Explainable Deep Convolutional Candlestick Learner

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Abstract

Candlesticks are graphical representations of price movements for a given period. The traders can discover the trend of the asset by looking at the candlestick patterns. Although deep convolutional neural networks have achieved great success for recognizing the candlestick patterns, their reasoning hides inside a black box. The traders cannot make sure what the model has learned. In this contribution, we provide a framework which is to explain the reasoning of the learned model determining the specific candlestick patterns of time series. Based on the local search adversarial attacks, we show that the learned model perceives the pattern of the candlesticks in a way similar to the human trader.

Keywords: local search adversarial attacks, explainable artificial intelligence, candlesticks, time series encoding, financial vision.

1 Introduction

The candlestick patterns recognition lies at the heart of trading and the foundation of all technical analysis. Therefore, understanding how to interpret candlestick is a critical step in becoming a trader. Traders need a candlestick patterns recognition tool to help them discover valuable information from candlestick. Although object detection and pattern recognition technologies have been prevailed in the computer vision field, traders generally cannot rely on these tools to gain insights of the candlestick patterns due to the lack of acquiring trading knowledge-based feature representations.

According to Tsai et al., they proposed an extended Convolutional Neural Networks (CNN) approach to recognize the candlestick patterns automatically [4]. Even though the deep learning based model has three significant advantages, including non-linearity, robustness, and adaptive manner, the traders cannot trust what the model recognizes the patterns from these charts precisely without explainability. However, the deep learning based models have several disadvantages, including lack of explanation capability [3] and difficulty in designing models. These difficulties will hinder the widely application of deep learning methodologies in critical fields. We provide a framework based on adversarial attacks to demonstrate the adaptiveness and robustness of our model.

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1.1 Candlestick Pattern of Time Series

The candlestick draws in a coordinate system, with the horizontal axis representing time and the vertical axis representing price. Time is from left to right on the X-axis. The nearest candlestick is the latest corresponding period. Price is from top to bottom on the Y-axis. The higher the position of the candlestick, the higher the price in those markets at the time. Conversely, the lower the position of the candlestick, the lower the market price at that time. Following the chart is drawn from historical prices according to specific rules. These features help traders to see the price trend. The three more common types of charts are histograms, line charts, and the most widely used candlestick. The candlestick is originated from Japan in the 17th century and has been popular in Europe and the United States for more than a century, especially in the foreign exchange market. As the most popular chart in technical analysis, traders should have an understanding of it. It is named after a candle, as shown in Figure 1. Each bar of candlestick draws from open price, high price,

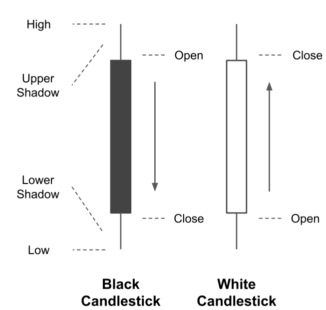


Figure 1: The shape of a candlestick.

lowe price, and close price. Open price is the first price during the period. High price is the highest price during the period. Low price is the lowest price during the period. Close price is the last price during the period. If the close price is higher than the open price, the candlestick follows the top of the candle body is the close price; the bottom is the open price; and the color is usually green or white. If the close price is lower than the open price, the candlestick follows the open price above the candle body; the close price below; and the color is usually red or black. In some cases, the candlestick has no hatching because the open or close price coincides with the high or low price. If the candle is very short, the open and close prices of the candlestick are very similar.

1.2 The 8 Most Powerful Candlestick Patterns

The trick is in identifying some commonly occurring candlestick patterns and then building a market context around it. We provide the most eight common candlestick patterns to analysis our explainable model as follows:

1. Morning Star is a visual pattern made up of a tall black bar, a smaller black or white bar with a short body and long shadows, and a third tall white bar. The middle bar of the morning star captures a moment of market indecision where the bears begin to give way to bulls. The third bar confirms the reversal and can mark a new uptrend. Figure 2 shows the morning star based on the description.
2. Evening Star is a bearish candlestick pattern consisting of the latest three bars: a large white bar, a small-bodied bar, and a black bar. The pattern will be more visible with a large black bar than with a small black bar. Figure 3 shows the evening star based on the description.
3. Bullish Engulfing forms when a small black bar is followed the next bar by a large white bar, the body of which completely overlaps or engulfs the body of the previous bar.
4. Bearish Engulfing consists of an up white bar followed by a large down black bar that eclipses or "engulfs" the smaller up bar.
5. Shooting Star is a bearish bar with a long upper shadow, little or no lower shadow, and a small real body nears the low of the day. It appears after an uptrend.
6. Inverted Hammer looks like an upside down version of the hammer candlestick pattern, and when it appears in an uptrend is called a shooting star.
7. Bullish Harami is a black long bar followed by a white smaller bar that the later one is completely covered by the former. It indicates the end of a bearish trend.
8. Bearish Harami is composed of a long white bar and a small black bar that the later one is completely covered by the former. It indicates the end of a bullish trend.

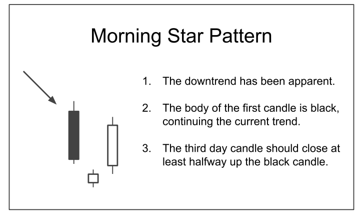


Figure 2: **Illustration of Morning Star Pattern.** The left-hand side shows the appearance of the Morning Star pattern. The right-hand side shows the critical rules of the Morning Star pattern.

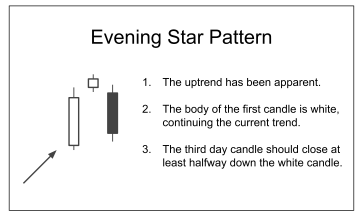


Figure 3: **Illustration of Evening Star Pattern.** The left-hand side shows the appearance of the Evening Star pattern. The right-hand side shows the critical rules of the Evening Star pattern.

1.3 Explain our Model

We use a Gramian Angular Field (GAF) time series encoder to emphasize the time series features for the Convolutional Neural Networks (CNN) model. The Gramian Angular Field (GAF) is a new time series encoder proposed by Wang and Oates [5]. It represents time series data in a polar coordinate system and uses various operations to convert these angles into the symmetry matrix. The GAF-CNN model is a two-step approach including Gramian Angular Field (GAF) time series encoder [5] and Convolutional Neural Networks (CNN) model. Teh GAF encoder makes time series data based on open, high, low, and close prices to GAF matrices. Our GAF-CNN model can capture the 8 major candlestick patterns with 90.0% accuracy. Then we would like to know if the model learned the features as human seen. We use the Local Search Attack Adversarial model [2] to attack the GAF matrices. The attacked regions are on the main diagonal of the GAF matrices. We defined these 10 bars based on the rules. The last 3 bars form the OHLC patterns, and a trend emerges in the rest of the bars. Figure 4 illustrates the attack region on GAF matrix. 1500 GAF matrices were attacked in each label. If most of the GAF matrices can be attacked successfully, it means the region human seen is similar to what the GAF-CNN model has learned.

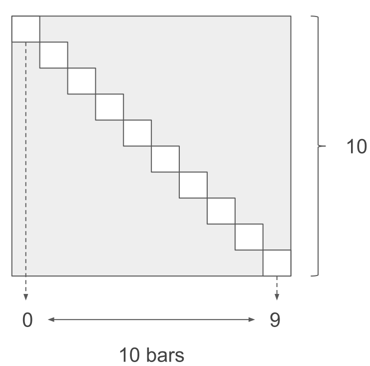


Figure 4: The GAF matrix for the local search attack. In this work, we attack the diagonal elements as these locations

2 Methods

2.1 GAF-CNN

The paper uses the summation version of the GAF. Each element of the GAF matrix is the cosine of the summation of aspects. Our first step is to making a GAF matrix to normalize the given time series data X into values between $[0, 1]$. The following equation shows the simple linear normalization method

$$\widetilde{x}_i = \frac{x_i - \min(X)}{\max(X) - \min(X)},$$

where $\widetilde{x}_i$ represents the normalized data. After normalization, our second step is to represent the normalized time series data in the polar coordinate system. The following two equations show how to get the angles and radius from the rescaled time series data. Finally, we sum the aspects and use the cosine function to make $GAF = \cos(\phi_i + \phi_j)$. Equation 1 and 2 show how to get the angles and radius from the rescaled time series data. Finally, we sum the angles and use the cosine function to make the GAF as equation 3.

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

$$r = \frac{t_i}{N}, t_i \in \mathbb{N} \tag{2}$$

$$\text{GAF} = \widetilde{X}^T \cdot \widetilde{X} - (I - \widetilde{X}^2)^{\frac{T}{2}} \cdot (I - \widetilde{X}^2)^{\frac{1}{2}} \tag{3}$$

The GAF has two essential properties.The first, the mapping function from the normalized time series data to GAF is bijective when $\phi \in [0, \pi]$. In other words, normalize data to $[0, 1]$ can transform the GAF back into normalized time series data by the diagonal elements. The second, in contrast to Cartesian coordinates, the polar coordinates preserve absolute temporal relations. Once the GAF transform completed, the 3-d data can be inputs for the CNN model training. The architecture of our CNN model is similar to LeNet [1], including two convolutional layers with 16 kernels and one fully-connected layer with 128 densest.

2.2 Local Search Attack

There are several *adversarial machine learning* models to study the robustness of trained deep neural networks (DNN) models. The aim of these models are to generate input examples that are very close to the legitimate ones while causing the model to misclassify. There are two types of such models. One of them is *white-box* attack, in which the attacker know the complete model parameters. The other one is the *black-box* attack, in this case, the attacker does not have the model parameters, however, the attacker can try or query this model and read its outputs. In general, it is harder to attack a model if we do not have the information about it. Surprisingly, it has been shown that it is possible to successfully attack a model without the knowledge of its parameters. Further, it is even not necessary to perturb the whole input image. In *local search adversarial attack* method [2], it is possible to attack a handful of points in an image through the local greedy search. With this in mind, we hypothesize that if we can make the classifier to misclassify through perturbing only a small number of pixels on the image, it is highly possible that these pixels are crucial for the model to classify.

Algorithm 1 Local Search Attack

Load a single GAF two-dimensional array A
Set T = length of the time series
Keep a copy of A in memory D
Initialize the counter $t = 0$
for episode $= 1, 2, \ldots, R$ **do**
  if $t = 10$ **then**
    Reinitialize the A to the original value from memory D
    Reset the counter $t = 0$
  end if
  for $l = 1, 2, \ldots, T$ **do**
    Sampling a random perturbation scale r_l from uniform distribution $[0.8, 1.2]$
    Calculate the perturbated result $= r_l \times A[l, l]$
    if $r_l \times A[l, l] \geq 0.5 \vee r_l \times A[l, l] \leq -0.5$ **then**
      $A[l, l]$ keeps the original value.
    else
      Set $A[l, l] = r_l \times A[l, l]$
    end if
  end for
  $t = t + 1$
  Recalculate the time series from perturbated A and then encode into a new GAF matrix A'
  if A' is adversarial **then return** A'
  end if
end for

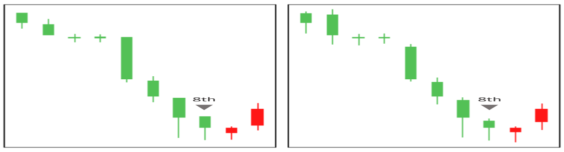
We apply the following scheme to investigate the possible regions that are critical for the classification process. Logically, if a pixel is important in the final classification result, then a perturbation of that pixel should result in a degradation of the confidence score or even a misclassification. To achieve of this, we propose a method which is modified from the *local search attack* [2]. First of all, we define the set of points that can be perturbed. In this work, in order to maintain the consistency of the original time series data and the GAF matrix, we only perturbate the diagonal elements in the GAF matrix. Once we obtain the perturbated diagonal elements, we then calculate the corresponding values of non-diagonal elements and output the perturbated GAF matrix. Secondly, send this perturbated GAF into the CNN model to get the classification results. If the perturbated input is not misclassified, simply repeat the procedure described above. The detail of the algorithm is in Algorithm 1.

The parameters of our local search attack model are r = uniform$(0.8, 1.2)$; $d = 0$; $t = 10$; $R = 150$; and reset $= 10$.

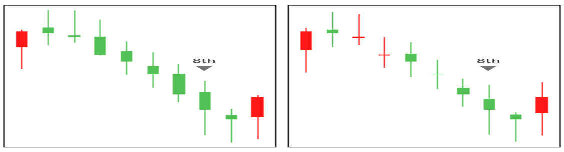
3 Experimental Results

We use EUR/USD 1-minute open, high, low, and close price data to produce our experimental results. The training data is from January 1, 2010 to January 1, 2016. The testing data is from January 2, 2016 to January 1, 2018. There are eight patterns and each label includes 1500 samples. If the pattern does not belong to any one of the eight patterns, we set the kind of patterns as the label 0 and there are 3000 samples. These data produce the following results. Figure 5 shows the result of attacked morning star pattern and Figure 6 shows the result of attacked evening star pattern. With the modified local search attack model, we can reach 64.36% success attack rate on average. Table 1 presents the full results with at least

40.0%. This result suggests that it's plausible to focus attack region on the diagonal. Our GAF-CNN model actually recognizes the diagonal patterns, where the last 3 bars form the major patterns and the rest represent the trend. According to

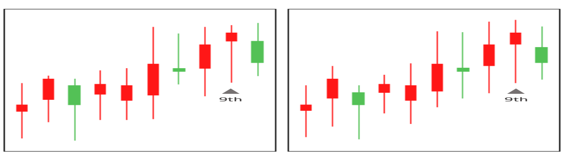


(a) The first attack result example.

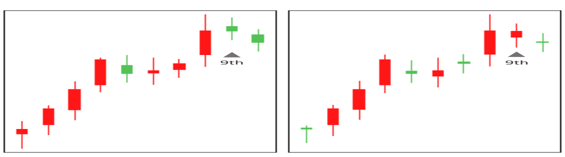


(b) The second attack result example.

Figure 5: The attack result example of morning star pattern. The left hand side shows the original pattern, and the right hand side shows the pattern after attack.



(a) The first attack result example.



(b) The second attack result example.

Figure 6: The attack result example of evening star pattern. The left hand side shows the original pattern, and the right hand side shows the pattern after attack.

subsection 1.2, the morning star composes a downtrend and three-bar pattern, including a large black bar, a small-bodied bar, and a white bar. Figure 5-(a) shows that most of the bars change insignificantly after the perturbation. The front portion of candlestick remains downtrend, but the 8th bar reduces significantly. The changing of the 8th bar makes the pattern violate the morning star rules and lead to misclassification. In Figure 5-(b), there is some changing in the front portion, but still, obey the downtrend rules. The 8th bar also reduces significantly, causing the misclassification. The evening star pattern composes of the uptrend and three-bar pattern: a large white bar, a small-bodied bar, and a black bar. After the perturbation, the three-bar design violates the rules. Figures 6-(a) and 6-(b) show that the 9th bar changes significantly, and

Label	Success Rate	Percent (%)
1	631 / 1500	42.1
2	972 / 1500	64.8
3	1079 / 1500	71.9
4	1319 / 1500	87.9
5	602 / 1500	40.1
6	932 / 1500	62.1
7	953 / 1500	63.5
8	1238 / 1500	82.5

Table 1: The attack ratio of local search attack for each label.

the last bar becomes smaller, making the whole pattern invisible. The results show that our local search adversarial attack approach can explain the GAF-CNN model learned as human has seen and understand how GAF-CNN model recognize candlestick pattern. Our explainable GAF-CNN model is trustworthy and reliable for traders compared to others without knowing the underlying learning experience.

4 Conclusion

The paper has two contributions. The first is that our GAF-CNN model constructs an innovation field of financial vision research for candlestick recognition. The second is that we propose an approach based on the modified local search adversarial attack to explain the reason for the GAF-CNN model on how to determine the different candlestick patterns. Our GAF-CNN model can identify eight types of the candlestick and understands the feeling as a human has seen. We can confirm that the GAF-CNN model has indeed learned the sense of the candlestick from the trader. The GAF-CNN will be perfect for building a complete explainable trading model. We provide an open-source implementation and training data for the paper in the following URL: https://github.com/pecu/FinancialVision.

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