Encoding Candlesticks as Images for Patterns Classification Using Convolutional Neural Networks

Yun-Cheng Tsai,[1] Jun-Hao Chen,[2] Jun-Jie Wang[3]

[1] *Center for General Education*
[2,3] *Department of Computer Science and Information Engineering*
[1,2] *National Taiwan University, Taipei 10617, Taiwan*
[3] *National Taipei University, New Taipei City 23741, Taiwan*

Abstract

Candlestick charts display the high, low, open and closing prices for a specific time series. Candlestick patterns emerge because human actions and reactions are patterned and continuously replicate and captured in the formation of the candles. According to Thomas Bulkowski's Encyclopedia of Candlestick Charts, there are 103 candlestick patterns. Traders use these patterns to determine when to enter and exit. However, the candlestick patterns classification takes the hard work out of identifying them visually. In this paper, we propose an extend Convolutional Neural Networks (CNN) approach "GASF-CNN" to recognize the candlestick patterns automatically. We use the Gramian Angular Field (GAF) to encode the time series as different types of images. Then we use the CNN with the GAF encoding images to learn eight critical kinds of candlestick patterns. The simulation and experimental results evidence that our approach can find the eight types of candlestick patterns over eighty percent accuracy automatically.

Keywords: Convolutional Neural Networks (CNN), Gramian Angular Field (GAF), Candlestick, Patterns Classification, Time Series

[1]The author was supported in part by the Ministry of Science and Technology of Taiwan under grant 107-2218-E-002 -031. To whom correspondence should be addressed; E-mail: pecutsai@ntu.edu.tw

1. Introduction

Financial market forecasts, such as predicting fluctuations or volatility forecasts for futures indices, are among the critical researches in commercial finance and information engineering. Since market prices are dependent and susceptible to the expected psychological impact of the overall market, it is possible to complete predictive models of financial demand through special pre-processing and coding, or more complex model architectures.

There are already many tools to help people predict stock price fluctuations and futures indices, such as neural networks, fuzzy time series analysis, gene algorithms, classification trees, statistical regression models, support vector machines, etc., but they are almost exclusively Machine learning models used for forecasting, which are generic techniques, are rarely combined with financial expertise. However, the average person pursues profit in the transaction, so the prediction results of the above model are not accurate enough in real-world operations. Investment forecasts and model predictions tend to have large gaps, and investors are more inclined to find a good entry and exit point rather than merely predicting prices. Many studies often focus on the accuracy of numerical predictions [1, 2, 3, 4, 5, 6], and they are unknown investors only concerned with the time of entry and exit (how much profit space they have). In other words, rather than blindly using machine learning or deep learning architecture to pursue unrealistic low-risk, high-accuracy profit models, it is better to combine the basic knowledge of transactions directly to create a reliable application model.

Candlestick patterns recognition is one of the essential tools for determining market conditions [7]. Traders often make judgments with a lot of complicated information to make trading decisions. The information are including technical indicators, news, candlestick patterns and so on. Among them, especially candlestick patterns recognition is at the core of the help of individual transactions [8]. Candlestick patterns recognition help traders determine what the current asset price is in the market, such as whether the current buying pressure will continue or whether the current selling pressure will reverse, to assist traders with other sources to predict the future. Price trend, a few more commonly heard morphology, such as the Morning Star and the Evening Star are examples of price reversal signals. However, candlestick patterns recognition is slowly on the analysis of traders expertise, rather than through numerical analysis. This recognition requires traders to make judgments on the visual perception of images.

The Convolutional Neural Networks (CNN) model is perfect for image recognition [9]. The CNN can update its convolution kernel by backward propagation and train the appropriate weights to extract the excellent image features. The correlation between traits and images is then compared to help the model make correct judgments. Further, the type of neural network suitable for image identification is carried out through a two-dimensional convolution. But basically, the financial time series data are represented by a one-dimensional array. So we need to find a way to convert the time series data into a reasonable matrix form.

After many experiments and discussions, we find that it is an unsuitable method to make the time series data as the image pixels directly [10]. We use the Gramian Angular Field (GAF) to encode the time series data [11]. This particular encoding method can significantly improve the performance of the neural network in the two-dimensional convolution time series. Based on this encoding, we can even use a straightforward neural network architecture to achieve outstanding results, even to the multi-layer perceptron (MLP) cannot easily exceed the performance.

Therefore, we base on the above approach and design a GAF-based CNN to emulate the trader to identify candlestick pattern characteristics of the experiment. We call our approach as "GASF-CNN". The first, we use the geometric Brownian Motion (GBM) model to simulate an amount of prices data. According to Zhiguo, we set the same parameters to make the price, and its volatility closes to the real data [12]. The second, we chose eight candlestick patterns from THE MAJOR CANDLESTICKS SIGNALS [13]. These eight types of pointers are Morning Star, Bullish Engulfing, Hammer, Shooting Star, Evening Star, Bearish Engulfing, Hanging Man, and Inverted Hammer. The difference between these eight candlesticks signals is very subtle, and it will challenge the traditional CNN model.

To improve the traditional CNN model, we use our GASF-CNN to train the GBM simulation data. Our model produces a good performance on the simulation data. Also, we use real data to verify the viability of our GASF-CNN in the real world. We expect that our GASF-CNN model allows the computer to look at the candlestick patterns as slightly as a trader. The results show that the GBM simulation data can achieve near 85% accuracy. We use the 2017 historical data of current exchange rate EURO (EUR) to US DOLLAR (USD) to test our GASF-CNN model. The experimental results can even achieve 93% accuracy and 89% of the rate of return. The simulation and experimental results show that our GASF-CNN is well suited for the shape identification of financial trading. Although this paper uses only eight of the most classical type indicators, the various morphological extensions that can be made based on our GASF-CNN are feasible, such as the W-head M-bottom.

The remainder of this paper is organized as follows. A review of the literature is given in the next section. In Section 3, we present our methodology. Then, a description of the empirical data employed in our study is provided in Section 4. Section 5 presents the conclusion of our study.

2. Preliminary

2.1. Candlestick

Some Japanese start using technical analysis to trade rice in the 17th century. While this early version of technical analysis was different from the US version initiated by Charles Dow around 1900, many of the guiding principles were very similar. The price action is more important than the news, earnings, and so on. All known information reflected in the price. Buyers and sellers move markets based on expectations and emotions. The actual price may not reflect the underlying value. According to Steve Nison, candlestick charting first appeared sometime after 1850. Much of the credit for candlestick development and mapping goes to a legendary rice trader named Homma from the town of Sakata. It is likely that his original ideas were modified and refined over many years of trading eventually resulting in the system of candlestick charting that we use today.

Figure 1 is the structure of a candlestick. The unit is the bar and takes the open, high, low and close prices for a certain period to draw information into a bar. The body is the price difference between the open and close price. The upper shadow is the price difference between the highest price and the body, and the lower shadow is the price difference between the lowest price and the body. The period of a bar can be arbitrarily customized, usually depending on the length of the transaction. If the open price is higher than the close price, the body will be rendered in black, indicating that the price is falling during this time. If the close price is higher than the open price, the body will be provided in white, noting that the price is rising during this time. The price is equal to the open price, and the body will disappear and replaced by a horizontal line.

As can be seen from the above, the candlestick can help investors filter out a lot of price noise. The bar only records the different price information

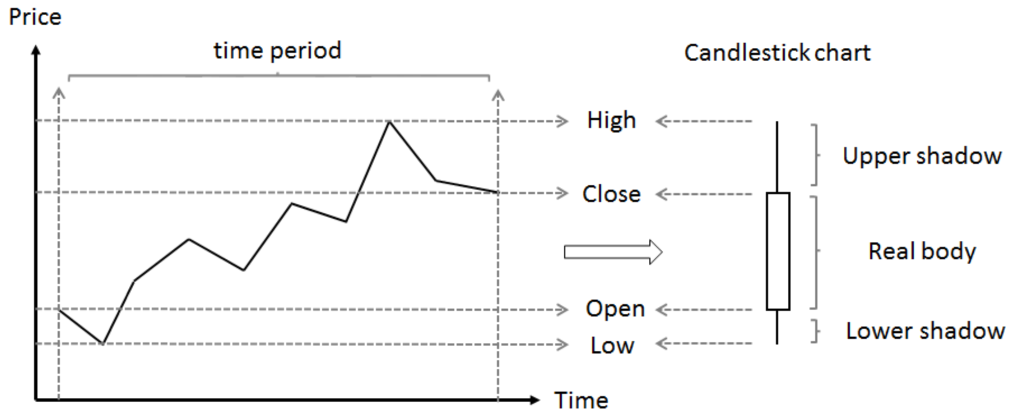

Figure 1: Candlesticks display all the market information you need such as the open, close, high, and low.

of the open, high, low, and close prices (OHLC) per unit time. When we put together multiple bar charts, we get a continuous market information map that he did not use to draw the closing price. He will present many unique shapes and call it a pattern.

The research of candlesticks has been paid attention for many years [14]. Many of the patterns used to identify trends have also been summarized, such as trend continuation indicators, or reversal indicators, etc. The candlestick analysis is one of the ways to get started with trading. However, some people think that it is difficult to observe the trend by observing the candlestick. It cannot be used as an indicator to predict the direction [15]. They began to systematize the patterns generated in the candlestick to gradually evolve into technical indicators of the system form the so-called candlestick patterns. The candlestick also uses together with the Average True Range (ATR), Relative Strength Index (RSI), Moving Average (MA), Moving Average Convergence and Divergence (MACD), Stochastic Oscillator (KD), etc [16].

2.2. Convolutional Neural Networks (CNN)

The Convolutional Neural Networks (CNN) is one of the best graph-based models in recent years. K. Fukushima introduced a model called Neocognitron, which is generally as the model that inspires the CNN on the computation side [17]. Neocognitron is a neural network designed to simulate the human visual cortex. It consists of two types of layers, called feature extractor layers and structured connection layers. The feature extractor layers, also called S-layers, simulate the cell in the primary visual cortex, helping human beings to perform feature extraction. The structured connection layers, also called C-layers, affect the complex cell in the higher pathway of the visual cortex, providing the model with its shifted invariant property.

The two most essential components of CNN are the convolution (Conv) layer and pooling (Pool) layer. Figure 2 shows that the convolution layer implements the convolution operation, which extracts image features by computing the inner product of an input image matrix and a kernel matrix. The number of channels of the input image and kernel matrix must be the same. For example, if the input image is an RGB color space, then the depth of the kernel matrix must be three; otherwise, the kernel matrix cannot capture the information between different color spaces. Another essential component is the pooling layer, also called the sub-sampling layer, which is mainly in charge of simpler tasks. Figure 3 shows that the pooling layer will only retain part of the data after the convolution layer. It reduces the number of significant features extracted by the convolution layer and makes the maintained features more refined.

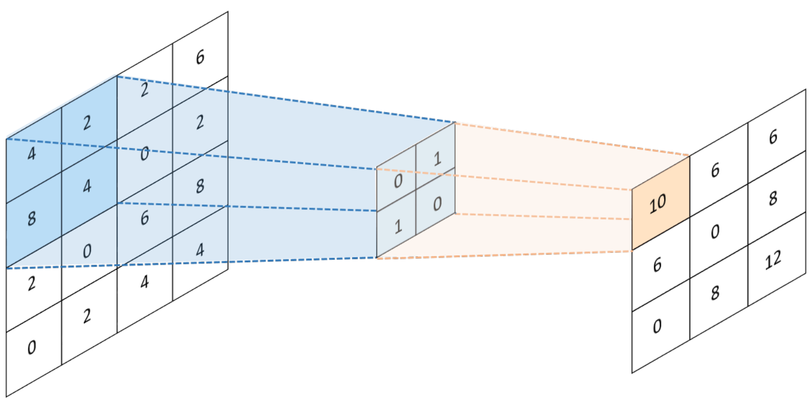

Figure 2: The convolution operation.

Only with these two components can the convolution model be used to imitate human vision. In practical applications, the CNN model usually combines the convolution layer and pooling layer. It is because the convolution layer often extracts a significant number of features, and most of the elements may be noise, which could lead to model learning in the wrong direction. It

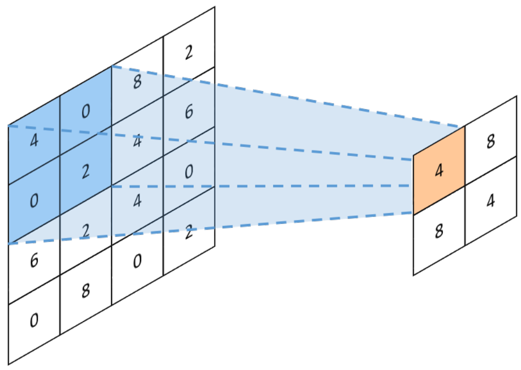

Figure 3: The pooling operation.

is the so-called model over-fitting problem. Furthermore, the fully connected layers usually connected at the end of the sequence. The function of the entire material layer is to organize the extracted features, which were processed by the convolution and pooling layer. The correlation between the extracted features learned in this layer.

Although the pooling layer can reduce the occurrence of over-fitting after convolution, it is inappropriate to use after the fully connected layer. Another widely known regularization technique called drop-out is designed to solve this issue. The drop-out technique randomly drops some neurons with a specific probability, and the dropped neurons are not involved in the forwarding and backward computation. This idea directly limits the model's learning; the model can only update its parameters subject to the remaining neurons in each epoch.

Inspired by the Neocognitron and the concept of back propagation, the most generally classic modern CNN, LeNet, was proposed by LeCun et al. in 1990. The potential of the modern convolution architecture can be seen in LeNet (1990), consisting of a convolution layer, a subsampling layer, and a full connection (FC) layer [18]. Figure 4 shows the LeNet model. As the concept of rectified linear unit (ReLU) and drop out were presented in recent years, a new convolution-based model, AlexNet, proposed by Hinton and Alex Krizhevsky, appeared and beat the previous champion of the ImageNet Challenge, with over 15M labelled high resolution images and roughly 22,000 categories.

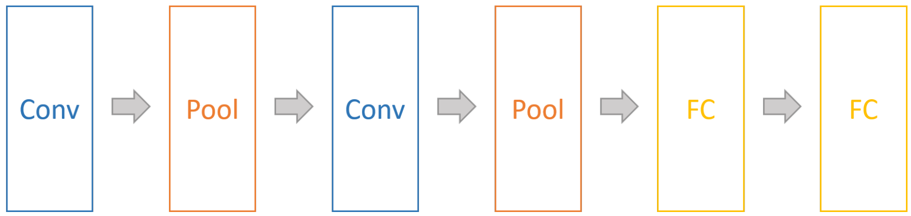

Figure 4: The classic LeNet model.

2.3. CNN for Patterns Classification

Human beings are visual animals. The eyes are the most compact structure of all the sensory organs, and the visual intelligence of the human brain is rich in content. Exercise, behavior, and thinking activities use visual sensory data as their most significant source of information. The more flexible and talented we become, the more we rely on visual intelligence. What general business and decision makers desire after analysis is not the data itself, but the value. Therefore, it is essential that data analyses be intuitive. In this way, the visualization of financial data can be more readily accepted: they can see the story and thus interpret the data more efficiently.

Although visualization analysis can benefit decision makers, many traditional statistical or machine learning methods for predicting currency movements use quantitative models. These methods do not consider visualization. We attempt to make good use of the advantages of display and comprehensively enhance the efficiency of intelligence analysis. For example, most traders use charts to analyze and predict currency movement trends, which carry apparent economic benefits. However, in this visualization, the analysis is artificial. We intend to teach machines to achieve display like a human brain. We then hope to use the tool to analyze robust financial data visually.

Convolutional neural networks (CNNs) are widely used in pattern and image recognition problems. In these applications, the best possible correction detection rates (CDRs) have been achieved using CNNs. For example, CNNs have achieved a CDR of 99.77% using the Modified National Institute of Standards and Technology (MNIST) database of handwritten digits, a CDR of 97.47% with the New York University Object Recognition Benchmark (NORB) dataset of 3D objects, and a CDR of 97.6% on over 5600 images of more than 10 objects. CNNs not only give the best performance compared to other detection algorithms but also outperform humans in cases such as classifying objects into fine-grained categories such as the particular breed of dogs or species of birds. The two main reasons for choosing a CNN model to predict currency movements are as follows:

1. CNN models are good at detecting patterns in images such as lines. We expect that this property can also be used to detect the trend of trading charts.
2. CNNs can detect relationships among images that humans cannot find easily; the structure of neural networks can help detect complicated relationships among features.

CNN is a graph-based model, which is different from quantitative models. People do not need to consider all possible features that affect currency movements using quantitative models alone.

2.4. Gramian Angular Field (GAF)

Gramian Angular Field (GAF) is a novel time series encoding method proposed by Zhiguang Wang and Tim Oates [11]. It represents time series data in a polar coordinate system and converts these angles with some operations into a symmetry matrix. Gramian Summation Angular Field (GASF) is a kind of GAF by using cosine function. Each element of the GASF matrix is the cosine of the summation of angles.

Our first step for making a GAF matrix is to normalize the given time series data into values between [-1, 1] or [0, 1]. The following two equations show the simple linear normalization method.

$$\widetilde{x}_{-1}^{i} = \frac{(x_i - \max(X)) + (x_i - \min(X))}{\max(X) - \min(X)} \tag{1}$$

$$\widetilde{x}_{0}^{i} = \frac{x_i - \min(X)}{\max(X) - \min(X)} \tag{2}$$

After the normalization, our second step can represent the normalized time series data in the polar coordinate system. The following two equations show how to get the angles and radius from rescaled time series data.

$$\phi = \arccos(\widetilde{x}_i), -1 \leqslant \widetilde{x}_i \leqslant 1, \widetilde{x}_i \in \widetilde{X} \tag{3}$$

$$r = \frac{t_i}{N}, t_i \in \mathbb{N} \tag{4}$$

Finally, we sum up the angles and use the cosine function to make the GASF by the following equation.

$$GASF = \cos(\phi_i + \phi_j) = \widetilde{X}' \cdot \widetilde{X} - \sqrt{I - \widetilde{X}^2}' \cdot \sqrt{I - \widetilde{X}^2} \tag{5}$$

The GASF has two essential properties. The first is that the mapping function from normalized time series data to GASF is bijective when $\phi \in [0, \pi]$. Only normalized data $[0, 1]$ can transform the GASF back to normalized time series data by the diagonal elements. The second is that polar coordinates preserve absolute temporal relations as opposed to Cartesian coordinates.

3. Methodology

In this section, we will introduce some of the most classic candlestick patterns in trading, and illustrate how we label these patterns. Next, we will talk about how we choose the features of the conventional model in our candlestick pattern recognition case. At last, we'll show our framework of using GASF and the conventional model to classify the candlestick pattern.

3.1. Crate Label Illustration

We select eight most classic candlestick patterns based on one of the classic candlestick patterns textbook "The Major Candlesticks Signals" as our training target. The eight candlestick patterns we chose are Morning Star, Bullish Engulfing, Hammer, Shooting Star, Evening Star, Bearish Engulfing, Hanging Man, and Inverted Hammer. All of these patterns are reversal pattern, which capture if the price is going to change. The first four patterns detect the price from downtrend to uptrend, and the last four patterns are the opposite. We will give each case an detail illustration below. The Morning Star pattern is the case of detecting the price from downtrend to uptrend. The description of this pattern has three stages. First, a downtrend must be confirmed, which means the whole market is in the absence of confidence. Second, the depressed atmosphere will finally end up with a big black bar. After a calm day, the third bar will become a big white bar. This is the investors expect the confidence of the market is going to reverse. Figure 5 shows the main appearance and rules of Morning Star in detail.

The Evening Star pattern is the case of detecting the price from uptrend to downtrend. The description of this pattern also has three stages. First, an uptrend must be confirmed, which means the whole market is in a very confident situation. Second, good days will end with a big white bar. After a calm day, the third bar will become a big black bar. This is the investors expect the confidence of the market is going to reverse. Figure 6 shows the main appearance and rules of Evening Star in detail.

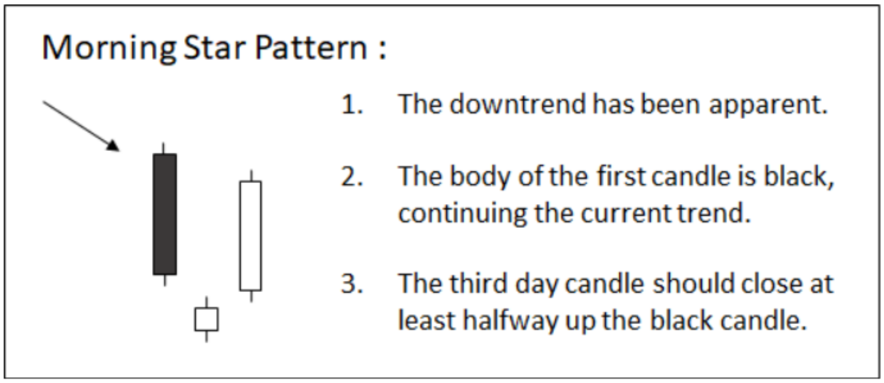

Figure 5: The left-hand side shows the appearance of the Morning Star pattern. The right-hand side shows the critical rules of the Morning Star pattern.

The definition of our label is based on the rules given in The Major Candlesticks Signals, which has been shown in Figure 5 and Figure 6. The part of the downtrend and uptrend is defined by regression. If the slope is higher or lower enough, then the trend will be confirmed. The last one need to note is that the other rules of patterns are slightly different between the simulation and the real data. The rules used in the simulation data are completely the same as the book. But in real data case, the number of samples is insufficient because of the strictness of the rules. So we will slightly relax the rules to get sufficient data. For example, the Bullish Engulfing pattern requires the open price of the last bar need to be lower than the close price of the previous bar. If this rule is too strict, we will relax the condition that the open price of the last bar only needs to be less than or equal to the half of the real body of the previous bar.

3.2. Features Selection

According to the previous section, we can see that Candlestick Patterns cannot be judged by a single close or open price alone. It needs the open, high, low, and close prices. Therefore, it's intuitively think about using open, high, low,a and close prices directly. Furthermore, we can also use the upper shadow, lower shadow, and real body, which is also reasonable features. Figure 7 and 8 below are based on the different features of Hanging Man pattern and Bearish Engulfing pattern through (1) open, high, low, and close prices and (2) close, upper shadow, lower shadow, and real body.

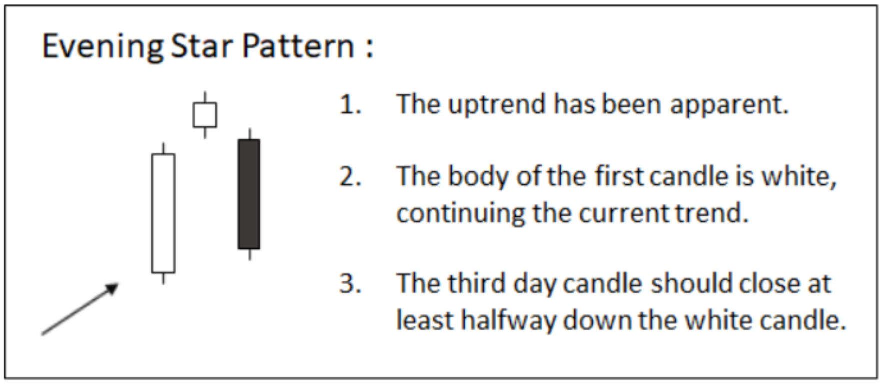

Figure 6: The left-hand side shows the appearance of the Evening Star pattern. The right-hand side shows the critical rules of the Evening Star pattern.

With the observation of the visualization of the GASF matrix in Figure 7 and 8, it can be clearly seen that the second method is more capable of extracting distinctive features than using open, high, low, and close prices. The main reason is that the difference between open, high, low, and close prices at the same time is very small, so it has high similarity between these four GASF matrices. To avoid too much repetitive information will let convolutional model hard to learn the critical features. We will process the data into the feature of using close, upper shadow, lower shadow, and real body. By using this transformation, it can clearly see that the four features are very different. From another perspective, this is a more intuitive way which just like the observation of the traders.

Therefore, we will design our experiments with using (1) open, high, low, close and (2) close, upper shadow, lower shadow, real body features in the simulation data. And the better one will be used in real data later.

3.3. GASF-CNN

In the framework of the simulation data, we will use GBM model, which is one of the financial classic models, to simulate a large amount of data. Training and testing data will respectively be 2000 and 500. In addition, in order to increase the robustness of the model, we used 3 times more simulation data for the other categories, the label 0. After the data is produced, we will calculate the open, high, low, and close prices at each time point by using 20 data per bar.

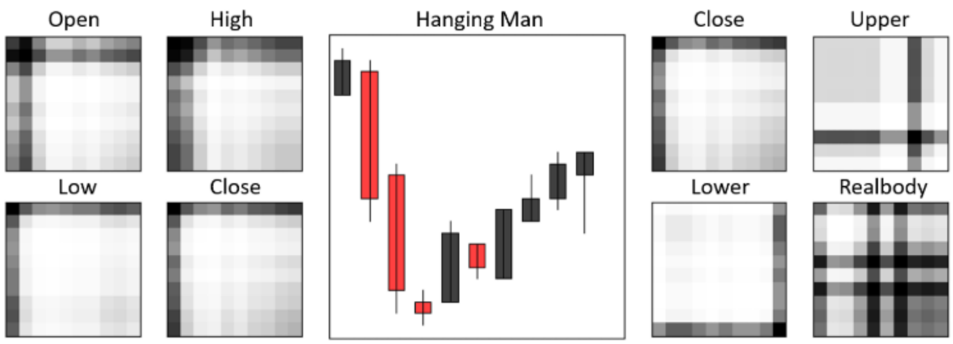

Figure 7: This figure is an example of the Hanging Man pattern. The left-hand side shows the GASF features using open, high, low, and close prices, and the right-hand side shows the GASF features using close, upper shadow, lower shadow, and real body.

Next, we will use 10 as our window size, and normalize the data with different features (1) open, high, low, close or (2) close, upper shadow, lower shadow, real body to [0, 1]. By calculating the cosine function of the angles, each normalized data can be transformed to GASF matrix. At last, we will train these matrices by using our simple customized convolutional model. Figure 9 illustrates our entire experimental architecture. After processing the data into (1) open, high, low, close or (2) close, upper shadow, lower shadow, real body, the four GASF feature matrices will pass through four channels to our convolutional model. This simple model only consists of two convolutional layers and one fully connected layers. Both of the convolutional layers only use 16 kernels with 2 by 2 sizes. In addition, in order to avoid the truncation of the characteristics of the time series, we chose not to use the pooling layer. We expect that these four features are critical for the training of convolutional model, and the model can capture these features more intuitive just like a trader.

Finally, we used 2017 EURUSD per minute data as our real framework data. We used the first 9 months as a training set and the last 3 months as a testing set. All categories of data will be evenly sampled to make it balanced. Due to the real data is insufficient, the sampling results are 1000 training set and 350 testind set under our relatively strict rules. Figure 10 shows the Morning Star and Evening Star patterns labeled by the real data.

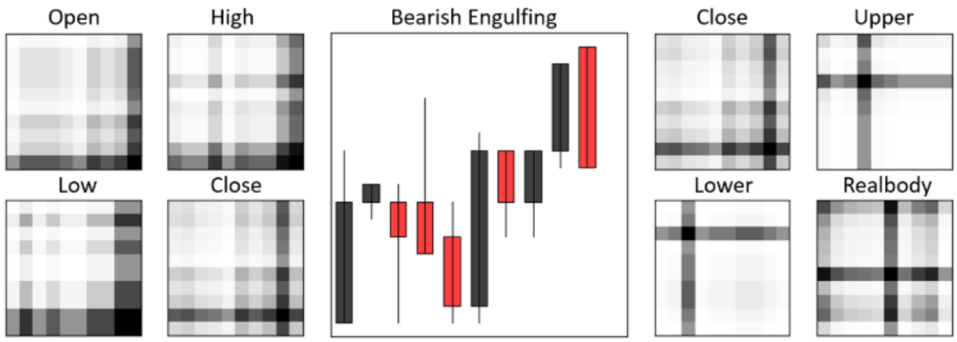

Figure 8: This figure is an example of the Bearish Engulfing pattern. The left-hand side shows the GASF features using open, high, low, and close prices, and the right-hand side shows the GASF features using close, upper shadow, lower shadow, and real body.

4. Results

4.1. Simulation Results

In the simulation framework, we use the most stringent label rules, and use the slope of regression to define the trend condition. The other descriptions are all same in The Major Candlesticks Signals. The model we used is only consists of two convolutional layers and one fully connected layers. In addition, because GASF matrices contain the whole time series information, we think it might not be appropriate to add the pooling layer to the model. Therefore, we design an experiment by (1) using pooling layers and (2) without pooling layers. After many experiments, the results are all same in Figure 11. It can be clearly seen that the performance of (2) without pooling layers is much better than (1) using pooling layers. Figure 12 shows the confusion matrix result by (1) using pooling layers. The average accuracy rate is only 84.9% and the 4th and 7th categories can only reach 77% and 80%. After discussion, we believe that the main reason is that GASF matrices contain the whole time series information, and the processing of pooling layers will truncate the information, which leads convolutional model hard to capture the features.

In addition, the previous section said that we design an experiment to compare the different features between (1) open, high, low, close and (2) close, upper shadow, lower shadow, real body. Then we will use the better features in the simulation data in order to train a better model in real data.

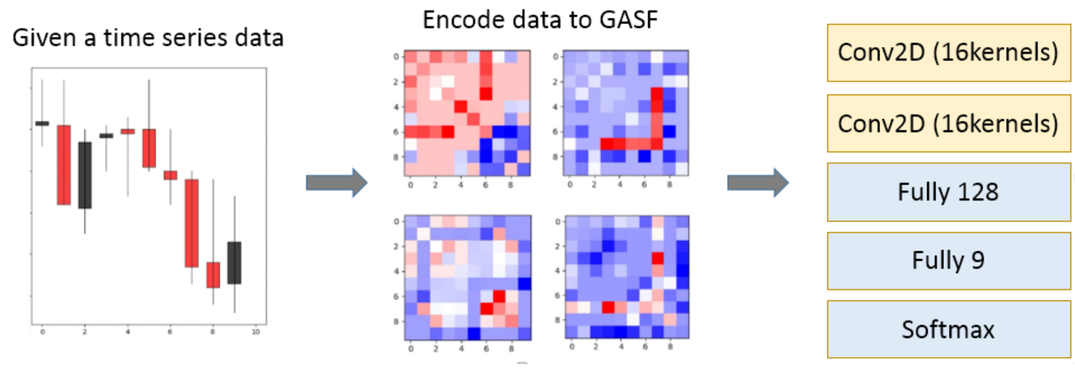

Figure 9: Entire architecture.

Figure 13 shows the training results of using GBM simulation data. We used adam as the optimizer to train 50 epochs in the model. From the training process, we can see that the training results of the second feature has been better the first one in the first few epochs. And the second feature converges significantly faster than the first one. The accuracy of the second feature is also better. We think this result is very intuitive, because the second feature is closer to the characteristics what traders observe. Therefore, in the following experiments, we will use the second feature, the close, upper shadow, lower shadow, and real body to conduct experiments.

Finally, Figure 14 and Figure 15 respectively shows the training results of using (1) close, upper shadow, lower shadow, and real body and (2) open, high, low, and close features. It can be seen that the difference between the confusion matrix and the individual accuracy is very small, and the maximum is no more than 6%, but in comparison, it is still better to use close, upper shadow, lower shadow, real body. In addition, our results show that class 0, which is the other class, has poor precision and recall. But this won't affect the usability of the framework, because although the class 0 does not perform well, as long as the accuracy of the other classes is high enough, the cost of the misclassification will be small. Moreover, it is better to have no loss if the model does not know how to classify the data, rather than misclassify each other between class 1 to class 9.

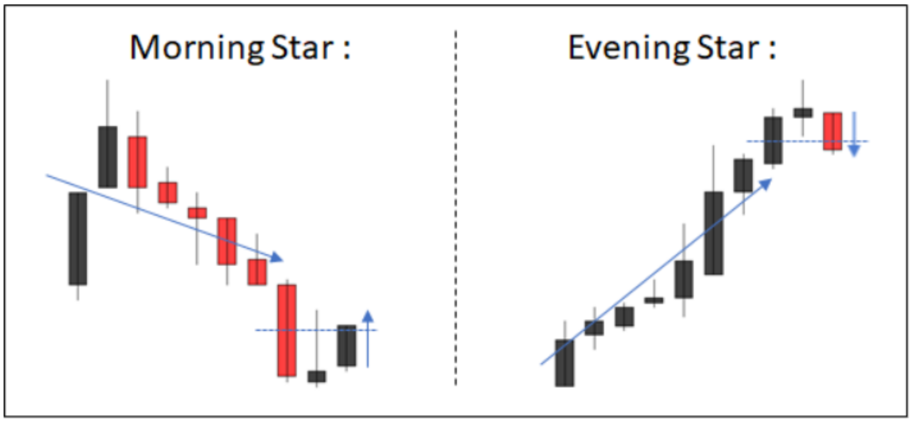

Figure 10: Different from the previous figures, this is the case by using the real data.

4.2. Experimental Results

We use 2017 EURUSD per minute data in our real data framework. Since the amount of data is not same as the simulated data, we relax the rules of label in the real data framework. We used the first nine months in 2017 as the training set, including 1000 data in each class. Then use the last three months as the testing set, containing 350 data for each class. Therefore, we used three time data for the 0th class in the training set, which is the noisy data for the other classes. The purpose of this is to help the model clearly distinguish the patterns and increase the robustness.

Based on the results of the simulation data, we chose to use close, upper shadow, lower shadow, real body as features, and without using the pooling layers in our model. Figure 16 shows the training process and Figure 17 is the confusion matrix of this real data framework. The result shows that the average accuracy of real data achieves 88.0%, which is only about 2% lower than the simulation model trained with a larger amount of data. Therefore, our experimental results show that the GAF and CNN framework is well suited for the Candlestick Patterns recognition not only in simulation but also in real trading data.

5. Conclusions

Candlestick patterns recognition is an indicator that traders often judge with news, fundamentals and technical indicators. But even today, most

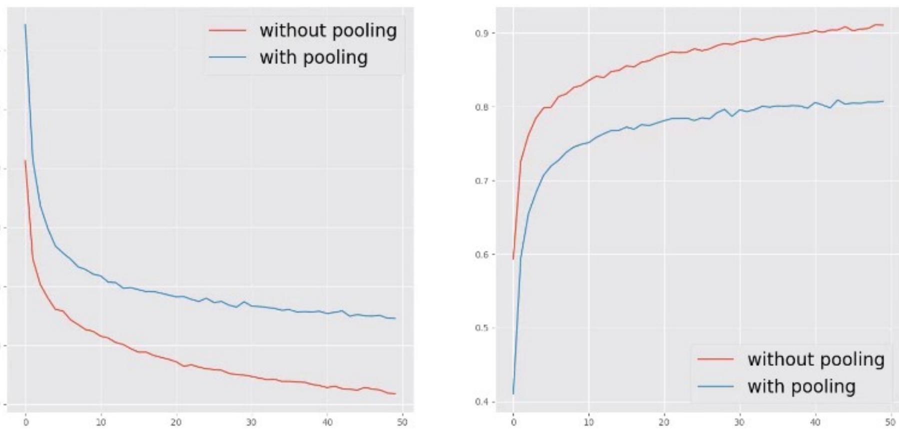

Figure 11: The left-hand side shows the training process of loss, and the right-hand side shows the accuracy.

traders decide by their vision and experience. Although many people have directly drawn up a lot of rules to find patterns, the process is too cumbersome and hard to judge without the provision of soft scores. To match the more similar to traders identification tool, we chose to use the two-dimensional CNN model to judge. Because the direct use of images to train will lead to underfitting results, we decide to use the GAF time series encoding for the traditional CNN model. Our GASF-CNN model produces the GBM simulation and experimental results.

For the simulation data, we use eight candlestick patterns to find the following essentials.

1. There is a pooling layer impact on our model.
2. Using original open, high, low, and close prices or using Upper-Shadow, Lower-Shadow, and the Real-Body as the features.

The results show as follows:

1. The pooling layer is good for the whole model. We think that the time series are truncated and lead to the loss of practical information.
2. Using Upper-Shadow, Lower-Shadow, and the Real-Body as the features is better than using original open, high, low, and close prices.

Simulation data on the model is best to achieve the average accuracy of 90%. Although in the 0 class is prone to miscarriage, the practical use as long as

true value \ prediction	0	1	2	3	4	5	6	7	8	precision	recall
0	303	16	26	19	53	12	13	28	30	0.51	0.61
1	10	472	0	8	8	0	2	0	0	0.94	0.94
2	39	0	447	0	2	0	0	12	0	0.93	0.89
3	54	0	0	419	26	0	1	0	0	0.93	0.84
4	38	4	0	3	408	0	0	47	0	0.77	0.82
5	19	0	8	0	0	466	0	0	7	0.97	0.93
6	22	7	0	0	0	0	471	0	0	0.97	0.94
7	85	2	0	0	30	0	0	362	21	0.80	0.72
8	21	0	0	0	0	0	0	5	474	0.89	0.95

Figure 12: The confusion matrix of using pooling layers.

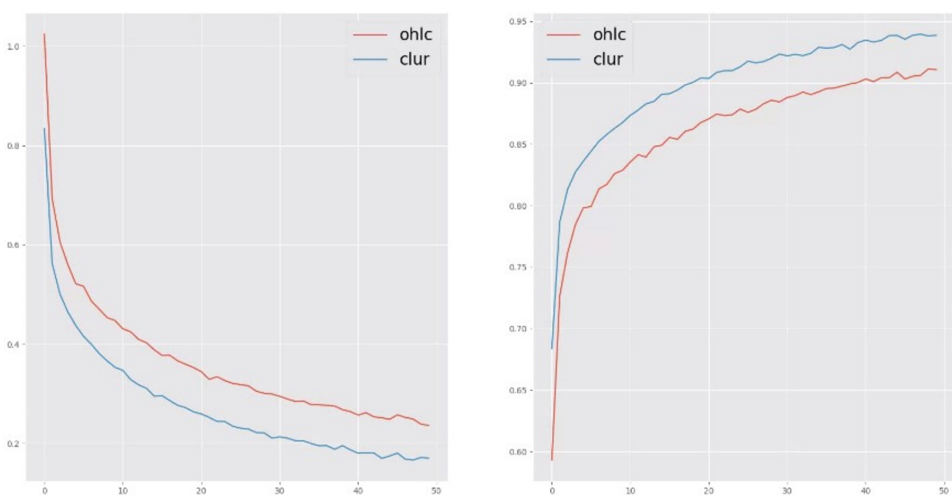

Figure 13: The left-hand side shows the training process of loss, and the right-hand side shows the accuracy.

the main patterns resolution and recall high enough, will only lose a few opportunities and will not give the wrong signal.

Again, our model has good results in the GBM simulation data. We use the same model for the 2017 EURUSD per minute real data retraining. The first nine months data are training data, and the rest of three months data are test data. The results obtain 88% average accuracy, which is very similar prediction

true value

	0	1	2	3	4	5	6	7	8	precision	recall
0	359	12	22	17	27	15	19	18	11	0.64	0.72
1	15	478	0	1	4	0	1	1	0	0.95	0.96
2	23	0	473	0	0	2	0	2	0	0.94	0.95
3	28	2	0	470	0	0	0	0	0	0.96	0.94
4	33	6	1	0	425	0	0	35	0	0.85	0.85
5	14	0	4	0	0	480	0	0	2	0.96	0.96
6	27	6	0	1	0	0	466	0	0	0.96	0.93
7	32	1	3	0	46	0	0	418	0	0.88	0.84
8	31	0	0	0	0	2	0	0	467	0.97	0.93

Figure 14: The confusion matrix of using (1) close, upper shadow, lower shadow, and real body features.

prediction

true value

	0	1	2	3	4	5	6	7	8	precision	recall
0	323	14	18	23	28	12	20	35	27	0.57	0.65
1	21	467	0	4	4	0	4	0	0	0.94	0.93
2	26	0	474	0	0	0	0	0	0	0.95	0.95
3	41	4	0	448	7	0	0	0	0	0.92	0.90
4	44	9	1	10	398	0	0	38	0	0.84	0.80
5	16	0	2	0	0	482	0	0	0	0.97	0.96
6	11	1	0	0	0	0	488	0	0	0.95	0.98
7	69	0	3	0	36	0	0	375	17	0.82	0.75
8	20	0	0	0	0	2	0	10	468	0.91	0.94

Figure 15: The confusion matrix of using (2) open, high, low, and close features.

to what we do in the simulation data. The respective accuracy is better than the simulation data. Only the class 0 has more false positives than other types. But the main kind of recall is a certain extent. It can just be said to be a more conservative model. Finally, the difference between these eight indicators is tiny. But our GASF-CNN has to extract subtle features. Although we have only used the eight main candlestick patterns, our GASF-CNN can apply to more candlestick patterns or technical indicators such as the W-head M-bottom and so on. So the entire architecture in finance candlestick and the extensibility on the models is enormous.

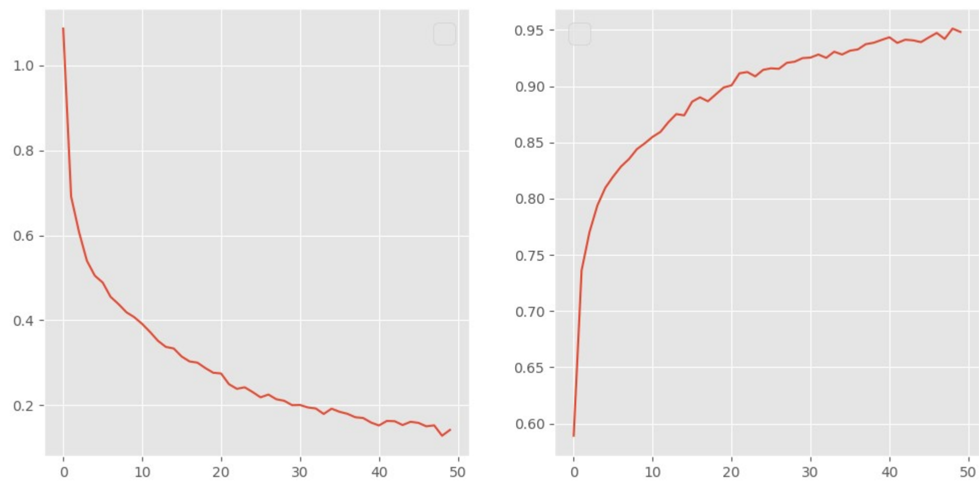

Figure 16: The left-hand side shows the training process of loss, and the right-hand side shows the accuracy.

true value \ prediction	0	1	2	3	4	5	6	7	8	precision	recall
0	243	7	15	6	16	17	14	15	17	0.55	0.69
1	15	324	0	3	4	0	4	0	0	0.98	0.96
2	16	0	325	0	1	6	0	2	0	0.94	0.93
3	12	0	0	335	2	0	1	0	0	0.96	0.96
4	50	0	0	0	285	1	0	14	0	0.92	0.81
5	23	0	5	0	0	309	0	0	13	0.90	0.88
6	17	1	0	5	0	0	327	0	0	0.95	0.93
7	44	0	1	0	2	0	0	302	1	0.91	0.86
8	19	0	0	0	0	9	0	0	322	0.91	0.92

Figure 17: The confusion matrix of the real data framework.

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