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Research Article

Candlestick chart based trading system using ensemble learning for financial assets

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ABSTRACT

The candlestick charts, which were developed in the 18th century and were initially used in the Japanese rice market, are widely used in trading strategies in all financial markets after 1991. Candlestick charts can interpret opening, high, low and closing values of an asset in a single visual. In addition to these advantages, the large number of candlestick chart patterns makes their practical use difficult. In the study developed for this purpose, a software framework that uses candlestick charts and predicts the trend direction was created. The study consists of four stages. In the first step, a system that recognizes candle patterns is created. In the second stage, the performance of the model is measured by running training and testing processes on data sets in which candlestick chart types and trend direction are labeled. In the machine learning phase, community methods such as xgboost were used. In the last stage of the study, it was seen that with the strategy based on only recognizing the candlestick pattern and taking position in the direction of the trend based on proposed approach, higher profit was obtained in 11 world indices compared to Buy&Hold strategy.

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INTRODUCTION

In financial markets, prices are assumed to move in a trend that bullish or bearihs as well as volatile. Investors and portfolio managers try to gain profits and minimize risks by taking positions in the right direction and at the right time. For this purpose, technical analysis is used to interpret price charts made up of time series [1]. It includes many tools such as technical analysis, moving averages, indicators and oscillators, statistical-based series and pattern-based formations. Therefore, it is widely used by real investors and technical analysts, as well as algorithmic robots that perform autonomous transactions in crypto and stock markets [2].

In the trading, some of the earliest technical trading analysis was used to track prices of rice in the 18th century. Much of the credit for candlestick charting goes to Munehisa Homma, a rice merchant from Sakata, Japan

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who traded in the Ojima Rice market in Osaka during the Tokugawa Shogunate. According to Steve Nison, however, candlestick charting came later, probably beginning after 18th century [3].

Candlestick charts and their interpretation are one of the technical analysis tools mentioned above. As shown in Fig. 1, they are formed by consolidating all price movements in a certain period, such as the hourly, daily, weekly in a single visual. Every candlestick consists of a real body and wicks (or shadows) that stand out vertically top and bottom from the body, looking like the wick of a candle, the body representing the candle body. Although the lengths of the candlestick charts are different, there is no assumption about their width, so all of them are the same width and it does not matter for technical analysis [4].

The size of the body is determined by the difference between the opening and closing levels in the time period the candlestick represents. If the closing price is higher than the opening price, the candle will have a green or white body. If the closing price is less than the opening price, a red or black body is formed. Considering the length of the body, upper and lower shadows the ratio of their height to each other and their positions (such as proximity), many types of candlestick are formed. Thus, they are also used in the interpretation of the trend of the markets and the psychology of the two types of investors (Bear/Bull) that dominate the market. The bulls open "long" positions in the upward direction while the bears open in the downward direction called "short". For example, as shown in Fig 2, when the opening and closing prices are equal and the candle called "Doji" indicates that the market is unstable and the war between bears and bulls has not yet been a winner. In this case, the next candle is waited to confirm the trend. There are not only dozens of different types of candlestick charts but also two or more candlestick charts that come together to form new patterns. Thus, many combinations can be formed. Therefore, it is not easy task for investors and analists possible to interpret it because there are many types of candlestick chart types and patterns [4].

Figure 1. Typical candlestick formation.

RELATED WORKS

Until recently, statistical based moving averages and indicators and oscillators derived from them were used for financial forecasting. However, the field of financial forecasting is a highly complex area. For determining pattern-based trend formations on time series, interpretation of candlestick charts, relations of stocks with each other, status of gold, oil and major world indices, processing semantic data reflecting investors' expectations and psychologies, real-time big data approaches, building machine learning and deep learning based models to predict trends are widely used today [5-10]. Supervised, unsupervised and reinforced learning approaches are widely used to forecast trends, prices, profits, risks, and periods using historical data and the indicator data obtained from these data. Algorithms such as LSTM and CNN are widely used in the creation of intelligent models thanks to their ability to be multi-layered and to extract attributes between layers [6-10]. These algorithms can perform training and testing operations in near-time (close to real-time) speed with the lowering of hardware costs and the widespread use of high-level graphics cards suitable for parallel programming [11]. However, there is still a disadvantage here. Instant data of hundreds of stocks can be generated during the trade on stock markets. Intelligent investor programs that will provide advice to investors and analysts need to process large amounts of data in real time. More importantly, high-frequency algorithmic robots must make very fast decisions

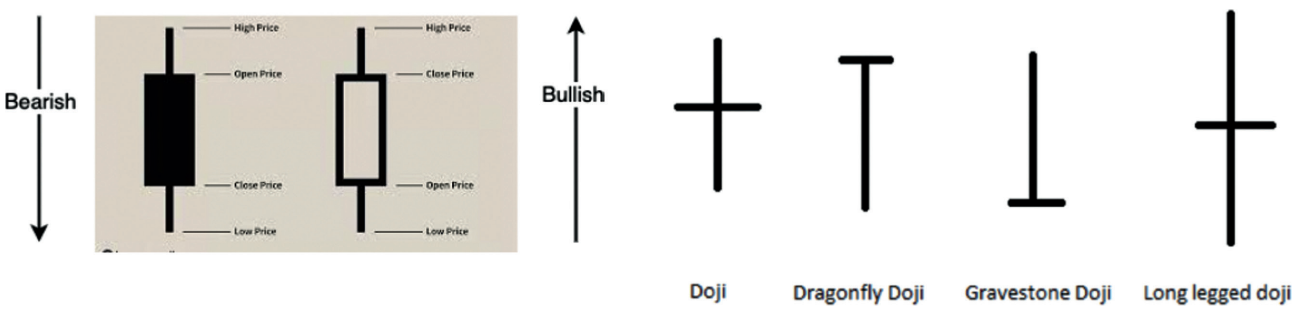


Figure 2. Bearish/Bullish candlestick and main types of Doji candlesticks.

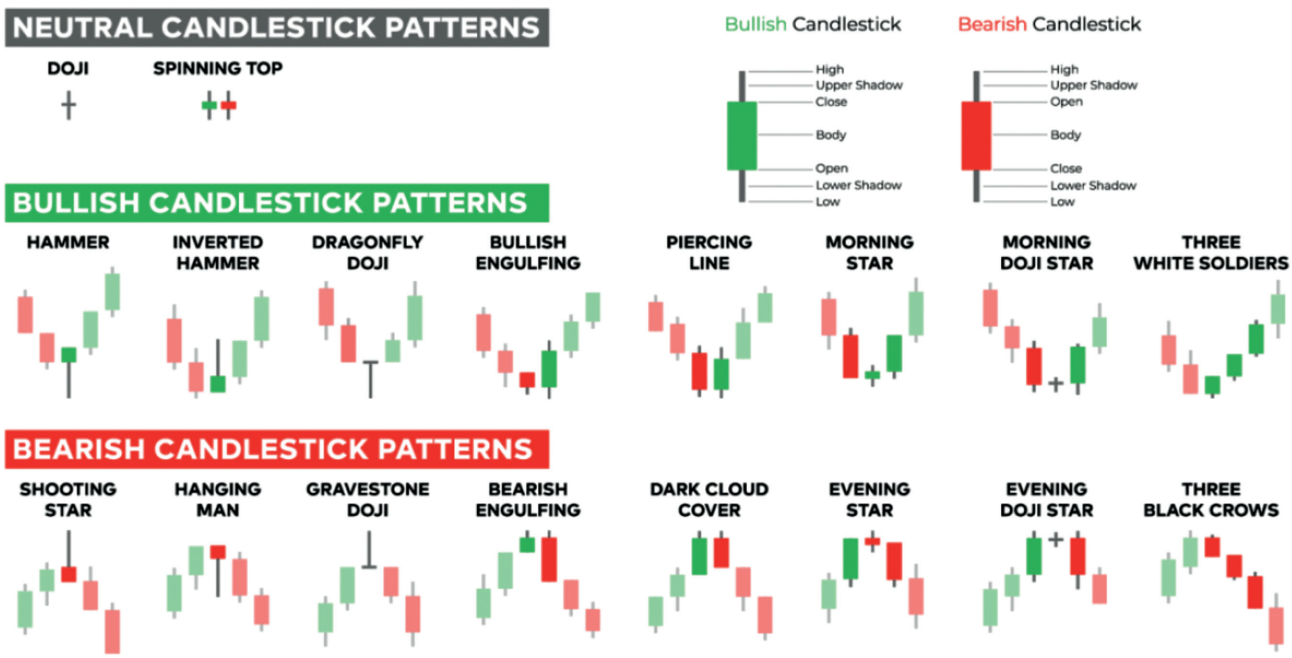


Figure 3. Some of candlestick patterns [14].

and send orders to the market in order to stay in the trend direction and maximize profits [12].

Deep learning based neural network models are non-linear methods. They have many advantages. However, they learn via a stochastic training algorithm which means that they are sensitive to the specifics of the training data and may find a different set of weights each time they are trained, which in turn produce different predictions. In this way, this can be referred to as neural networks having a high variance. A successful approach to reducing the variance of neural network models is to train multiple models instead of a single model and to combine the predictions from these models. This is called ensemble learning and not only reduces the variance of predictions but also can result in predictions that are better than any single model [13].

As a result, there are many potential hybrid models that can be developed for financial forecasting. One of them is the candlestick charts that mentioned in the introduction. Although it consists of a single image, it is known that there are more than a hundred candlestick patterns due to the many combinations. For this reason, it is very difficult to memorize and interpret it especially on live data [4]. In Fig 3, only some of the more commonly used patterns are given [14].

Chen et al. (2020) developed a hybrid approach using Convolutional Neural Network (CNN) and Gramian Angular Field (GAF) to classify 8 candlestick chart patterns based on image pattern classification. In their experiments, it can identify the eight types of candlestick patterns with 90.7 % average accuracy automatically in real-world data, outperforming the Long Short-Term Memory (LSTM) model [15].

Pattern-based candlestick chart type classification is an approach that can be automated. However, the fact that there are 103 graphic types and many of them are expressed subjettively and in natural language makes this difficult. According to Hu et al. (2019) were proposed a comprehensive formal spesification of 103 known candlestick patternts to alleviate these problems. Their goal is to establish an unambiguous reference model which can be used in future pattern classification research without significant modifications [16]. Since the study is based on a rule-based system and it is suitable for generating synthetic data, it will be able to form an entry in pattern classification-based studies.

Biroğul et al. (2020) developed a hybrid model using You Only Look Once (YOLO) and CNN by labeling as "Buy" or "Sell" signal the indicators and 2-D image-based candle patterns obtained from the data of the borsa istanbul (BIST). When they used the data from 2000-2018 for training and post-2018 data for testing, they were able to earn -7% to 30% earnings on stock groups divided into 13 groups with the trading strategy of the developed approach [17].

Andriyanto et al. (2020) were able to achieve 99.3% accuracy in trend prediction in a study comparing CNN and LSTM by using two-year IDX Mining (JKMING) data. In their study, candlesticks were used by labeling them as "bearish" or "bullish" [18].

Some specific studies in this area are to extract data mining information that will help to maximize gain or minimize loss. Fengqian and Chao (2020) examined the patterns of three white soldiers and three black crows, which point to strong trend reversal in the Taiwan market using 2002-2008 data. They find in their study, that three bullish reversal patterns are profitable in the Taiwan stock market. For robustness checks, they evaluate the applicability of their results to diverse market conditions, conduct an out-of-sample test and employ a bootstrap methodology [19].

Kusuma et al. (2019) developed a model that predicts trends in Taiwan and Indonesia stock markets using the deep convolutional network and candlestick. The effectiveness of their method is evaluated in stock market prediction with a promising results abova 92% accuracy for Taiwan and Indonesian stock market dataset respectively. The constructed model have been implemented as a web-based system freely available at the web based application for predicting stock market using candlestick chart and deep learning neural networks [20].

This study was carried out in four stages to prove the strength and usability of candlestick charts in trend forecast. In the following sections, the approach used in the study is detailed and experimental results are given. The experimental results includes both the accuracy of the trend direction forecasting and the backtest process that includes the portfolio earnings in order to show the profit rates to be obtained in the positions opened in the direction of trend forecasting. The study results have been verified using major world stock market indexies.

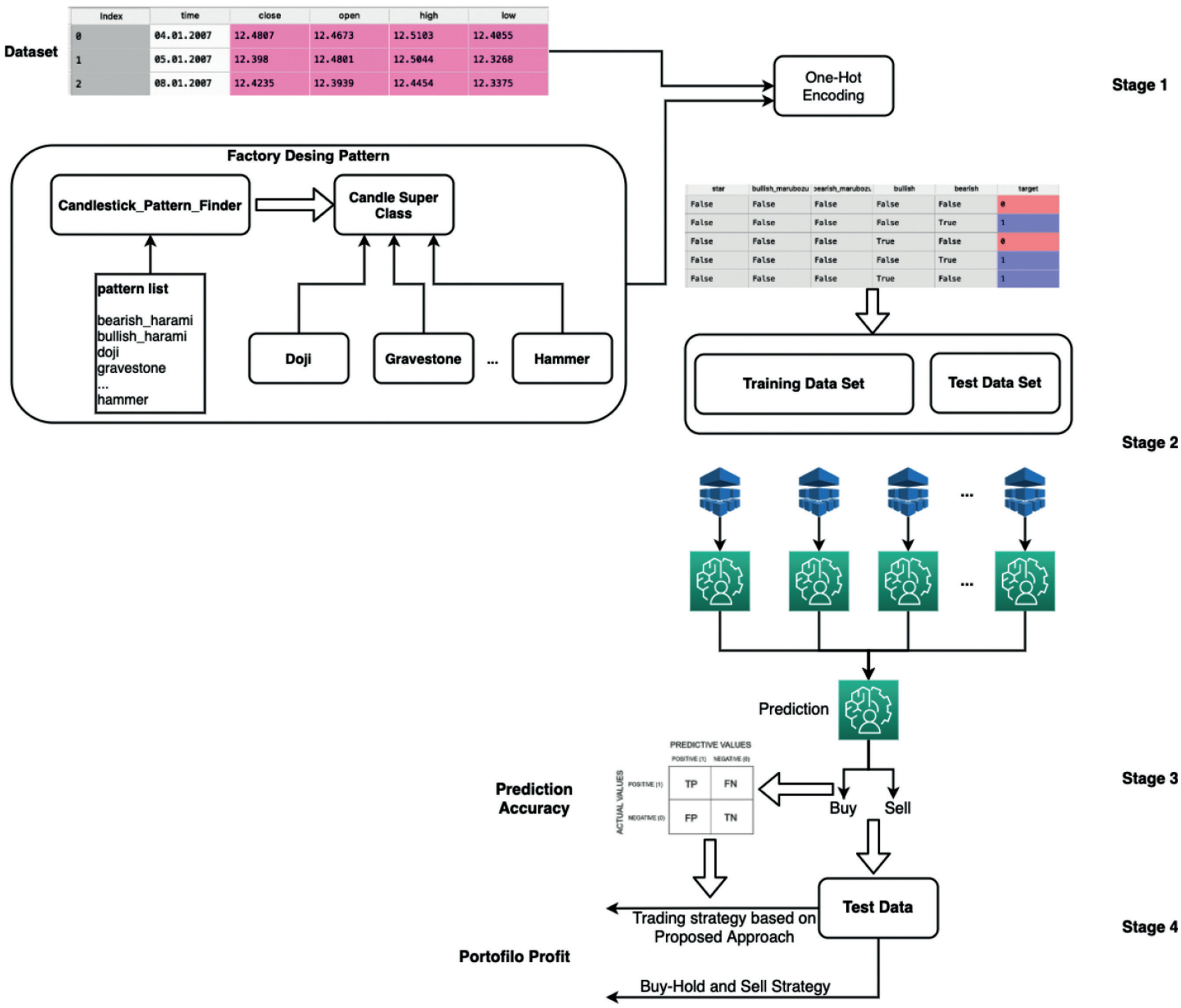


Figure 4. Proposed Approach.

METHODOLGY

A four-stage approach is proposed in the study. In the first stage, a rule-based system was created for the 24 candlestick chart patterns used in the study. At this stage, in order to increase the patterns with minimum code and cost for future studies, an object-oriented programming and factory design pattern was used. In the second stage, one-hot encoding was performed to determine the daily candle type generated by each data set. At the same time, data set pre-processing steps were completed by labeling the data automatically as "bearish", "bullish" based on daily closing values. In the third stage, the data set was separated as training and test, and the model was created using the training data set using the community learning algorithm xgboost. At this stage, a confusion matrix was created from the test data and trend estimation accuracy was obtained. At the same time, using both training and test data, basic metrics such as candlestick chart recognition rate were obtained for statistical purposes. Because it is known that there are 103 candlestick charts in the literature, but only 24 of them were used in the study. Because, It is predicted that the results obtained in the study will improve more by including more candle charts into the system. The last step is portfolio simulation on test data. Portfolio simulation includes the comparison of the Buy-Sell transaction by taking a position in the direction of the trend forecast based on the proposed syste and the Buy-Hold-Sell (BHS) strategy based on the principle of buying the relevant index at the beginning of the test period and selling it at the end of the period. A detailed block diagram of the proposed approach is given in Fig 4. The candlestick patterns used in the study are as follows:

Candlestick patterns: "bearish engulfing", "bearihs harami", "bullish engulfing", "bullish harami", "dark cloud", "doji star", "doji", "dragonfly doji", "evening star doji", "evening star", "gravestone", "hammer", "hanging man", "inverted hammer", "morning star", "piercing pattern", "rain drop doji", "rain drop", "shooting star", "star", "bullish", "bearish", "bullish marubozu", "bearish marubozu"

Stage 1: Candlestick Pattern Finder

Factory pattern is one of the most used design patterns in software engineering [21]. This type of design pattern comes under creational pattern as this pattern provides one of the best ways to create an object. In Factory pattern is created an object without exposing the creation logic to the client and refer to newly created object using a common interface. A new class is written for each candlestick pattern, and all created classes inherit common traits from the superclass. In this way, it is easy to include a new pattern in the system. Python programming language Pandas, Skelearn and Numpy libraries were used in all steps in the proposed approach [22].

At this stage, after data pre-processing is done, candlestick patterns are found and one-hot encoding transformation is made. The categorical values start from 0 goes all the way up to N-1 categories. This situation may cause a disadvantage that causes some input data to be expressed more heavily in the ML model compared to the numerical value it receives. One hot encoding is a process by which categorical variables are converted into a form that could be provided to ML algorithms to do a better job in prediction. This ensures that all entries are represented with equal weight in the network and it is easy to add new entries.

Stage 2: Ensemlbe Learning – Xgboost

Extreme Gradient Boosting (XGBoost) is an open-source library that provides an efficient and effective implementation of the gradient boosting algorithm. Shortly after its development and initial release, XGBoost became the go-to method and often the key component in winning solutions for classification and regression problems in machine learning competitions. Gradient boosting refers to a class of ensemble machine learning algorithms that can be used for classification or regression predictive modeling problems. Ensembles are constructed from decision tree models. Trees are added one at a time to the ensemble and fit to correct the prediction errors made by prior models. This is a type of ensemble machine learning model referred to as boosting. Models are fit using any arbitrary differentiable loss function and gradient descent optimization algorithm. This gives the technique its name, "gradient boosting," as the loss gradient is minimized as the model is fit, much like a neural network [23].

Stage 3: Prediction Accuracy

A confusion matrix is a summary of prediction results on a classification problem that shown in Fig 4. The number of correct and incorrect predictions are summarized with count values and broken down by each class. This is the key to the confusion matrix. Accuracy is obtained by dividing the sum of True Positives (TP) and True Negatives (TN) by the total number of samples (N).

$$Acc = \frac{(TP + TN)}{N} \tag{1}$$

Stage 4: Portfolio Profitabilty

Two strategies have been devised for portfolio simulation on test data sets. Both strategies are based on closing prices and compared the earnings of the two portfolios at the end of the period.

Buy&Hold Strategy (B&H): It is based on the principle of opening position at the beginning of the test period and closing the position at the end.

Proposed Approach (PA): For this strategy, the confusion matrix obtained in the previous step is used. If the predicted trend is "Bullish" then "Buy" transaction; If

Table 1. Datasets that used for this study

Index code	Index	Start date	Finish date	Data count
dow	Dow Jones (ABD)	04.01.2007	11.12.2019	3258
nifty	Nifty 50 (India)	04.01.2000	11.12.2019	4959
sp	S&P 500 (ABD)	04.01.2006	11.12.2019	3509
shanqhai	Shanghai (China)	04.01.2000	11.12.2019	4835
dax	Dax (Germany)	03.01.2001	11.12.2019	4818
cac	Cac 40 (France)	03.01.2001	23.07.2019	5001
tsx	S&P TSX (Toronto)	04.01.2000	27.11.2019	5001
russel	Russel 2000 (London)	03.01.2001	27.12.2019	4777
ibex	Ibex 35 (Madrid)	03.01.2001	05.09.2019	5001
kospi	Kospi (Korea)	04.01.2000	27.12.2019	4937
bist30	Bist 30 (Turkey)	04.01.2000	10.12.2019	5001

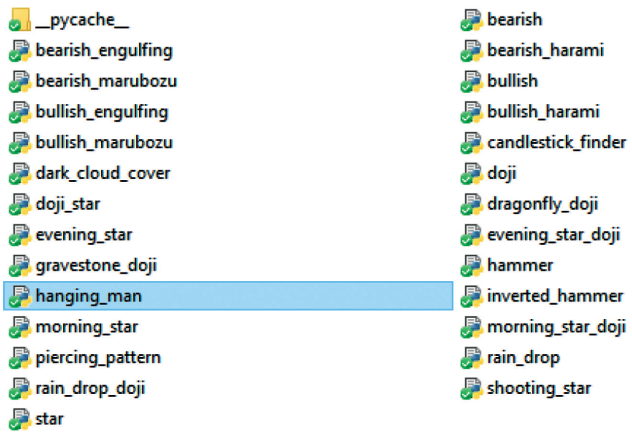


Figure 5. Screenshot of candlestick pattern finder classes.

the predicted trend is "Bearish" then "Sell" transaction is realized.

Datasets

The datasets and summary information used in the study are as follows. The datasets were obtained from investing [24].

EXPERIMENTAL RESULTS

The experimental results are given in the order discussed in the proposed approach in this section.

Stage 1

In this section, more than 30 classes have been programmed for object-based and factory design pattern-based coding to find 24 candlestick patterns. The module screenshot of the coded objects is given in Fig 5. A total of 24 candlestick patterns were defined for the study. The datasets used in the study and the number and percentage of patterns detected in these data sets are given in Table 2. It is known that there are 103 candlestick patterns. The study was carried out for 24 of them. In order to avoid missing data in the input data, the following approach is used for unidentified patterns: two more patterns are used that If the closing price is higher than the opening price as "Bullish" otherwise "Bearish".

Table 2. The number of data set and detectable patterns and their percentage

Index code	Data count	Patternt count	Percentage (%)
dow	3258	1360	41.7
nifty	4959	1760	35.4
shanqhai	4835	1897	39.2
dax	4818	1912	39.6
cac	5001	1975	39.5
tsx	5001	1996	39.9
russel	4777	2201	46.1
ibex	5001	2032	40.6
kospi	4937	1844	37.3
bist30	5001	2345	46.9
Mean			**40.7**

Stage 2

Xgboost, one of the community learning algorithms, is used in this study. The extent to which training and test data are separated is given in the following section. The hyperparameters used for Xgboost are given in Table 3 below.

Stage 3

In Table 4, trend direction prediction accuracy for each data set is given by comparing it with the actual value. The trend direction of the indices used in the study could be predicted with an accuracy of 53.8%. Recognized pattern rate is 40.7% as given in the previous section. If the combined ratio is used, it is possible that the trend direction accuracy will be 70% or above by integrating more patterns into the system in future studies and increasing the detected pattern rate to 90%.

Table 3. Hyperparameters for Xgboost algorithm

Hyprerparameter	Value
Depth	5
Eta	0.1
Gamma	0.01
eval metric	'rmse'
Estimator	50

Table 4. Trend forecasting accuracy

Index code	Accuracy (%)
dow	55
nifty	53
sp	54
shanqhai	54
dax	56
cac	54
tsx	53
russel	54
ibex	52
kospi	53
bist30	54
Mean	**53,8**

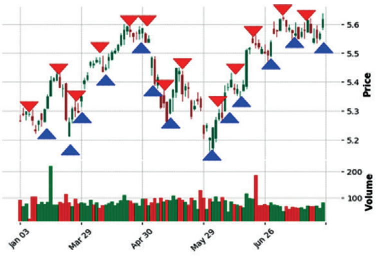
Stage 4

In this section, the two portfolio strategies discussed in the study are given comparatively for the data sets used. The first strategy is the B&H strategy based on buying the initial capital index at the closing price at the beginning of the test period and holding it until the end of the periyod. At the end of the period, it is assumed that it is sold at its current closing value. The starting capital is chosen as 100 in local currency for all data sets (initial capital=100). This approach is suitable for investor profiles that do not have technical analysis or investment strategy information. The biggest advantage is that the commission rate is minimum since it is only traded once. The second strategy is the approach presented in the study. In this strategy, when the "Buy" signal is generated by the system, it is based on the principle of making a purchase transaction with the capital at hand at the current closing price, staying in position until the "Sell" signal and selling the relevant instrument at the current closing price when the "Sell" signal is received. As can be seen from Table 4, on average, the approach presented in the study is more profitable.

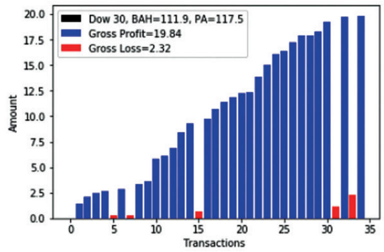
The biggest disadvantage is that more commissions are paid by buying / selling more than the B&H strategy. However, the recommended approach is still more profitable, even considering the commission payments (*Brokerage firms commission rates are fixed at 000.2% per transactions, and are calculated by taking into account the average number of 58 transactions for each data set*). In the table, profitable strategies for the 11 world indices analyzed are highlighted in bold. In the table, profitable strategies for the 11 world indices analyzed are highlighted in bold. The

Table 5. Portfolio strategies

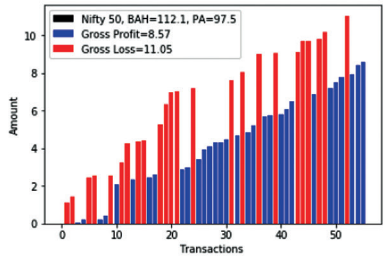
Index code	Portfolio profit (B&H approach)	Portfolio profit (Proposed approach)	Winning transactions	Losing transactions
dow	111.9	**117.5**	29	5
nifty	**112.1**	97.5	32	55
sp	121.2	**123.4**	40	13
shanqhai	93.9	**98.1**	35	43
dax	113.3	**121.8**	42	12
cac	125.9	**151.7**	84	63
tsx	**113.7**	101.3	12	12
russel	**119.6**	102.6	9	19
ibex	102.2	**121.5**	64	33
kospi	90.1	**106.9**	13	3
bist30	99.3	**112.4**	24	11
Mean profit	109.38	**114.06**	34	24
Mean profit (%)	9.38	**14.06**	Mean transactions = 58	



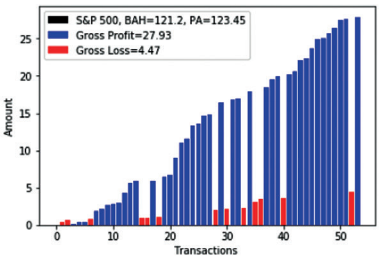
a) Obtaining Buy / Sell signals with the proposed approach



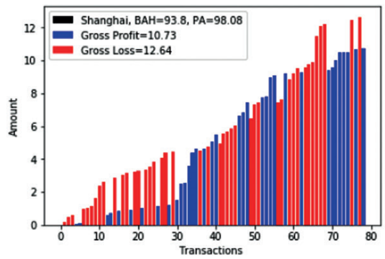
b) Dow 30: Transactions, Gross profit and Gross Loss



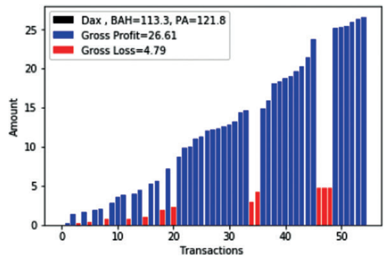
c) Nifty 50: Transactions, Gross profit and Gross Loss



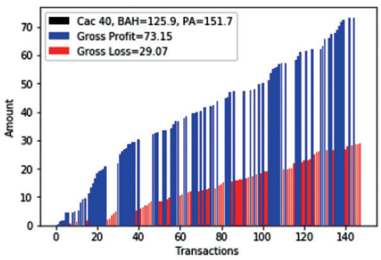
d) S&P 500: Transactions, Gross profit and Gross Loss



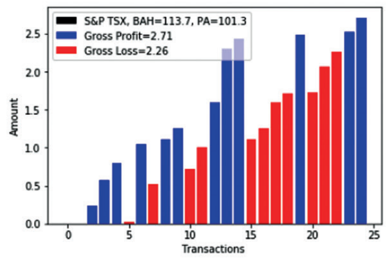
e) Shanghai: Transactions, Gross profit and Gross Loss



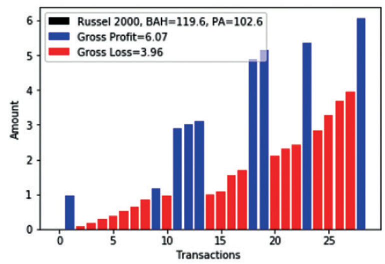
f) Dax: Transactions, Gross profit and Gross Loss



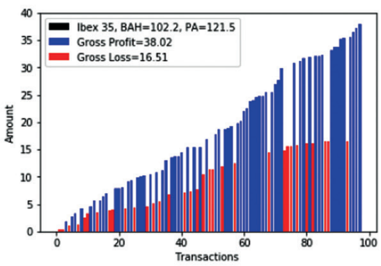
g) Cac 40: Transactions, Gross profit and Gross Loss



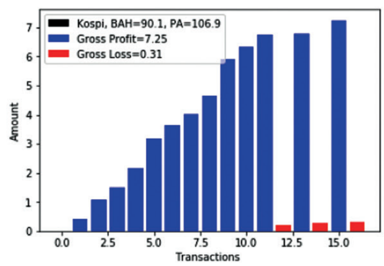
h) S&P TSX: Transactions, Gross profit and Gross Loss



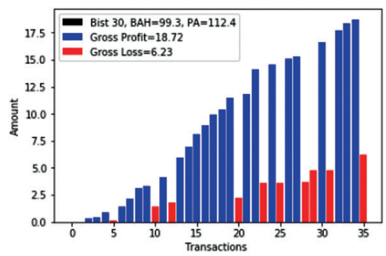
k) Russel 2000: Transactions, Gross profit and Gross Loss



l) Ibex 35: Transactions, Gross profit and Gross Loss



m) Kospi: Transactions, Gross profit and Gross Loss



n) Bist 30: Transactions, Gross profit and Gross Loss

Figure 6. Screenshot of candlestick pattern finder classes.

proposed approach in 8 of these is more profitable, in the other 3, B&H strategy is more profitable. The approach suggested in 3 of them failed to make a profit in the portfolio and closed the position with a loss. As can be seen in the Shanghai index, both strategies closed the positions with a loss. Interpreting the results, it is not claimed that the proposed approach can be used for a single buying / selling strategy. However, it has been observed that the Buy / Sell signals obtained from the candlestick charts, by combining with other technical analysis data, will support the trading and algo robot strategies set out in the literature, and will increase the performance and portfolio profitability in these.

The results is also graphically summarized in Figure 6. In the first image, buy / sell signals (blue arrow = Buy, red arrow = Sell) are shown. In others, Gross Profit (blue bars), Gross Loss (red bars) and sequential transactions are shown as histogram bars for each 11 world indices, respectively.

DISCUSSIONS AND FUTURE WORKS

In this study, index trend accuracy estimation and portfolio profitability strategy were performed by using candlestick chart. It is known that there are 103 candlestick patterns in the literature [16]. 24 patterns were used in this study. In order to make the proposed approach extensible, coding has been made using object-oriented and Factory design patterns. The average candlestick pattern finding in the training data set was 40.7%. The trend direction could be predicted with an average accuracy of 53.8%. In the future works, when the number of candlestick patterns is increased, it is predicted that the trend forecast value will increase proportionally. In the tradign strategy based on the proposed approach, an average return of 14% was obtained for the 11 world indices used in the study. This ratio is better than the B&H strategy, even if only slightly better. In fact, this study is a part of future studies. Two detailed studies planned to be carried out in the future are as follows: For dynamic detection of candlestick patterns, a study using a Generative Adversarial Network (GAN) will be carried out. The aim of the study is to find candlestick patterns based on image processing. An architecture that uses patterns synthetically will be developed to create input for the study. Then the data set will be expanded synthetically using GAN. In this way, a study that can work in real time and detect almost all candlestick patterns based on image processing on the graph will be realized. The second work is the development of a trend prediction system using technical analysis, big data, and deep learning. Due to the large number of types of candlestick patterns, most of the examples in the literature do not use candlestick patterns as input. However, the results of the study showed that satisfactory results can be obtained even when candlestick patterns are used alone. It is predicted that the success of the mentioned systems will increase if they are supported with detected candlestick patterns. For example, in a study conducted by the author for Bist30, a system that generates a Buy/Sell signal based on a moving average and real price intersections based on deep learning worked with an accuracy of 87% with test data [9]. It is predicted that better results can be obtained by integrating these and similar studies in a hybrid manner with the approach proposed in this study.

ACKNOWLEDGEMENTS

The datasets used in this study were provided from investing.com [24].

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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