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Implementing Histogram of Oriented Gradients to Recognize Crypto Price Graphic Patterns with Artificial Neural Network

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ABSTRACT

Technical analysis stands as a pivotal strategy in analyzing graphic patterns to forecast future movements in crypto asset prices. However, comprehending numerous patterns poses a significant challenge for novice investors venturing into the investment realm. This study aims to facilitate investors in recognizing crypto price graph forms by classifying cryptographic price chart patterns. The dataset comprises images of seven types of crypto price graphic patterns obtained from the Kagle website, totaling 210 data points. A 70:30 training and testing data split is employed to ensure robust model evaluation. The study explores nine different Histogram of Oriented Gradients (HOG) parameter combinations for graphic pattern extraction. Leveraging the artificial neural network (ANN) classification method with parameter hyper tuning, the study assesses various HOG parameter configurations to optimize classification performance. The most optimal results are achieved with parameters Bin = 9, Cell Size = 16x16, and Block Size = 1x1, boasting an accuracy rate of 95.23%, precision of 95.55%, and recall of 95.23%. This classification approach streamlines the process for investors, enabling them to discern crypto price graph patterns effectively, thereby enhancing their investment decision-making capabilities in the dynamic cryptocurrency market landscape. By providing a structured method for pattern recognition, this study contributes to democratizing access to technical analysis tools, particularly benefiting novice investors seeking to navigate the complexities of cryptocurrency investment.

Keywords: Artificial Neural Network, Crypto, Graphic Patterns, HOG, Technical Analysis

1. INTRODUCTION

Investment is the activity of holding or investing capital for a certain period in the hope that the funds held will generate a profit or increase in value in the future (Maharani & Farhan Saputra, 2021). There are all kinds of investments, like deposits, bonds, gold, stocks, oil, forex, and crypto (Ciner et al., 2013). To make a decision, investors must identify the assets they are going to buy through technical and fundamental analysis before making a decision to make an investment. Technical analysis is a type of analysis that is based on the history of the stock or crypto market price. In contrast, fundamental analysis is an asset analysis based on relevant economic, industrial, and corporate situations (Virk, 2022).

Technical analysis is one of the strategies for analyzing and predicting future price movements of an investment asset using past data (Han et al., 2024). On the historical chart of the price of an asset, there are many movements with recurring patterns (Vo et al., 2015). In the stock market, there are three types of chart patterns that are commonly found. This type of pattern is a trend reversal pattern, a trend extension pattern or continuation pattern, and a trend or bilateral trend expansion pattern. A reversal pattern is a graphic pattern that identifies reversals of prices from previous trends and forms a new trend. An example of a reversal pattern is a double top and double bottom. While a bilateral chart pattern has two possible upside or downside price patterns, examples include an ascending triangle, a declining triangle, and a symmetrical triangle (Ong, 2016). With technical analysis, investors can implement investment strategies more easily because it will give a signal of future price movements. But there are many patterns that investors need to understand to do technical analysis, so it will be hard for a beginner who wants to plunge into the world of investment. It would then require a system to recognize and classify graphic patterns in the price movements of crypto so that investors decisions to enter the market would be more directed and the risk of losses would be smaller.

In previous studies, researchers created a signature identification system using HOG characteristic extraction

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features and the Fuzzy Min Max Classification method (FMMC). In this study, use a signature pattern image for the dataset. There are about 240 signature images in use. The signature was taken from 12 people. To train the system, a subset of 120 signatures is used, and the remaining signatures are used for testing. This study has 96% accuracy (Melhaoui & Benchaou, 2021).

In other similar studies, researchers created a computerized system to predict a person's characteristic characteristics based on their style of handwriting using the support vector machine classification method and the histogram of oriented gradients characteristics extraction. The study used a sample of handwriting from 50 different authors, of whom 50 were asked to write several texts with the same content. The classification was made to identify the five personality traits of active, extrovert, introvert, negligent, and optimistic. This study has achieved an accuracy rate of 80% (Chitlangia & Malathi, 2019).

From previous research, it can be concluded that the feature histogram of oriented gradients is a good feature extraction feature to recognize pattern shapes on objects, and methods of classification for hypnotic neural networks proved to have good results in recognizing an object. This research aims to identify the type of pattern on the crypto price chart using the classification algorithm of the hypocritical neural network and the extraction of the feature histogram of oriented gradients. In previous studies, no one had classified the type of object. So far, it has not been known what the accuracy level of the features and methods generated in classifying the pattern type on the crypto price chart is. Therefore, this research is very important to do in order to know the accurate level generated.

2. LITERATURE REVIEW

In general, chart patterns are objects in technical investment analysis that describe situations, more precisely fluctuations, of the price of cryptocurrencies in the crypto market. With the help of this information, both investors and traders can make better predictions of future price movements. The pattern chart becomes a countermeasure of the estimated profit or risk in every transaction that will occur. Equipped with good strategy and risk management, traders will be able to reach their goals faster.

There are some examples of chart patterns that are commonly found in the historical price charts of a crypto asset, such as the ascending triangle, the declining triangle, the symmetrical triangles, the falling wedges, the rising wedge, the double bottom, and the double top (Ong, 2016). Below is an example image of a chart pattern.

Ascending Triangle

The characteristics of the ascending triangle pattern are bullish patterns with a flat upper trend line and a lower trend line that climbs with narrow ends so that it resembles a triangle shape that indicates accumulation. The following is an example of an ascending triangle pattern image shown in Fig. 1.

Fig. 1 Ascending Triangle Chart Pattern

Descending Triangle

The characteristics of the descending triangle pattern are bearish patterns with a flat bottom trend line and a descending top trend line with narrow pattern ends so that it resembles a triangle shape, indicating a distribution. The following is an example of a descending triangle pattern image shown in Fig. 2.

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Fig. 2 Descending Triangle Chart Pattern

Symmetrical Triangle

The characteristics of the symmetrical triangle pattern are patterns that do not show a definite direction with upper and lower trend lines that converge and narrow to form a symmetrical triangle that indicates uncertainty. The following is an example of a symmetrical triangle pattern image shown in Fig. 3.

Fig. 3 Symmetrical Triangle Chart Pattern

Falling Wedge

The characteristics of the falling wedge pattern are a bullish pattern with descending and narrow upper and lower trend lines, indicating a potential reversal in a bullish direction. The following is an example of a falling wedge pattern image shown in Fig. 4.

Fig. 4 Falling Wedge Chart Pattern

Rising Wedge

The characteristics of the rising wedge pattern are bearish patterns with rising and narrowing upper and lower trend lines, indicating a potential reversal in a bearish direction. The following is an example of an image of the rising wedge pattern shown in Fig. 5.

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Fig. 5 Rising Wedge Chart Pattern

Double Bottom

The characteristics of the Double Bottom pattern are a bullish pattern with two adjacent valleys and an intersecting resistance line, indicating a potential reversal in the bullish direction. The following is an example of a double bottom pattern image shown in Fig. 6.

Fig. 6 Double Bottom Chart Pattern

Double Top

The characteristics of the double-top pattern are a bearish pattern with two adjacent tops and an intersecting support line, indicating a potential reversal in a bearish direction. The following is an example of a double-top pattern image shown in Fig. 7.

Fig. 7 Double Top Chart Pattern

3. METHOD

This section is divided into four sections, including data collection, feature extraction, data splitting, machine learning models, and evaluation metrics, and the proposed workflow is shown in Fig. 8.

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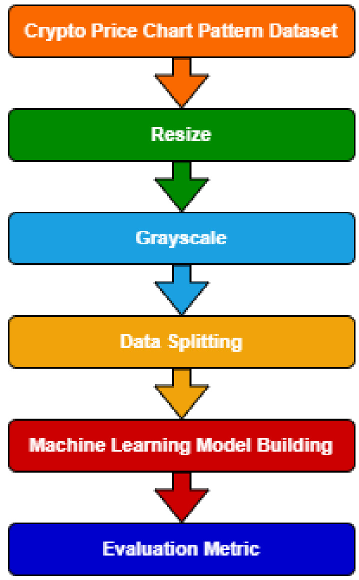

Fig 8. Proposed Workflow

Data Collection

The data set used is an image of a cryptographic price chart pattern taken from Kagle. The dataset contains 7 types of charts, such as ascending triangles, ascending triangles, symmetrical triangles, falling wedges, rising wedges, double bottoms, and double tops, each with 30 images.

Resize

Image resizing, or scaling, is the process of changing the image size to be smaller. The resize process or scaling in this study does not use a special method. The process of resizing in this research involves comparing the size of the image from the segmentation with the target image size (Mukhopadhyay, 2017). Image resizing needs to be done so that, at the time, the image processing by the computer will be faster and not spend much of the storage memory in the temporary memory.

Grayscale

Grayscale is an image with values from white with the highest intensity (255) to black with the lower intensity (0). The image format is called a dimming scale because generally the color used is black as the minimum color (0) and white as the maximum color (255), so the color between them is gray (Saravanan, 2010). Converting RGB color images to grayscales according to the following equation.

Feature Extraction

Histogram of Oriented Gradients is a technique for extracting shape features from images by making histograms based on the direction or gradient orientation of pixels in images. The way it works is by calculating the gradient value of an image to obtain the result that will be used to detect an object (Virk, 2022). Each image has a characteristic called a gradient contribution. This characteristic is obtained by dividing the image into a small area called a cell. This combination of histograms is used as a descriptor to represent an object. In this method, HOG features can be obtained by dividing images into n x n-sized cells and then grouping them in rows with each other. From each cell, each block will be counted for gradient, magnitude, and orientation (Dalal & Triggs, 2005).

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The HOG feature extraction can be summarized into three parts (Zhang et al., 2020):

(1) Gradient computation in this step, the horizontal gradients *Gx* and vertical gradients *Gy* for the pixels within a local spatial region called a cell is computed. *Let I(x, y)* be the intensity at pixel location *(x, y)*, the gradients at *(x,y)* can be computed as

$$Gx(x, y) = I(x + 1, y) - I(x - 1, y) \qquad (1)$$

$$Gy(x, y) = I(x, y + 1) - I(x, y - 1) \qquad (2)$$

The gradient magnitude *M(x, y)* and angle *θ(x, y)* are given by

$$M(x, y) = \sqrt{Gx(x, y)^2 + Gy(x, y)^2} \qquad (3)$$

$$\theta = arctan\left(\frac{Gy(x,y)}{Gy(x,y)}\right) \qquad (4)$$

(2) Orientation binning. To form a histogram, the gradient The magnitude of each pixel within a cell is voted into different orientation bins according to their gradient angle.
(3) Normalization and feature description. In this step, the cell histograms are normalized within a group of cells called blocks. All the histograms within a detection window are concatenated to form a HOG feature descriptor.

Data Splitting

Dividing datasets is an important practice in machine learning, in which the entire data set is divided into two or more different sub-sets. The primary purpose is to isolate part of the data for training and testing of predictive models. In this process, the model's learning revolves around its ability to execute a task by leveraging the training data. Subsequently, the testing data is employed to validate the model's functionality and ensure its correctness (Medar et al., 2017). In this study, the division of the datasets was done in a 70:30 ratio, with 70% as training data and 30% as test data (Medar et al., 2017).

Machine Learning Model

Classification using the machine learning model is done to classify and recognize the image of the cryptographic price chart pattern into a specified class (Vasavi et al., 2022). This allows the method of machine learning to apply classifications to the data sets that have been categorized so that it can classify future data into the relevant class (Benlachmi et al., 2022). For classification, the proposed method is an artificial neural network.

At this stage, in building a machine learning model, artificial neural networks are used. An artificial neural network is a computer program that consists of a neuronal network that receives information from an input variable or from another neuron, performs calculations independently, and transmits its output to other neurons in the network. Each neuron in the tissue is an autonomous entity consisting of a weight used to weigh input values, a bias that prevents division with zero values, and an activation function that passes neuron values to the next neuron (Kang et al., 2012). The main advantage of an artificial neural network is its ability to learn from given examples or training data, while the main disadvantage is that it takes a long time to do its training. Here's a picture of the artificial neural network process for processing input data to get output values (Tu, 1996).

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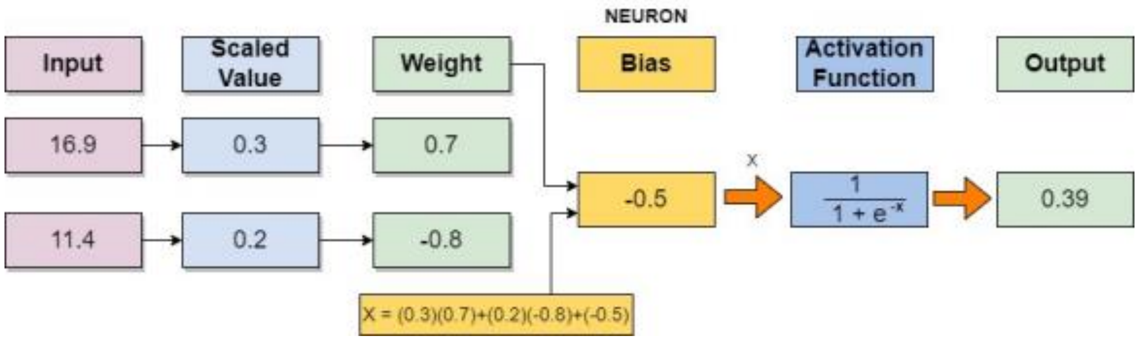

Fig. 9 Computation process of artificial neural network

Evaluation Metrics

In the field of machine learning and predictive modeling, selecting the appropriate evaluation metrics is crucial to measuring the extent to which a model or system successfully accomplishes the given task. Evaluation metrics help measure the quality of prediction outcomes and compare the performance of different models (Pistorius et al., 2020). Here are some evaluation metrics used:

(1) Accuracy. Accuracy is a general measure to measure how many correct predictions a model makes compared to the total amount of data. Expressed as a percentage, accuracy gives an idea of how well a model is able to correctly classify data.
(2) Precission. Precision measures how well a model correctly predicts a positive case. This is expressed as a comparison between the true positive number predicted (true positive) and the total positive prediction made by the model.

Recall. Recall, also known as sensitivity or true positive rate, measures the ability of a model to find all the real positive cases. It is calculated by comparing the number of true positive cases with the actual number of positive ones.

4. RESULT

This section implements the research process to obtain the results of the research, the implementation covers the stages of image resizing, grayscale, HOG extraction, encoder labels, and simulated neural network architecture modeling.

Table 1
Image resizes result

Before Resize	After Resize

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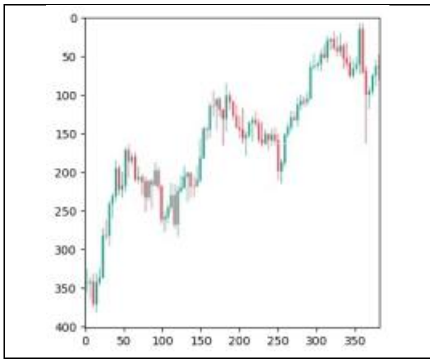
	

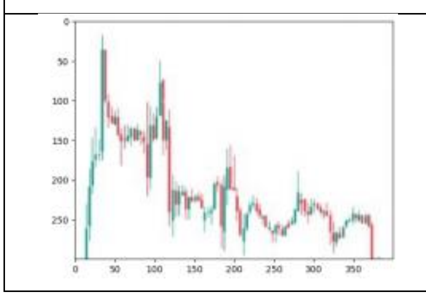
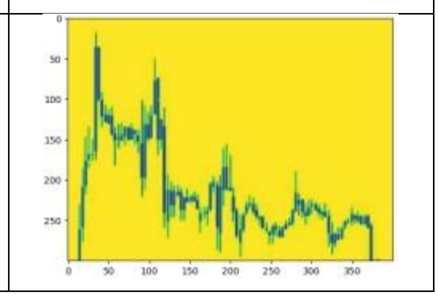
Image Resize Result

Resize an image. This process may involve changing the image size to be larger or smaller, according to specific needs. Before extracting the histogram of oriented gradients, resize the image to the size of 300 x 400 using the software paint tool. The result can be seen in the table 1.

Image Grayscale Result

Grayscale is used to convert a colored image to a grayscale image. This process removes color information from the image, leaving only the brightness of each pixel that affects the display of the image. Image resize is done using scikit - image library, can be seen in table 2. below.

Table 2
Image grayscale result

Before Grayscale	After Grayscale
	

Histogram of Oriented Gradients Extraction Result

The extraction of the histogram of oriented gradients is done on the data set, where the image data has been resized with the size of 300 x 400 pixels and grayscale. This process is done with 9 combinations of the parameters of the histogram of oriented gradients by changing several parameters such as bin, block size and cell size. The process obtains results that can be seen in Figure 10.

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	A	B	C	D	E	F	G	H	I	J	K	L	M
1	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
2	2,9E-08	0	3,1E-09	0	2,9E-08	0	1,5E-09	0	0,64129	0,24607	0,09058	0,19031	0,04415
3	2,6E-08	0	0	0	2,5E-08	0	0	0	3,4E-08	0	1,5E-09	0	2,6E-08
4	2,4E-07	1,5E-08	2,2E-07	0	3,7E-07	3,2E-08	1,9E-07	0	2,6E-07	9,7E-09	2E-07	0	3,6E-07
5	3,5E-08	0	3,1E-09	0	3,6E-08	0	0	0	0,37554	0,26702	0,35365	0,37554	0,37554
6	0,53746	0,33814	0,17661	0,16722	0,18653	0,20863	0,41285	0,53746	2,1E-08	0	0	0	2,2E-08
7	0,63135	0,22723	0,08841	0,01829	0,15019	0,13636	0,31915	0,63135	0,4316	0,42081	0,39918	0,4316	0,4316
8	0,7071	0,0024	0,00024	0,00043	0,00183	0,00158	0,00248	0,7071	0,78102	0,16695	0,1912	0,52037	0,02375
9	0,53387	0,33009	0,24249	0,18266	0,32214	0,22211	0,2752	0,53387	2,7E-08	0	0	0	2,7E-08
10	0,55786	0,13374	0,14169	0,11063	0,50729	0,17724	0,19656	0,55786	5,9E-08	0	0	0	4,3E-08
11	0,53753	0,33786	0,15781	0,22186	0,32603	0,23595	0,2681	0,53753	0,04177	0,16967	0	0,13472	0,55274
12	0,62199	0,3053	0,07807	0,07367	0,06973	0,1191	0,32014	0,62199	0,49972	0,15718	0,16305	0,09908	0,12129
13	0,44774	0,0931	0,03147	0,44774	0,42313	0,20244	0,411	0,44774	2E-08	0	0	0	2,1E-08
14	0,68918	0,1534	0,00668	0,01624	0,07214	0,06927	0,12738	0,68918	1	0	1,5E-13	0	2,6E-12
15	0,41273	0,15831	0,3361	0,22894	0,41273	0,35802	0,41273	0,41273	4,2E-08	0	0	0	4E-08
16	3,6E-08	0	0	0	3,4E-08	0	0	0	0,38704	0,38704	0,37638	0,38198	0,38704
17	0,64936	0,17515	0,04903	0,13728	0,22228	0,12274	0,20063	0,64936	4E-08	0	0	0	2,8E-08
18	1,6E-08	0	0	0	2E-08	0	3,1E-09	0	0,39366	0,39366	0,39366	0,34086	0,20162
19	0,39294	0,18865	0,31977	0,39294	0,39294	0,30025	0,39294	0,39294	0,35355	0,35355	0,35355	0,35355	0,35355

Fig. 10 Histogram of oriented gradients extraction result

Implementation of Artificial Neural Network

The implementation of artificial neural networks aims to form an architecture of artificial neuronal networks that will be applied at the time of training. The artificial neural network architecture used was defined using the hypertunning parameter technique using the GridSearchCV function in the python scikit-learn library (Sklearn), commonly used to perform the best parameter search in the machine learning model. Some parameters are determined by hypertunning parameters, including neuron, hidden layer, activation, solver, and learning init.

The test results are obtained from the evaluation of models derived from training and testing using histogram extraction data of oriented gradients previously obtained by determining several parameters such as bin, cell size, and block size. These parameters affect the quality and quantity of features resulting from the extraction of histograms of oriented gradients and also influence the performance of models produced by artificial neural networks.

Result

This phase is the result of the evaluation metrics obtained from the test performed with 9 histrogram of oriented gradients data extracted from a graphic pattern image with different parameter values. The parameters of the histogram of oriented gradients used are bin, cell size, and block size. The test uses an artificial neural network algorithm with a parameter hypertuning technique to obtain the best artificial neural network parameter from each data point being tested. The comparison results of each histogram parameter of oriented gradients can be seen in table 3.

Table 3
Comparison of accuracy results based on histogram parameters of oriented gradients

Parameter HOG	Best Activation	Best Hiden layer Size	Best solver	Best Learning Rate	Accuracy	Precision	Recall
Bin = 9, Cell Size = 64x64, Block Size = 1x1	Logistic	1 hidden layer 75 neuron	Sgd	0.01	80.95%	81.91%	80.95%
Bin = 9, Cell Size = 32x32, Block Size = 1x1	Tanh	1 hidden layer 25 neuron	sgd	0.1	93.65%	94.12%	93.65%
Bin = 9, Cell Size = 16x16, Block Size = 1x1	Relu	1 hidden layer 55 neuron	sgd	0.01	95.23%	95.55%	95.23%
Bin = 8, Cell Size = 64x64, Block Size = 1x1	Logistic	1 hidden layer 50 neuron	sgd	0.01	84.12%	85.27%	84.12%
Bin = 8, Cell Size = 32x32, Block Size = 1x1	Tanh	1 hidden layer 20 neuron	sgd	0.1	92.06%	92.95%	92.06%

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Bin = 8, Cell Size = 16x16, Block Size = 1x1	Logistic	1 hidden layer 50 neuron	sgd	0.01	93.65%	94.31%	93.65%
Bin = 7, Cell Size = 64x64, Block Size = 1x1	Logistic	1 hidden layer 20 neuron	sgd	0.01	74.6%	75.28%	74.6%
Bin = 7, Cell Size = 32x32, Block Size = 1x1	Logistic	1 hidden layer 35 neuron	sgd	0.01	92.06%	92.63%	92.06%
Bin = 7, Cell Size = 16x16, Block Size = 1x1	Logistic	1 hidden layer 95 neuron	sgd	0.01	93.65%	95%	93.65%

DISCUSSIONS

From the experimental testing with 9 graphic model image extraction data, the best result obtained is a combination of bin = 9, cell size = 16x16, and block size = 1x1. With an accuracy rate of 95.23%, precision of 95.55%, and recall of 95.23.

5. CONCLUSION

Based on the research that has been carried out, the tests were conducted on nine extraction data points using the histogram of oriented gradients with different combinations of parameters, and it was concluded that the features of histograms of oriented gradients and artificial neural networks can be implemented to classify the patterns of the cryptographic price graph. Out of the results of the tests, nine data extractions of the histogram of oriented gradients with the method of an artificial neural network using the technique of hypertunning parameters obtained the highest results on the combination of the parameters bin = 9, cell size = 16x16, and block size = 1x1, with an accuracy rate of 95.23%, precision of 95.55%, and recall of 95.23.

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