}) - (1 - y)log(1 - \hat{y})$$

Here is the softmax output from the final step in the CNN, which represents the probability of the stocks' going up in the next few days. As for the regularization procedures to combat overfit and aid efficient computation, we apply Xavier initializer for weights in each layer. In this way we can promotes faster convergence by generating starting values for weights to ensure that prediction variance begins on a comparable scale to that of the labels. As for the loss function, we uses stochastic descent and the Adam algorithm with initial learning rate of 5×10^{-5} and batch size of 256. We also apply 50% dropout to the fully connected layer. Finally we use early stoppling to halt training once the validation sample loss function fails to improve for two consecutive epochs.

3 Experiments on China A share stock market

3.1 Data preprocessing and model training

Our sample data contains all stocks in China A share stocks market from 4^{st} January 2000 to 29^{th} September 2021. Considering that China A share stocks are not as developed as American stock market, we restrict our scale of stocks into CSI1800 so that some inferior stocks will not have a bad influence on our training models.

As for the separation of datasets, we let the data from 4^{st} January 2000 to 29^{th} December 2014 to be the training set and data from 4^{st} January 2015 to 29^{th} September 2021 be the testing set. Furthermore, in the training set, we randomly choose 70% of the data for training and 30% of the data for validation.

For instance, when we train the model of 5-day images trend, for each stock, we preprocess the data and create our OHLC images for the stocks in 5 days. Then for each image, we label it according to its return after 5 days. If the stocks generate positive return in 5 days, we label the image as 1 and vice versa. Finally we randomly split the data into training set and validation set to train our models. The 20-day and 60-day models follow the same procedure.

3.2 model performance and accuracy

First, we present the loss and accuracy during the training process of different models:

Figure 24: 5days loss

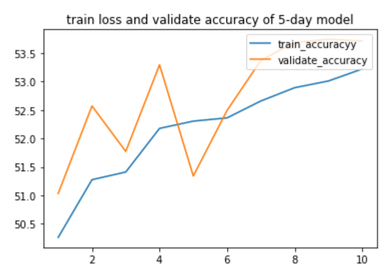

Figure 25: 5days accuracy

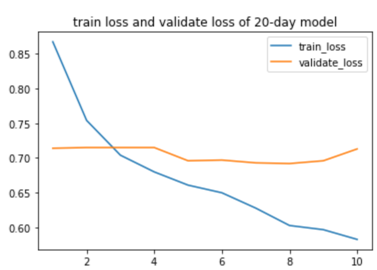

Figure 26: 20days loss

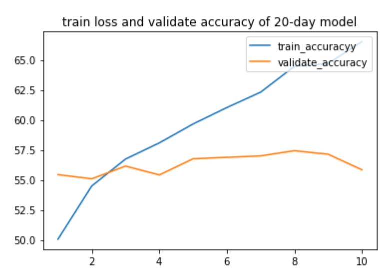

Figure 27: 20days accuracy

From the result we can see that the 5-days model reveal a good performance on validate loss and accuracy. However, the 20-days and 60-days models seem not efficient in identifying the up or down of the images. To further analyse the performance of models on test data, we present the test loss and accuracy of the data here:

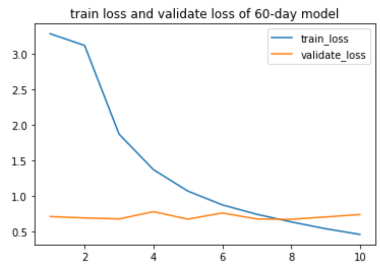

Figure 28: 60days loss

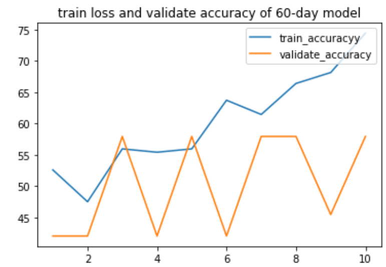

Figure 29: 60days accuracy

Test	5-days	20-days	60-days
Loss	0.698	0.762	0.696
Accuracy	0.51018	0.49173	0.50054

Table 1: Test loss and accuracy of different models.

Here we observed that the 5-days model should a 51 % accuracy on the out-of sample data. In fact, this makes sense in the financial industry since the return on a trading strategy does not depends totally on the accuracy of the prediction on the direction, but the ability to predict return. Therefore, we will show the 5-days model actually generate efficient and robust trading strategy in the later part.

4 Performance of portfolio

4.1 Backtesting scheme

To Further present the potential of the CNN models, we design our back-test scheme as follows. First, we test our strategy on the stocks from 4^{st} January 2015 to 29^{th} September 2021 and build up a weekly-adjusted strategy. To be specific, on the first day of each five trading days, we calculate the indicators based on the corresponding historical price trend images for each stock (For example, 5 - days images for 5-day models). Then we sort the stocks by the softmax output of the model into 20 percentiles and long stocks in the first percentile and short the ones in the last percentile. Besides, we compared the portfolio performance with the strategies generated by benchmark indicators. We use three benchmark strategies containing Momentum, Reversal and Weekly reversal. For Momentum strategy, we use the average return of the past month of a stock as the indicator. For reversal strategy we use the average loss of the past month of a stock as the indicator. For the weekly-reversal strategy, we use the average loss of the past week of a stock as the indicator.

4.2 Analysis on the portfolio performance

The portfolio performance are shown as follows.

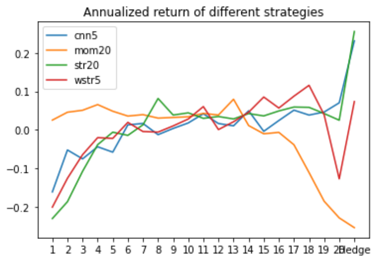

Figure 30: annualized return

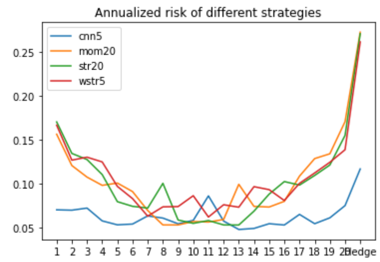

Figure 31: annualized risk

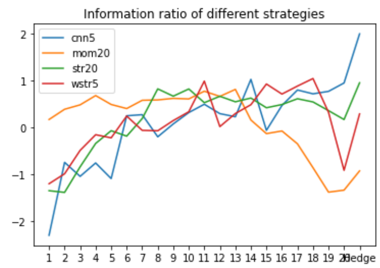

Figure 32: annualized information ratio

Here we observed that in annualized return, the 5-days cnn beats the MOM and STR benchmark models but not the WSTR models. However, we can see from the annualized risk and annualized information ratio that the CNN models is far better than the other benchmark models, which means the CNN model is more robust and can generate consistent profits. It is very essential for the trading since risk management is of great importance for a successful trading strategies.

Furthermore, we show the different results of different CNN models of 5, 20 and 60 days:

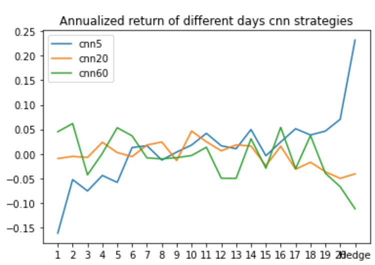

Figure 33: annualized return

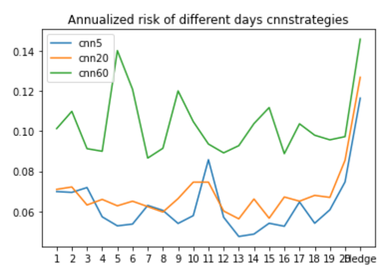

Figure 34: annualized risk

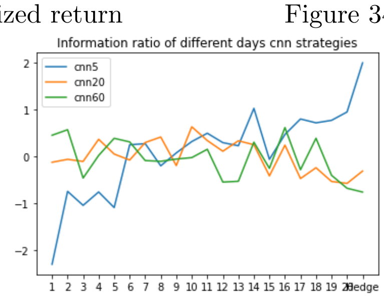

Figure 35: annualized information ratio

From the result we can observe that the 5-days CNN model is better than 20-days models and 60-days models no matter in Annualized return, annualized risk or annualized information ratio. It make sense since the price trend has its efficient time period. The longer the time period, the more ambiguous the predict ability of the short-term period.

To further study the profit ability of the models, we plot the annualized return of the cnn models of each year and other evaluation metrics.

Subperiod Performance of the Hedged Portfolio of cnn5

horizon	P1W	P4W	P13W	P26W	P52W	2021	2020	2019	2018	2017	2016	2015
ret1	2.96%	2.91%	6.69%	9.96%	11.47%	11.04%	18.38%	16.13%	19.55%	18.58%	39.40%	29.71%
ret2	-0.72%	-3.71%	-4.29%	3.55%	9.63%	10.44%	-2.29%	14.38%	0.34%	-2.31%	-1.60%	6.12%
ret3	-0.82%	-5.51%	-1.61%	-2.13%	4.58%	-1.43%	-4.91%	13.95%	9.03%	-3.95%	-0.30%	-20.99%
ret4	0.96%	1.56%	2.02%	-5.79%	-7.73%	-9.50%	-5.58%	11.43%	21.42%	-3.04%	-4.27%	-16.61%
ret5	0.49%	2.75%	-0.01%	7.74%	6.27%	4.41%	5.78%	7.52%	-4.89%	8.55%	-8.74%	23.76%
ret6	1.29%	0.51%	-7.62%	-3.37%	-13.16%	-4.17%	3.15%	-1.19%	5.74%	4.49%	-0.75%	-4.55%

Figure 36: hedged portfolio of CNN5.

Subperiod Performance of the Hedged Portfolio of mom20

horizon	P1W	P4W	P13W	P26W	P52W	2021	2020	2019	2018	2017	2016	2015
ret1	-4.94%	-2.77%	18.53%	33.59%	39.22%	24.45%	13.15%	-34.10%	-28.32%	-7.12%	-56.27%	-82.80%
ret2	-7.62%	-9.44%	16.00%	28.59%	40.56%	21.99%	23.18%	-30.01%	-12.93%	-0.98%	-36.20%	-91.51%
ret3	-6.12%	-10.70%	10.18%	10.89%	13.91%	2.00%	13.20%	-6.57%	-23.99%	6.94%	-23.87%	-96.44%
ret4	-6.27%	-7.38%	18.69%	27.62%	31.66%	18.90%	9.09%	-4.83%	-9.80%	4.68%	-12.95%	-96.92%
ret5	-4.09%	-7.19%	12.70%	9.25%	20.63%	1.89%	2.19%	22.54%	-2.71%	9.96%	-6.90%	-48.92%
ret6	-4.20%	-1.81%	15.05%	15.81%	33.88%	10.93%	19.75%	13.86%	16.36%	19.49%	-9.96%	-11.14%

Figure 37: hedged portfolio of mom.

Subperiod Performance of the Hedged Portfolio of str20

horizon	P1W	P4W	P13W	P26W	P52W	2021	2020	2019	2018	2017	2016	2015
ret1	4.94%	2.77%	-18.53%	-33.59%	-39.22%	-24.45%	-13.15%	34.10%	28.69%	7.12%	55.26%	84.38%
ret2	7.62%	9.44%	-16.00%	-28.59%	-40.56%	-21.99%	-23.18%	30.01%	13.18%	0.98%	36.34%	90.89%
ret3	6.12%	10.70%	-10.18%	-10.89%	-13.91%	-2.00%	-13.20%	6.57%	23.58%	-6.94%	22.55%	97.10%
ret4	6.27%	7.38%	-18.69%	-27.62%	-31.66%	-18.90%	-9.09%	4.83%	9.66%	-4.68%	11.57%	95.39%
ret5	4.09%	7.19%	-12.70%	-9.25%	-20.63%	-1.89%	-2.19%	-22.54%	2.79%	-9.96%	6.52%	48.15%
ret6	4.20%	1.81%	-15.05%	-15.81%	-33.88%	-10.93%	-19.75%	-13.86%	-17.01%	-19.49%	10.25%	13.39%

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Figure 38: hedged portfolio of STR.

Subperiod Performance of the Hedged Portfolio of wstr5

horizon	P1W	P4W	P13W	P26W	P52W	2021	2020	2019	2018	2017	2016	2015
ret1	-2.30%	-6.89%	-4.88%	-11.14%	-18.84%	-7.45%	-3.28%	12.67%	6.44%	2.67%	30.74%	15.09%
ret2	2.69%	3.99%	-13.80%	-14.99%	-12.24%	-2.62%	-13.91%	5.77%	-12.26%	3.71%	20.18%	35.79%
ret3	3.02%	6.58%	-3.46%	-19.58%	-9.04%	-6.94%	-14.22%	4.83%	5.52%	-13.87%	7.10%	14.24%
ret4	4.58%	7.81%	-13.26%	-18.30%	-17.63%	-13.91%	-12.95%	25.22%	13.83%	4.30%	18.84%	29.32%
ret5	4.80%	7.29%	-7.71%	-5.31%	12.42%	8.40%	10.56%	-8.82%	5.67%	0.03%	7.27%	38.58%
ret6	1.07%	3.60%	-9.35%	-3.33%	-12.95%	-2.83%	9.68%	-0.33%	-5.33%	-9.39%	-5.75%	57.03%

Figure 39: hedged portfolio of WSTR.

The results again support our argument that the CNN model is more robust than the other trading indicators. It is easy to observe that MOM and WSTR generate positive and negative returns in different years. Some of years MOM strategy wins a lot and other years it causes a lot loss. It is the same for the WSTR strategy. However, the CNN model can generate steady and consistent profits in different years which is a key characteristics of a useful and reliabel indicators.

5 Other interesting indicators potential in the Chinese A share stocks market

In addition to the CNN model, we also try to analyse some other indicators from Professor Haifeng's documents. We present three potential indicators here:

The first indicator is the beta20 where beta20 is the 20-days beta of the following equation.

$$r_t - r_{ft} = \alpha + \beta * r_m + \epsilon \tag{1}$$

Here r_t is the return of the specific stock and r_{ft} is the risk free return and r_m is chosen as the Shanghai Shenzhen 300 Index. This indicator shows the correlation of the stock with the market and its systematic risk under the current market.

The second indicator is the DAVOL20 which means the difference between the 20-days average turnover rate and 120-days average turnover rate.

$$DAVOL20 = VOL_{20} - VOL)120 \tag{2}$$

This indicator detects the volume change of the stock in the recent time period. Since the change of prices come from the change of volume, indicator on the change of volume can present the market's confidence on the stocks.

The last indicator is the FiftyTwoWeeksHigh. This indicator is calculated by the rank of the current price of a stock in the previous year. This indicator can be seen as a more robust and strengthen momentum indicators.

The performance compared with cnn 5-days model is shown belows

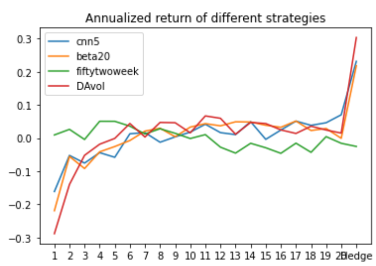

Figure 40: annualized return

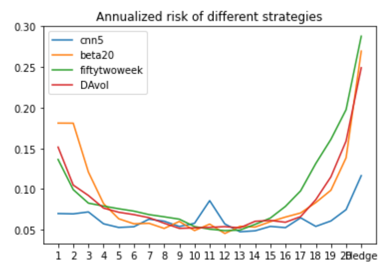

Figure 41: annualized risk

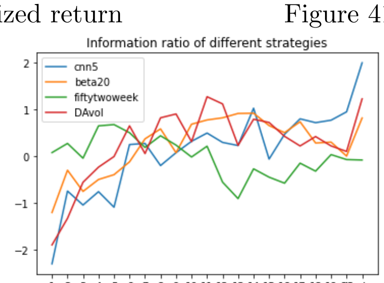

Figure 42: annualized information ratio

From the result we can observe that these 3 new indicators can generate good positive returns in the out-of-sample data. Especially for DAvol20 and beta20, they both generate high returns as cnn 5-days model. However, we still observe that the cnn 5-days model has the lowest risk thus is the most robust one.

To further analyze the performance of these 3 new indicators, we show their performance each year.

Subperiod Performance of the Hedged Portfolio of beta20

horizon	P1W	P4W	P13W	P26W	P52W	2021	2020	2019	2018	2017	2016	2015
ret1	3.18%	3.19%	8.69%	17.56%	20.11%	15.57%	18.55%	24.14%	54.44%	19.31%	3.83%	32.20%
ret2	3.76%	1.81%	3.82%	8.82%	-0.78%	0.09%	11.39%	14.57%	46.62%	6.65%	28.31%	51.69%
ret3	4.43%	7.19%	5.32%	18.62%	14.48%	6.66%	4.16%	28.63%	31.75%	8.41%	18.61%	40.87%
ret4	6.22%	7.88%	12.73%	27.63%	22.10%	17.04%	4.15%	16.61%	36.09%	14.53%	13.48%	34.34%
ret5	5.72%	7.26%	2.44%	13.37%	0.57%	-3.29%	13.27%	7.41%	20.77%	6.96%	-1.33%	-10.17%
ret6	2.21%	4.99%	-0.58%	13.42%	9.74%	2.90%	19.56%	-5.20%	10.33%	11.50%	-8.79%	-13.64%

Figure 43: hedged portfolio of beta20.

Subperiod Performance of the Hedged Portfolio of DAvol120

horizon	P1W	P4W	P13W	P26W	P52W	2021	2020	2019	2018	2017	2016	2015
ret1	3.69%	4.93%	7.64%	8.82%	1.77%	15.37%	6.39%	31.13%	37.34%	28.47%	27.76%	50.96%
ret2	3.69%	7.44%	7.90%	9.57%	0.16%	13.83%	11.70%	26.29%	21.34%	21.79%	26.64%	36.46%
ret3	3.76%	8.99%	14.79%	19.19%	7.65%	20.21%	11.81%	12.66%	15.68%	15.61%	26.31%	28.59%
ret4	3.38%	8.60%	21.47%	27.77%	19.52%	28.20%	9.16%	7.22%	6.62%	9.58%	20.09%	24.48%
ret5	2.26%	5.07%	18.74%	26.16%	16.39%	21.47%	13.56%	12.73%	-0.46%	5.81%	16.50%	25.49%
ret6	2.34%	4.38%	22.75%	25.64%	17.41%	20.10%	-0.34%	10.33%	-1.80%	1.60%	18.87%	-0.38%

Figure 44: hedged portfolio of DAVOL20.

Subperiod Performance of the Hedged Portfolio of fiftytwohigh240

horizon	P1W	P4W	P13W	P26W	P52W	2021	2020	2019	2018	2017	2016	2015
ret1	-4.13%	-2.88%	15.99%	28.93%	62.28%	33.80%	56.67%	1.04%	31.48%	32.82%	-51.72%	-118.24%
ret2	-6.06%	-4.31%	12.79%	16.59%	35.42%	15.07%	41.77%	18.21%	13.37%	29.48%	-43.54%	-122.81%
ret3	-5.36%	-6.46%	10.79%	11.22%	27.13%	7.44%	54.51%	18.08%	3.41%	34.06%	-33.32%	-119.57%
ret4	-5.80%	-10.94%	8.21%	14.30%	34.37%	10.90%	43.67%	20.87%	8.49%	20.03%	-27.81%	-128.29%
ret5	-5.42%	-5.39%	11.89%	14.61%	23.51%	5.15%	33.53%	29.41%	5.86%	23.81%	-27.34%	-115.14%
ret6	-4.11%	-5.74%	12.70%	9.85%	33.79%	10.63%	55.90%	27.37%	10.25%	30.63%	-24.39%	-86.40%

Figure 45: hedged portfolio of fiftytwoweekshigh.

Here we notice that DAvol and beta20 can both consistently generate positive return while the fiftytwohigh also genearte postive return in recent years except it suffers great loss in 2015 mainly because of the market crash that year.

6 Conclusion

During the research period in the independent project, we build up a new image price trend model with CNN and verify that CNN 5-days model can help us build up a robust and consistent profitable strategy. Besides, we also find some potential indicators useful in the China A share stocks market. However, problems still remains since the cnn 5-days model doesn't generate significant better profit compared with some good indicators and the performance of 20-dyas and 60-days models are not satisfying. Nevertheless, its robust characteristics is noticeable. It is tested that the CNN imaging price trend is potential and worth more in-depth contribution.

7 Reference

'(Re-)Imag(in)ing Price Trends', Jingwen Jiang, Bryan Kelly, Dacheng Xiu, 2021