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Candlestick Patterns Recognition using CNN-LSTM Model to Predict Financial Trading Position in Stock Market

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Abstract−Investors need analytical tools to predict the price and to determine trading positions. Candlestick pattern is one of the analytical tools that predict price trends. However, the patterns are difficult to recognize, and some studies show doubts regarding the robustness of the recognizing system. In this study, we tested the predictive ability of candlestick patterns to determine trading positions. We use Gramian Angular Field (GAF) to encode candlestick patterns as images to recognize 3-hour and 5-hour of 6 candlestick patterns with Convolutional Neural Network (CNN), coupled with the Long short-term memory (LSTM) model to predict the close price. The trading position consists of buying and selling position with a hold period of several hours. Our results show CNN successfully detected 3-hour and 5-hour GAF candlestick patterns with an accuracy of 90% and 93%. LSTM can predict the close price trend with 155.458 RMSE scores and 0.9754% MAPE with 10-hour look back. With a hold duration of three hours and CNN-LSTM as an additional model, the test data's 85 candlestick patterns are recognized with 82.7% accuracy, compared to 60% accuracy of profitable trading positions when CNN candlestick pattern recognition is used alone. Compared to employing CNN candlestick pattern identification alone, the CNN-LSTM model combination can improve the prediction power of candlestick patterns and offer more lucrative trading positions.

Keywords: Candlestick Patterns; Trading Positions; Long Short-Term Memory; Convolutional Neural Network; Predict

1. INTRODUCTION

Investors in the stock market can choose between long and short selling positions when deciding on their trading positions to maximize profits. The typical position is long when investors purchase a stock with the expectation that its price will increase. They can also speculate that the stock price will decline by taking a short selling position, which can be profitable [1]. Investors frequently use technical analysis to choose trading positions [2]. The candlestick pattern is one instrument used in technical analysis. In financial time series, Thomas N. Bulkowski identified 103 candlestick patterns that potentially forecast the course of price trends [3]. However, the absence of a thorough definition of a pattern might lead to classification discrepancies, necessitating market investors use of pattern recognition abilities when making judgments based on visual data [4]. According to related studies, Candlestick patterns can predict price changes or make money for participants in the capital markets. However, according to Fock et al., candlestick patterns have no predictive ability. Duvinge et.al also conducted tests to assess the predictive power of Candlestick patterns using 5-minute intervals with DJIA Index data and showed that candlestick patterns do not improve the profit performance of stock market participants [5].

The convolutional neural network (CNN) model is employed in deep learning for image identification because it is suitable for recognizing images that are challenging for the human eye to perceive, such as candlestick patterns. In [6], a Gramian Angular Field (GAF) technique encodes time series data with CNN to detect 10-minute candlestick patterns. The goal is to improve CNN outcomes in candlestick pattern detection. On real-world data, the GAF-CNN model's predictions for identifying candlestick patterns had an average accuracy of 90.7%. However, in earlier studies, GAF was used frequently to encode univariate data. As a result, research [7] aggregated numerous photos using the appending approach. CNN was able to extract and learn from the combined image characteristics to increase CNN classification accuracy. Long Short-Term Memory (LSTM), which can forecast the movement of time series price trends utilizing the open/close feature with an RMSE result of 0.01027, is used in research [8] for the prediction of stock data time series. To aid investors in making future price trend predictions, LSTM is used.

As a result, we compare trading positions obtained using the candlestick pattern alone and with an additional LSTM model to see if candlestick patterns can predict profitable trading. GAF is used to encode time series data as candlestick pattern images to mimic human eyes because identifying candlestick patterns requires expertise. The GAF model is used to detect candlestick patterns in the Nasdaq100 stock price data input, and it detects six out of 103 candlestick patterns. To identify the shape of the candlestick pattern, GAF extract four features from the formed pattern: close, upper-shadow, lower-shadow, and real-body (CULR). Candlestick patterns cannot be detected using a single feature because it does not accurately describe the candlestick in its natural state. This study made an innovative move by combining the four feature images into a single symmetrical image, allowing CNN to learn the patterns formed when the human eye sees candlestick patterns.

This research aims to design a recognition system for candlestick patterns from stock time series data using GAF-based images, which are processed by the CNN method to classify the patterns. The result is then used to predict the trading positions for a given future time. To improve the performance, we involve the LSTM future price prediction combined with the resulting reference from GAF-based CNN and compare it to CNN candlestick recognition alone. Candlestick patterns that are considered successful for predicting profitable trading positions

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are patterns that are already recognized by CNN and successfully predict the close price trend of 1,2 or 3 hours after the pattern is formed. If the candlestick pattern formed predicts an upward price trend, then the close price afterward is required to be higher than the previous close price, as well as the prediction of a downward price trend. The trading position that is compared for this research is based on the candlestick pattern that was already recognized with CNN and validated by the LSTM close price prediction for 1, 2, or 3 hours, which has a hold scenario after the candlestick pattern is detected to calculate the success of the model so that the position is considered profitable. If the candlestick pattern predicts a bullish price and within 1, 2, or 3 hours after it is predicted by LSTM to have a bullish close price trend, the trading position decision is to buy and hold for the selected period. Vice versa for candlestick patterns that predict a falling price and within a period of 1, 2, or 3 hours after it is predicted by LSTM to have a downward close price trend, the trading position decision is to sell and hold during the selected period. The trading position decision is compared with the real close price data whether the price trend is in accordance with the LSTM results as well as compared to the decision to take a trading position using candlestick patterns only.

2. RESEARCH METHODOLOGY

2.1 Research Phases

The CNN and LSTM methods are used to predict trading positions. The input for CNN are six candlestick patterns that have already been encoded as GAF Images, whereas the input for the LSTM are rescaled to range[0,1] of the close price. There are two scenarios for each method: CNN with 3-hour candlestick pattern GAF encoding, CNN with 5-hour candlestick pattern GAF encoding, LSTM with 10-hour look back, and LSTM with 20-hour look back. Based on that scenario, we then select the best result from both methods. Assume we have a candlestick pattern produced by CNN at t times and $t + N$, where N is the number of hours to hold. The trading position is determined based on the CNN candlestick pattern prediction at t times and the $t + N$ LSTM predicted close price. The trading position taken with both models is evaluated using the actual $t + N$ close price compared to the trading position taken with only candlestick pattern recognition without LSTM, which gives a more profitable trading position. Figure 1 shows a flow chart of the system design process.

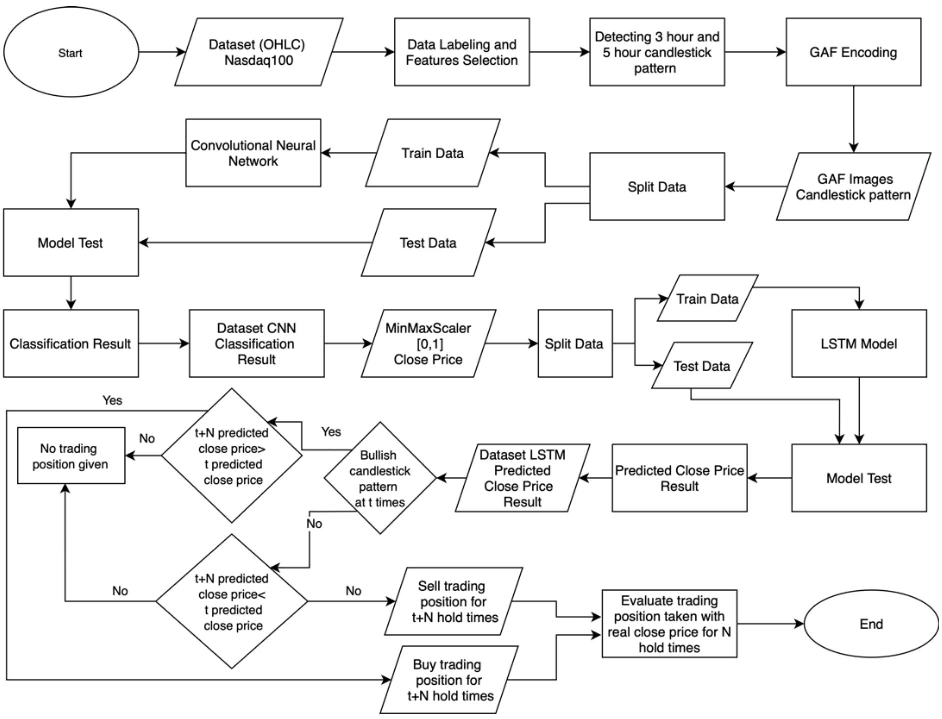

Figure 1. System Flowchart

2.2 Dataset, Data Labeling, and Features Selection

This study used hourly Nasdaq100 time series historical data from January 17th, 2007 to July 8th, 2022 from firstratedata.com. There are 34192 rows and four columns in this data set. Each column has the numbers 1,2,3,4 to represent open, high, low, and close. We renamed the labels open, high, low, and close to reflecting the features' actual names. To match the feature selection used in the previous study [6], we require an additional feature selection. Three new columns are added: lower-shadow, upper-shadow, and real-body. Table 1 labels the dataset obtained from firstratedata.com, and Table 2 labels the additional feature selection.

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Table 1. Raw Data Labeling

Date	Open	High	Low	Close
17/01/2007 09:00	1838.62	1840.95	1839.40	1839.47
17/01/2007 10:00	1839.44	1839.54	1834.36	1837.58
17/01/2007 11:00	1838.48	1841.26	1836.00	1839.33

Table 2. Additional Feature Selection

Date	Open	High	Low	Close	Lower-shadow	Upper-shadow	Real-body
17/01/2007 09:00	1838.62	1840.95	1839.40	1839.47	0.07	1.33	0.15
17/01/2007 10:00	1839.44	1839.54	1834.36	1837.58	3.22	0.10	1.86
17/01/2007 11:00	1838.48	1841.26	1836.00	1839.33	2.48	1.93	0.85

2.3 Candlestick Pattern Detection

A candlestick chart is a graphical representation of stock price movements in chronological order, with time intervals ranging from one minute to one hour, day to month, and prices such as open, high, low, and close. In his book "Japanese Candlestick Charting Techniques," Steve Nison popularized the use of candlesticks in the stock market [9]. The candlestick components are depicted in Figure 2.

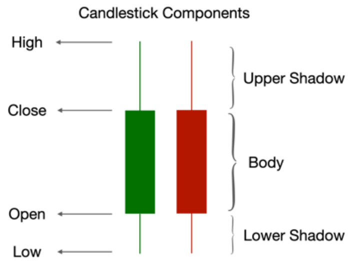

Figure 2. Candlestick components

Figure 2 depicts the candlestick structure as a unit bar containing the open, high, low, and closing prices (OHLC) for a given period. If the bars in the image above are combined into several bars, a unique graphic shape known as a candlestick pattern is obtained. Many candlestick patterns have been developed, including one by Thomas N. Bulkowski, who recorded 103 Candlestick Patterns in financial time series that can predict price trends [6]. However, the authors of this study used six candlestick patterns from The Major Candlestick Signals [10] for later testing with the CNN model. The patterns are Bullish Engulfing Signal, Bearish Engulfing Signal, Bullish Harami, Bearish Harami, Hammer Signal, and Shooting Star. Please remember that when applying the candlestick pattern rules from the book, we use the 5-hour moving average (5h-MA) to determine the previous trend for detecting 3-hour and 5-hour candlestick patterns. If three of the five candlesticks in the pattern close below the 5h-MA, the previous trend was a downtrend and vice versa. Thus, the downtrend or uptrend trend used in this work is formed by following the same rules as when the candlestick pattern is formed. We tested CNN's ability to recognize 3-hour and 5-hour candlestick patterns using such rules. Table 3 depicts the downtrend and uptrend using the 5h-MA, Table 4 depicts the number of candlestick patterns per class (a total of 1731), and Figure 2 depicts the 3-hour and 5-hour candlestick patterns.

Table 3. Determining downtrend and uptrend using 5 Hour Moving-Average(MA)

Date	Open	High	Low	Close	Lower-shadow	Upper-shadow	Real-body	5h-MA	Trend
2007-01-17 09:00:00	1838.62	1840.95	1839.40	1839.47	0.07	1.33	0.15	1839.47	Down
2007-01-17 10:00:00	1839.44	1839.54	1834.36	1837.58	3.22	0.10	1.86	1838.525	Down
2007-01-17 11:00:00	1838.48	1841.26	1836.00	1839.33	2.48	1.93	0.85	1838.793	Up

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Table 4. Number of candlestick patterns per class

Bullish Engulfing	Bearish Engulfing	Bullish Harami	Bearish Hammer	Hammer	Shooting Star	Total Candlestick Pattern
227	390	409	286	237	182	1731

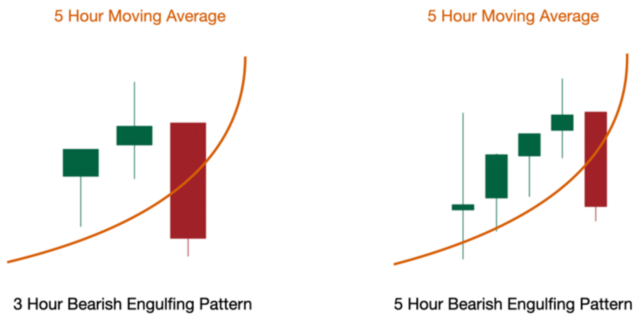

Figure 3. Comparison of 3-Hour and 5-Hour Candlestick Pattern

2.4 Gramian Angular Field Encoding

Image encoding is needed to determine the input of the CNN model to represent the Candlestick pattern. The GAF method was introduced in [11] by Wang and Oates to encode time series data represented as a polar coordinate system and use operations to convert angles into symmetrical matrices. There are two GAF methods, namely using Gramian Summation Angular Field (GASF) and Gramian Difference Angular Field (GADF). The difference is that the matrix calculation used by GASF uses cosine while GADF uses sine[12]. For this research, we use GADF to encode 3-hour and 5-hour candlestick patterns time series data as images to feed into the CNN model. To obtain the GAF matrix, the data is rescaled, because according to [12] data with certain intervals have different angular limits. The time series data (X) used is then rescaled with a value between [0,1]. The following equation is done to regularize the time series data.

$$\tilde{x}_i = \frac{x_i - \min(X)}{\max(X) - \min(X)} \in [0,1] \tag{1}$$

After regularizing the dataset, the next step is to transform the result into polar coordinate system using (2) and (3), which are respectively radian and radius.

$$\phi = \arccos(\tilde{x}_i)\ , 0 \leq\ \tilde{x}_i\ \leq 1 \ , \phi \in [-\tfrac{\pi}{2}, \tfrac{\pi}{2}] \tag{2}$$

$$r = \frac{t_i}{\mathrm{N}} \in [0,1], for\ t_i > 0 \tag{3}$$

After doing all that, here is the calculation to get the GADF matrix with I as the unit vector [1,1,...,1]. GADF =

$$\sin(\phi_i - \phi_j) = \sqrt{I - \tilde{X}^2}^{T} \cdot \tilde{X} - \tilde{X}^T \cdot \sqrt{I - \tilde{X}^2} \tag{4}$$

GAF can only encode univariate time series, but to mimic how the human eyes see the features in candlestick patterns, we cannot use only a single feature. So we innovate to combine 4 features from univariate lower-shadow, real-body, upper-shadow, and close as one image. The matrix that we get from GADF encoding for each features can be plotted with the rainbow color map resulting a symmetrical nxn 2D images. After we get all of the features images, then we can unify four features as one symmetry image. For the 3-hour and 5-hour GAF candlestick pattern, GAF images consist of nxnx4 2D images size (60,60) and (100,100) with n representing time intervals and 4 representing the features. The image conversion for n=3 and n=5 when it occurs to be a candlestick pattern can be seen in Figure 4.

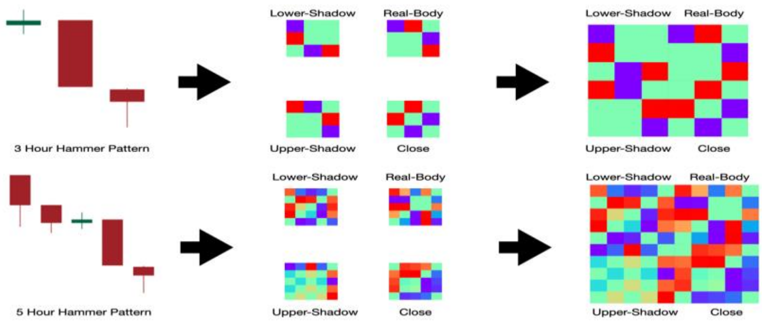

Figure 4. Process for GAF encoding CULR features as one 2D image of (60,60) and (100,100) dimension

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2.5 Convolutional Neural Network(CNN)

CNN is a network model proposed by Lecun et al. in 1998 [13]. CNN is one of the deep learning algorithms commonly used to analyze visual images. The architecture of CNN has several layers as input, several hidden layers, and output to process data with the form of training and testing dimensions in deep learning [14]. CNN has two important components which are the convolutional layer and pooling-layer. Based on the conclusion of [6] the use of the max pooling-layer causes bad results for time series data. Time series data can be truncated due to using pooling-layer so that it affects the accuracy of candlestick pattern recognition. So the use of pooling-layer can be avoided using no pooling-layer with the consequence of more features and larger data. From 6 candlestick patterns that have been encoded into GAF images as CNN input, the data spliting turns the dataset into 80% train data, 20% test data from the total of 1731 GAF images. The architecture that we use are two convolutional networks with 16 filters RelU activation, no pooling-layer, fully connected layer 128 denses with RelU activation, and 6 denses output layer with SoftMax activation. The architecture model that we built for each 3-hour and 5-hour GAF images candlestick pattern input can be seen in Tables 5 and 6.

Table 5. CNN Architecture for 3-hour 2D (60,60) GAF images candlestick patterns

Layer(type)	Output shape	Param
Conv2D	(None, 58, 58, 16)	448
Conv2D	(None, 56, 56, 16)	2320
Flatten	(None, 50176)	0
Dense	(None,128)	6422656
Dense	(None,6)	774

Table 6. CNN Architecture for 5-hour 2D (100,100) GAF images candlestick patterns

Layer(type)	Output shape	Param
Conv2D	(None, 98, 98, 16)	448
Conv2D	(None, 96, 96, 16)	2320
Flatten	(None, 147456)	0
Dense	(None,128)	18874496
Dense	(None,6)	774

2.6 Long Short-term Memory(LSTM)

LSTM is a network model proposed by Schmidhuber et al. in 1997 [15]. The LSTM model has been widely used for speech recognition, emotional analysis, and text analysis because it has its own memory and can predict quite accurately. In recent years, LSTM has also been used to predict stock market prices.

LSTM has three gates: an input gate that determines whether or not to include new input, a forget gate that determines which unimportant information should be removed, and an output gate that determines what information is output [16]. The LSTM architecture can be seen in Figure 5.

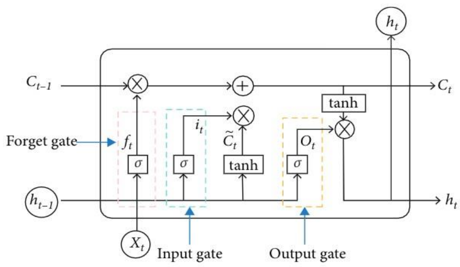

Figure 5. Memory cell architecture of LSTM

The values of the gate input and gate output are entered into the forget gate. Because the data is a time series data, the gate input move continuesly. The number of hour we used to predict the next hour price is the look back period with a total input of 10 or 20 look back of the hour type and one time series output. The LSTM calculation process is as follows:

(1) The last moment's output value and the current input value are entered into the forget gate with the formulation:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) , \quad (5)$$

With the value of f_t between (0,1), W_f is the weight of the forget gate, b_f is the bias of the forget gate, x_t is the input value of the current time, and h_{t-1} is the output value of the last time.

(2) The output value of the last time and the input value of the current time are input into the input gate, and the output value and candidate cell of the input gate are obtained by calculation:

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$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (6)$$

$$\tilde{C}_t = tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \;, \quad (7)$$

With the value range of i_t is (0,1), W_i is the weight of the input gate, b_i is the bias of the input gate, W_c is the weight of the candidate input gate, and b_c is the bias of the candidate input gate.

(3) Perform cell state renewal with the formulation:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \;, \quad (8)$$

With a range of values from C_t is (0,1).

(4) Output value h_{t-1} and input value x_t accepted as the input value of the output gate at time *t*, and output o_t from output gate obtained by:

$$o_t = \sigma(W_o\, [h_{t-1}, x_t] + b_o) \;, \quad (9)$$

With the range of values of o_t is (0,1), W_o is the weight of the output gate, and b_o is the bias of the *output gate*.

(5) The output value of the LSTM is obtained by calculating the output of the output gate and cell conditions, as shown in the equation below.:

$$h_t = o_t * \tanh(C_t). \quad (10)$$

From the data that has the classification result from the CNN model, the LSTM model only used the hourly close price data for its input. We have to scale the close price into [0,1] range for the LSTM model and the data is divided into 70% train data and 30% test data from overall 31492 close price data. Each input shape has 10 or 20 look back with one output shape. After we have the model from training, we predict the whole close price on test data and compare it to the real close price. The architecture that we used for LSTM is composed of a sequential input layer with (10,1) or (20,1) input shape, followed by 2 LSTM layers, denses layer with RelU activation, and one output denses layer. The real architecture for each input shape can be seen in Tables 7 and 8.

Table 7. LSTM Architecture for (10,1) input shape

Layer(type)	Output shape	Param
LSTM	(None, 10,50)	10400
LSTM	(None, 50)	20200
Dense	(None, 16)	816
Dense	(None,1)	17

Table 8. LSTM Architecture for (20,1) input shape

Layer(type)	Output shape	Param
LSTM	(None, 20,50)	10400
LSTM	(None, 50)	20200
Dense	(None, 16)	816
Dense	(None,1)	17

2.7 Performance Analysis

In this study, to calculate the accuracy of each CNN and LSTM model, the evaluation used for the CNN model is a confusion matrix, for LSTM using Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE). The confusion matrix analyze how well a model recognizes a particular class, in this case, 6 candlestick patterns by showing the precision, recall, f1-score, and accuracy of each class of GAF candlestick patterns. Where RMSE and MAPE are used to determine the performance of LSTM in calculating the error of the difference between predictions and actual values to get an idea of how well the model works to predict the close price.

To measure the evaluation of the final trading position prediction given by CNN-LSTM, we compare the number of candlestick patterns that predict profitable trading positions by CNN-LSTM with the number of candlestick patterns that have profitable trading positions on real data for a holding period of 1, 2, or 3 hours. Suppose we have time t as the time the candlestick pattern is detected, and N as the hold time with N being 1,2, or 3 hours after t. The trading positions are determined based on the close price and predicted close price that has been predicted by LSTM. The close price is the original close price in the test data, while the predicted close price is the close price predicted by LSTM on the test data. Then the real buy position is a trading position obtained if the close price at time t is less than the close price at $t + N$. A real sell position is a trading position obtained if the close price at time t is more than the close price at t+N. A predicted buy position is a trading position obtained if the predicted close price at time t is less than the predicted close price at time t+N. A predicted sell position is a trading position obtained if the predicted close price at time t is more than the predicted close price at time t+N. Because predicted buy position and predicted sell position are predicted positions, intersection with real buy

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position and real sell position must be done to find out how many positions are valid compared to real data. The total pattern is the sum of all original candlestick patterns in the test data, while the total predicted pattern is the sum of all candlestick patterns predicted to be profitable by CNN-LSTM models. The total profitable pattern is the real sum of profitable buy and sell positions using real close price at t+N. The total predicted profitable pattern is the sum of predicted profitable buy and sell positions using the predicted close price at t+N with the comparison of the real close price at t+N.

3. RESULT DAN DISCUSSION

3.1 CNN testing with 3-hour and 5-hour GAF candlestick pattern input

In this test, there are six candlestick patterns: Bullish Engulfing Signal, Bearish Engulfing Signal, Bullish Harami, Bearish Harami, Hammer Signal, and Shooting Star. Each is labeled as 0,1,2,3,4,5 so that we can see CNN's ability to recognize GAF images candlestick patterns at 3 hours and 5 hours intervals. The overall precision, recall, f1-score, support, and accuracy for each candlestick pattern in each interval can be seen in Tables 9 and 10.

Table 9. Confusion matrix from CNN model with 5-hour GAF candlestick patterns

Label	Precision	Recall	F1-Score
0	0.92	1.00	0.96
1	0.98	0.93	0.95
2	0.93	0.99	0.96
3	0.96	0.91	0.93
4	0.93	0.89	0.91
5	0.85	0.74	0.79
Accuracy			0.93
Macro Avg	0.93	0.91	0.92
Weighted Avg	0.93	0.93	0.93

Table 10. Confusion matrix from CNN model with 3-hour GAF candlestick patterns

Label	Precision	Recall	F1-Score
0	0.94	0.93	0.93
1	0.93	0.95	0.94
2	0.92	0.96	0.94
3	0.94	0.93	0.93
4	0.79	0.87	0.83
5	0.79	0.61	0.69
Accuracy			0.90
Macro Avg	0.90	0.86	0.87
Weighted Avg	0.90	0.90	0.89

According to the confusion matrix results, CNN can recognize GAF images candlestick patterns quite well at each interval. However, 5-hour GAF candlestick patterns have higher overall accuracy and precision, with 93% accuracy versus 90% accuracy for 3-hour GAF candlestick patterns. This is because the 5-hour GAF candlesticks pattern contains more information, allowing CNN to learn more effectively than the 3-hour GAF candlesticks pattern. Because there is more GAF matrix information in the 5-hour GAF candlestick pattern, the trend before the candlestick occurs is also better illustrated.

3.2 LSTM testing with 10 and 20 look back close price input

We use different input shapes of (10,1) or 10-hour look back and input shapes of (20,1) or 20-hour look back to get the best close price prediction. Figures 6 and 7 show the visualization of actual close price data versus LSTM predicted close price for each input shape.

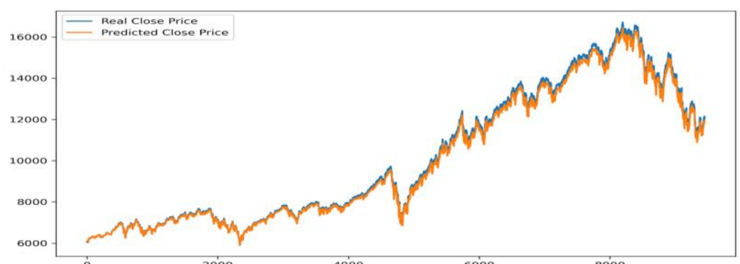

Figure 6. LSTM close price prediction with (10,1) input shape

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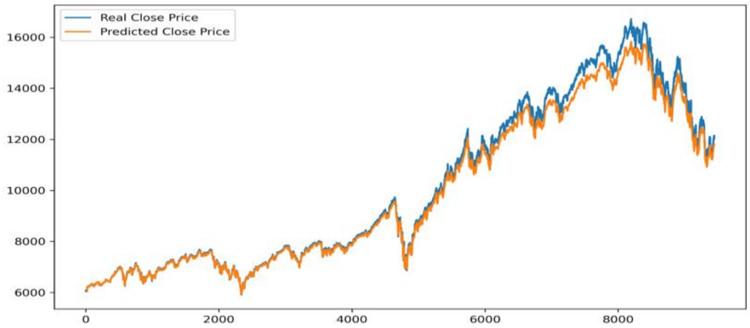

Figure 7. LSTM close price prediction with (20,1) input shape

LSTM can predict the close price with 155.458 RMSE and 0.9754% MAPE using an input shape of (10,1) or a 10-hour look back. LSTM can predict the close price with 310.22 RMSE and 1.925% MAPE using an input shape of (20,1) or a 20-hour look back. The visualization results of the LSTM close price prediction results show that LSTM can accurately predict the close price. However, when a more detailed visualization is performed, LSTM can only predict where the close price direction is going up or down, not the actual price. Based on our findings, the (10,1) input shape or 10-hour look back is the best input shape for the LSTM model to predict the close price. Not only are the RMSE and MAPE lower, but we can see a significant difference between each input shape predicted close price on the visualization. As a result, to calculate the final trading position, we used the model with a (10,1) input shape or a 10-hour look back.

3.3 Comparing and Evaluate both model's trading position

To compare trading positions taken using candlestick pattern CNN recognition alone versus CNN-LSTM, we must first determine how many patterns are recognized by CNN in the test data and how many profitable trading positions are taken out of all patterns formed. We want to see how well trading decisions based on candlestick patterns recognized by CNN and validated by LSTM perform compared to using CNN alone. Tables 11 and 12 compare the accuracy of trading positions taken using CNN alone or CNN-LSTM to take trading positions based on candlestick pattern recognition at t times and the close price or predicted close price at t+N times.

Table 11. Evaluation for CNN candlestick pattern recognition profitable trading position

Model Scenario	Profitable buy trading position	Profitable sell trading position	Total Profitable Pattern	Total Pattern	Profitable trading position accuracy
CNN Candlestick Recognition 1 Hour	21	17	38	85	44.7%
CNN Candlestick Recognition 2 Hour	23	23	46	85	54.1%
CNN Candlestick Recognition 3 Hour	24	27	51	85	60%

Table 12. Evaluation for CNN-LSTM candlestick pattern recognition profitable trading position

Model Scenario	Profitable buy trading position	Profitable sell trading position	Total Profitable Predicted Pattern	Total Predicted Pattern	Profitable trading position accuracy
CNN-LSTM Trading Position 1 Hour	27	24	36	51	70.5%
CNN-LSTM Trading Position 2 Hour	29	29	44	58	75.8%
CNN-LSTM Trading Position 3 Hour	29	29	48	58	82.7%

4. CONCLUSION

Based on the research, CNN can recognize 3-hour and 5-hour candlestick patterns well using GAF images. CNN accuracy results are better when using 5-hour candlestick pattern GAF image input with 93% accuracy because more info is captured on the 5-hour GAF for the CNN to study. For LSTM, we get the best close price prediction

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accuracy results with input shape(10,1) compared to input shape(20,1). The best LSTM result is obtained with 155.458 RMSE and 0.9754% MAPE with (10,1) input shape or 10-hour look back. Although quite good results are also seen in the visualization of close price predictions, LSTM can only predict where the price direction goes up or down and cannot predict the actual close price. So with the ability of both CNN-LSTM models, the best results can predict 82.7% profitable trading positions with a holding time of 3 hours compared to only using CNN to recognize candlestick patterns, resulting in 60% profitable trading positions. Thus it can be concluded that the combination of the two CNN-LSTM models can increase the predictive ability of candlestick patterns and provide more profitable trading positions than just using CNN candlestick patterns recognition alone. For further research, it may be possible to use more candlestick patterns that are tested using CNN to be recognized so that more trading positions can be obtained; it can also test the ability of candlestick patterns to predict profitable trading positions more deeply.

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