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RESEARCH ARTICLE

# Comparison of Stock "Trading" Decision Support Systems Based on Object Recognition Algorithms on Candlestick Charts

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**ABSTRACT** The fundamental purpose of every investor making investments in financial fields, is to make profit by buying an investment instrument at a low price and selling the same at a higher price. In this study, within the framework of the aforementioned standpoint, an effective "Trading" decision support model was designed, which can be used for stock market analyses, parity analyses, index analyses, and for the stock analyses of other stock exchanges, briefly for all investment instruments for which candlestick charts are created. An innovative model design was achieved through a bilateral perspective with both financial and scientific aspects by designing these models that operated on a pattern detection basis. The study incorporated the use of 2D candlestick charts of the BIST stocks. The charts were labeled in two separate data sets. Initially, 10,000 pieces of data were labeled on 550 2D candlestick charts, which were trained with YoloV3 Data Group-1 (DG-1). Subsequently, the data set was increased to 20,000 pieces. Out of this set of 20,000 labeled data prepared, 10,000 labeled data were picked randomly. The newly-created set of 10,000 labeled data was named DG-2, which was trained with the YoloV3, YoloV4, Faster R-CNN, SDD algorithms. An assessment was made regarding the performance results obtained following the trainings implemented for these four chosen algorithms. For the aforementioned assessment, three different scenarios were created, and out of all these scenarios, the YoloV3 DG-2 algorithm, which was trained with an improved data set, was observed to be most successful one. As a result of the comparative test scenarios, the YoloV3 DG-2 model achieved a pattern recognition success of 98%. On the other hand, it was also observed to have achieved a prediction success of 100%, while bringing in a return by 89.94%, regarding the object class detected. In addition, no additional parameters were used in this observed gain success. Consequently, the YoloV3 DG-2, determined as the final model, could be implemented as a decision support model for all investment instruments for which a candlestick chart can be created.

**INDEX TERMS** Deep learning, CNN, object recognition, object detection, finance, candlestick chart, trend decision.

## I. INTRODUCTION

It is possible find in the literature a number of studies conducted so far on the subject of time series prediction, particularly in financial fields; what's more, quite successful results have been achieved on the matter. Nevertheless, the approach that the majority of the developed mathematical methods, are neural network-based approaches through which future analyses are made, depending either on the assessment of time series data as if they were a regression problem, or on price prediction, or on a specific past behavior of the investment instrument [2], [3], [4], [5], [6]. On the other hand, particularly prediction and classification models based on deep learning algorithms, are observed to have performed

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really well in the fields of image, video, and audio processing, while their use in financial fields has tended to increase. Within this context, studies, such as the development of autonomous and smart expert systems that are capable of making decisions in particular, have become quite important in the market for investors who aim to win. As a matter of fact, recently, nearly all investment transactions for buying and selling purposes have been executed by robots, which are called "smart systems".

There are various methods, which are employed to make predictions about future values and formulate policies by using the past data from the time series analyses. Some of these methods consist of multilayer artificial neural networks [7], [8], recurrent artificial neural networks, Long Short-Term Memory Networks [9], [10], restricted Boltzmann machine and deep-thinking networks [11], which are the mainly used deep learning algorithms. Each method has different advantages and disadvantages. In this context;

In their studies, Singh and Srivastava (2017) used deep learning methods for stock prediction and evaluated the performance of the method in Google stock price multimedia data (chart) obtained from NASDAQ [12]. In their study, Bao et al. (2017) presented a new deep learning framework in which wavelet transforms (WT), stacked autoencoders (SAE) and long short-term memory (LSTM) were combined for stock price prediction [13]. For the stock daily return prediction problem, Hakan et al. has expanded the feature set to include indicators not only for the stock itself, but also for a number of other stocks and currencies. Later, they used different feature selection and classification methods for estimation [14]. Huynh et al. developed a new prediction model based on both online financial news and past stock price data to predict stock movements in advance [7]. Chung and Shin aimed at developing a new stock market prediction model through a mixed approach including a long short-term memory network (LSTM) and genetic algorithm (GA) by using the available financial data [10]. Li et al. used the Attention-Based Multi-Input LSTM method for stock price prediction [15]. In their study titled "Deep Active Learning for Object Detection", Roy et al. (2018) proposed the active learning approaches which produced cutting-edge technological results in the object detection using only a part of the training images [16]. In their respective price predictions with Arima, LSTM and Hybrid models, Temür et al. estimated the housing sales in Turkey for the future [17]. In their study, Sezer and Ozbayoglu (2019) suggested a non-traditional approach for stock prediction using the convolutional neural network to determine the "Buy", "Sell" and "Hold" scenarios directly over 2-D stock bar chart views without presenting any additional time series related to the basic stock [18].

The model approach recommended in this study, is a decision support model that is generally based on an object recognition and classification algorithm. As it is beyond numerical processes, it is quite different than the deep learning-based prediction models being exemplified, as is seen in the literature review. The objective of the model is to ensure that the points at which trading transactions would be made for investment instruments through 2D candlestick charts, are determined as objects. Labels were created in a systematic manner for the model created based on the object recognition and classification algorithms, and a series of trainings was implemented with those labels. Consequently, it was ensured that the model recognized the points at which trading transactions would be made, and that it could make a decision by learning this transaction only through the images for once, like an autonomous vehicle could recognize road lines, traffic signs, other different vehicles, and pedestrians.

In our study, an innovative approach has been adopted: The points at which trading transactions for investment instruments will be made are identified as objects on 2D candlestick charts. This approach allows for operations based on visual data, unlike existing models. This innovative approach has been continued in the processes of data labeling and training. Our study has been implemented using popular recent algorithms such as YOLO, Faster R-CNN, and SDD, and their performances have been evaluated.

The reason why candlestick charts were preferred as the chart type, which is another issue, is caused by the fact that this type of charts have more object-related meanings, compared to other types of charts. Even though there is a great number of types of charts that could represent the time series in today's financial markets, it is possible to say that the candlestick, bar chart, and line chart are the most commonly used types. In this context, it was thought that more fruitful results would be obtained in the computer vision, in that the candlestick chart type, unlike other types of charts, has a larger body area, in addition to its capability to represent upwards/downwards movements with different colors.

The 2D candlestick images of the price information of the current stocks listed on BIST were used for the training and test procedures of the recommended models. Initially, images were recorded that would represent 330-370 pieces of daily candlesticks on 550 pieces of 2D candlestick chart views. Subsequently, in order to expand the study, 709 pieces of 2D candlestick chart images were added to the data set, which increased the data set amount to 1,259.

Primarily, one needs as many object-related data as possible, considering the machine-learning aspects. The execution of significant labeling procedures on the data obtained, is another point of importance. As a matter of fact, this is a procedure in which a human brain defines objects to transform them into a language that a machine could learn. When considered in respect of traditional models, although it does not require any professionalism to pick a human face or human body, a vehicle class, or an animal species on any image, the procedure of labeling tens of thousands of objects on an image is a task that takes quite a long time and requires lots of manual work. Hence, the data selection and labeling procedures constitute the most toilsome parts of modeling the object recognition algorithms. Furthermore, when taken into consideration regarding the model study crafted, the labels of the classes within the study have quite an extraordinary

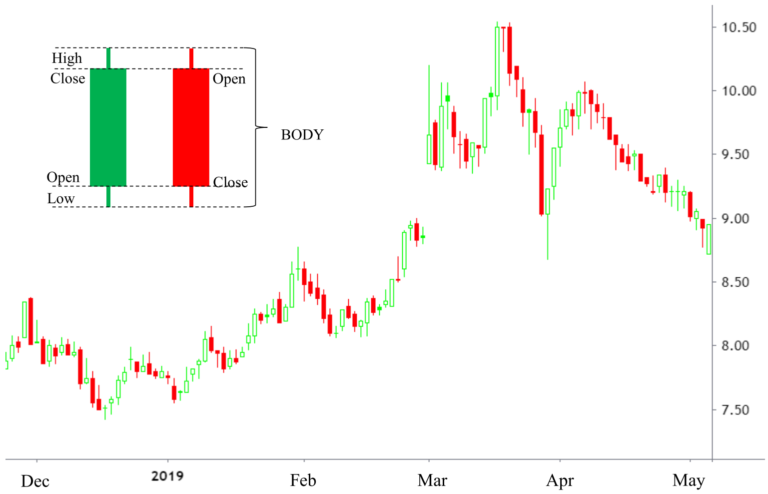



**FIGURE 1.** Candlestick chart [13].

structure, compared to conventional object labels. Therefore, a financial perspective is categorically needed at the phase of labeling. Every single labeling process within the scope of the study, was conducted based on the ''Dow Theory''. In this context, the labeling phase constitutes one of the most fundamental and most important phases of the study. As a result of this study, a major labeled data set was obtained, which would motivate further studies.

The labeling processes initially included the labeling of 10,000 pieces of data on 550 2D candlestick charts, and it was named ''Data Group-1 (DG-1)''. DG-1 was trained with YoloV3, [19] then the labeled data set was increased to 20,000 pieces. Out of this set of 20,000 labeled data prepared, 10,000 labeled data were picked randomly. The newly-created set of 10,000 labeled data was named DG-2, which was trained with the YoloV3, YoloV4, Faster R-CNN, SDD algorithms. Following the training of the algorithms, new weight values were created for the objects, and the models were separately tested using these weight values. As a result of these tests, the YoloV3 DG-2 model was determined as the most successful and most profitable decision support model.

Within this scope, the second part of the study saw the identification of the types of charts, and object recognition algorithms used. The third part included the study itself, in which data improvement and training studies were explained. The results within the fourth part, however, included the performance assessments of the algorithms. The final part covered a general assessment regarding the study.

## II. BACKGROUND

### A. CANDLESTICK CHART

''Homma'', a well-known rice merchant from the city of Sakata/Japan, was the person who paved the way for the development of candlestick charts, which then became a significant technical analysis. The studies, which were conducted as it started to be used by increasingly more people in years, enabled the advancement of chart technologies, leading them to take their current shape.

The presence of an initial value is a prerequisite for the creation of a candlestick chart. A candlestick chart is created using the opening price, along with the closing price, and the highest and lowest daily values. The most distinct difference between candlestick charts and bar charts, is that the candlestick charts have a body. As is seen in Figure 1, the thick part of the candlestick shows the distance between the opening and closing values of the session. This distance always has maximum and minimum limits in markets, such as BIST.

The candlestick with the green body indicates that the closing price is higher than the opening price, which means that the demand is high, while the candlestick with the red body points out the presence of a session in which the supply is high, meaning that the prices opened at high levels and closed at low levels [13]. The lines at both ends of the bodies represent shadows.

### B. OBJECT RECOGNITION ALGORITHMS

Object detection, a long-lasting fundamental and challenging problem in the field of computer vision, has been actively researched for decades. The purpose of object detection is to detect whether a specific image has any object samples from predetermined categories (such as humans, vehicles, bicycles, dogs, cats), and to report the spatial location and scope of an object sample, if any (with a specific bounding box [20], [21]). Being the building block of image perception and computer vision, object detection constitutes a basis for the solution of more complicated or high-level image tasks, such as segmentation, scene perception, object monitoring, image subtitling, event detection, and activity recognition. Object detection has a vast field of application in a number of domains, such as artificial intelligence and information technologies, robot imaging, consumer electronics, security, autonomous driving, human-computer interaction, content-based image acquisition, smart video surveillance, and augmented reality. Deep learning methods have become the focus of the studies conducted in the majority of the fields of application regarding computer vision. A great majority of the deep learning-based approaches have appeared mostly in the generic object detection [22], [23], [24], [25], [26], [27] studies. In this context, a study titled "Towards Real-Time Object Detection with Region Proposal Networks", followed by the first YOLO study that took place a couple of months later, [27]and subsequently the studies on object detectors [28] SSD [29], YOLOv3 [30] and YOLOv4 [31] were conducted gradually.

### C. METRIC PERFORMANCE CRITERIA OF OBJECT RECOGNITION ALGORITHMS

Object recognition criteria are used in order to assess how well a model performs in the object recognition duty. Furthermore, they enable that multiple recognition systems are objectively compared, or that they are compared among themselves. In such studies, both classification performance, and localization of bounding boxes on images are assessed while measuring metric values. For this assessment process, it is required to determine how many objects are recognized accurately and how many inaccurately on a predetermined image. This assessment process is carried out using the IoU (Intersection over Union) metric. The IoU score, the formula representation of which is given in Figure 2, varies between 0 and 1; the closer any two boxes get, the higher the IoU score becomes. While a metric value with an IoU threshold of 0.5 is used for the PASCAL VOC data set, different metric values are used at the 0.5 step for the IoU thresholds of MS COCO (0.5, 0.55, ……, 0.8, 0.85, 0.9, 0.95) [32].

In order to convert each object detection into classifications, a threshold value with a real value of *0.5* is determined as a general acceptance factor. If the object determined based on this threshold value has an IoU that is $\geq 0.5$, the object recognition *is classified as True Positive (TP),* whereas if *IoU<0.5,* then this is a false recognition, which *is classified as False Positive (FP).* When the model fails to recognize the object although the image has labels, this situation *is classified as False Negative (FN)*. Figure 3 gives the images related to the expressions.

Following these calculations, it is required to calculate the *Precision* and *Recall*. *While Precision* measures how accurate the predictions are, *Recall* measures to what degree the model has been successful in predicting the items it should predict. The equations of these calculation methods are given in (1) and (2) [33].

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

## III. DESIGN OF THE STUDY

The recommended model is a "*Trading*" support decision model, which would support the investors in regards to the trading decisions made by the technical and fundamental analysis techniques on candlestick charts of alternative market instruments. Figure 4 gives the flowchart of its design.

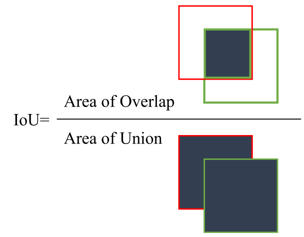



**FIGURE 2. An example of IoU calculation [32].**

### A. DATA PREPROCESSING

As specified in the flowchart in Figure 2, a data set is needed for the training and test processes of the recommended models. The 2D candlestick images of the price information of the current stocks listed on BIST were used for this data set that was needed. In order to create the candlestick charts, the information on the stock prices was obtained from BIST, and from Yahoo.Finance, *which is an open source.* The data obtained were in the *.csv* format, and they consisted of the data on the daily opening, lowest, highest, and closing prices. These data were transformed into a 2D candlestick chart. These visual 2D candlestick charts were saved in the image format, under the name of *stockname_month_year* with a size of $1800 \times 650$, to create the data set. Following the addition of 709 pieces of 2D candlestick chart images to the 550 pieces of 2D candlestick chart images [1], which were created for the first study to have been conducted, the data set reached a total of 1,259 pieces of chart images.

### B. DATA LABELING

Labeling process is the initial step of computer vision studies. This study employed the use of the "LabelIMG" image labeling tool that provided the opportunity to function in the bounding boxes feature, through which the processes were conducted on 2D images [34]. This software uses the Phyton PyQt for its graphic interface. While the Pascal VOC format is employed to save the additional remarks, created in the labeling process, in the XML file format, the YOLO format is employed to save them in the TXT file format. Separate remark files were created for each image while executing the labeling process. The labeling process was carried out on 709 pieces of additional images, along with the 550 pieces of images labeled in the first study. A total of 20,000 pieces of labeled data were obtained.

The labeling processes were entirely carried out in a manual manner, and within the scope of the "Dow Theory [35]". Through artificial trends drawn on the charts, attempts were made to facilitate the labeling processes and make them significant in compliance with the theory. Figure 5 gives an example regarding the trend study that was conducted on a stock image for this process.

As is seen in the example, attempts were made to create the labels by determining the bottoms and peaks of the

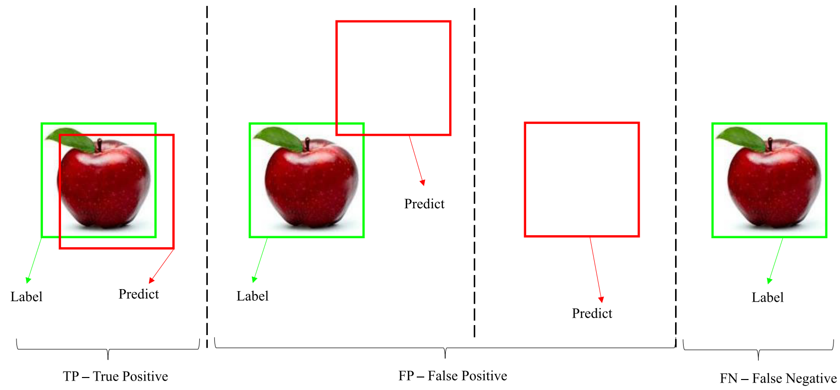



**FIGURE 3.** Label-prediction relation (IoU).

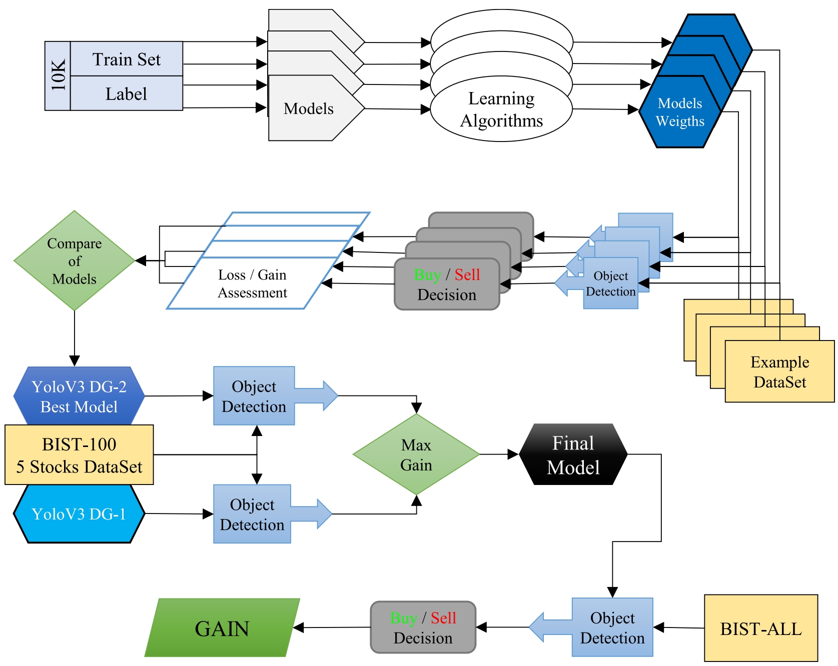



**FIGURE 4.** Flowchart of the study.

trends as much as possible. According to the Dow Theory, all investment instruments have temporal data charts, and not a single chart can have upwards or downwards movements on a continuous basis (except for Speculative and Manipulative behaviors). Hence, all technical analysis methods and algorithms, which are well-known in the financial circles and which have been created for prediction-oriented studies, try to determine such bottoms and peaks of trends. As is seen in the figure, the clustering candlestick images, which formed at the bottom and peak, behave quite differently than one another even on a single image. These differences are of importance in terms of the strength of the study. Thus, a number of different label groups were obtained.

### C. DATA AUGMENTATIONS

This study constitutes the second step of the two-phase study structure. Obtained from 550 pieces of images that were initially created, 10,000 pieces of labeled data were grouped as 20% test data, and 80% training data. Subsequently, this datum was trained as YoloV3 DG-1, and performance assessments were made [1]. Then, following the addition of 709 pieces of data sets within the scope of this study, a total of 1,259 data sets were created, on which 20,000 pieces of data were labeled. Out of this set of 20,000 pieces of labeled data that was created, 10,000 labeled data were picked randomly. In a similar manner to the previous groups, the newly-created set of 10,000 pieces of labeled data were grouped as 20% test data, and 80% training data. Figure 6 gives a visual representation of this grouping process.

### D. DETERMINATION OF ALGORITHMS FOR THE MODEL

The YoloV3, YoloV4, Faster RCNN, and SSD object recognition algorithms with high popularity in the literature, were used for the necessary training processes. Trainings were carried out for these four chosen algorithms, and the performance results of each algorithm were assessed.

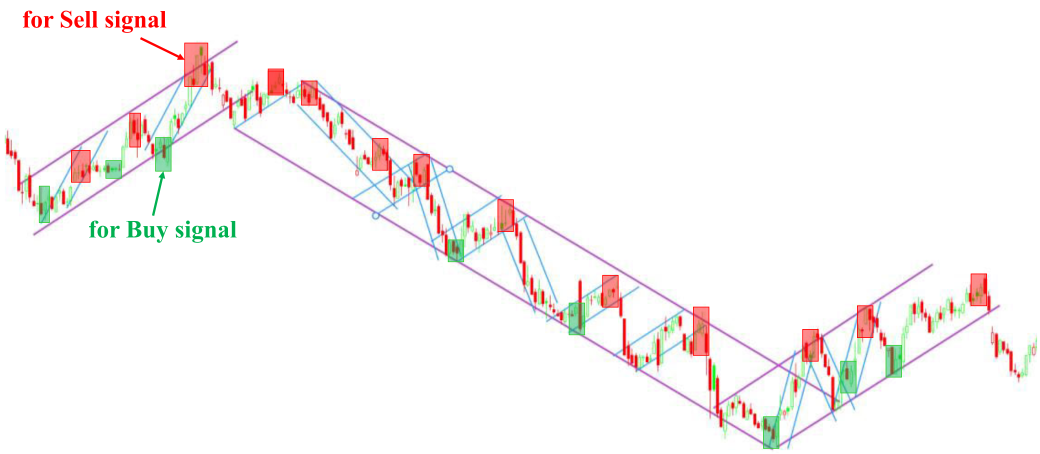



**FIGURE 5.** Artificial trend study.

## IV. RESULTS

Following the training phase of the models, a series of tests was implemented in order to assess the object recognition performances of the weight values obtained. Initially, training outputs were analyzed in terms of Precision and Recall values. Initially, in regards to these processes, the algorithms having new weight values obtained as a result of the training, as well as the test data set, were put into the system, which was followed by the process of saving the output images, whose object recognition was realized. Subsequently, following the detections made on the output images, a positioning study was conducted using the *LabelIMG* software once again. Thus, both an object label and a prediction decision visual were created on the image. Figure 7 gives an exemplary representation of the image created.

The calculation does not include the *True Negative* (*TN*) values, which are emphasized in the general literature. As exemplified in the figure, a number of TN predictions were created, along with TP predictions. As mentioned in the background, the TP predictions stand for the accurate prediction of an unlabeled situation. Thus, they can also be expressed as "missed positives". Model training software do not usually have the attributes to re-predict the valuations on the image. Therefore, they assess the TN values directly as FP. This situation does not substantially affect the results in major data sets consisting of 80-200 classes (COCO-PASCAL-VOC, etc.). Nevertheless, the situation is considerably changed by the fact that there are only two classes in this study (*Buy-Sell*), as well as the classes included in the study being extraordinary label classes. In this context, the test prediction outputs were analyzed one by one on the images. Table 1 provides a representation of the results obtained.

As is seen in the table, the results are very good for the YOLO versions. Nonetheless, this does not necessarily mean that it is successful, even though the prediction accuracy rates were high or even better than the overall models in the literature for the Faster R-CNN and SSD models within the scope of this study. Considering that the study aims to support investment decisions, it is not possible to say that the models are successful, due to the fact that even an error by 1% could lead to unsuccessful investments.

In another test assessment, the training successes of the models were compared. Table 2 provides the test-detection results obtained from the comparisons.

This data set assessment process is a comparison process that is conducted regarding the prediction accuracy by testing the test data set with the models that have new weight values. As per the detection results, the YoloV3 DG-2 object detection algorithm made the highest number of and most successful detections. Figure 8 gives the minimized sample representations of the outputs produced by the algorithms on a common candlestick chart at the testing phase.

The prediction percentage in the assessment results given in Table 2, specifies the number of predictions produced by the model, compared to the number of labels placed. The test data set consists of 110 pieces of chart images. There are 1,948 labels on these chart images. On the other hand, the YoloV3 DG-2 algorithm detected 1,912 pieces of objects on the charts. At this step, the detection success was 98%. The accuracy rates of the decisions detected, are a part of another comparison. Considering the results produced, the YoloV3 DG-2 did not produce any false decisions at this point, yielding an accuracy rate of 100%. Even though the number of decisions predicted was low, the YoloV4 DG-2 version achieved a prediction success by 100%. On the other hand, while the Faster R-CNN DG-2 algorithm achieved a success rate of 93% with 1,813 pieces of objects detected, the SSD DG-2 algorithm achieved a detection rate of 63%. Nonetheless, at this point, the criterion that we seek in regards to the success of the algorithms, is not the success shown in the number of detections, but the accuracy rate regarding object detected. This is caused by the fact that a false decision produced by the model, could lead to an unsuccessful investment.

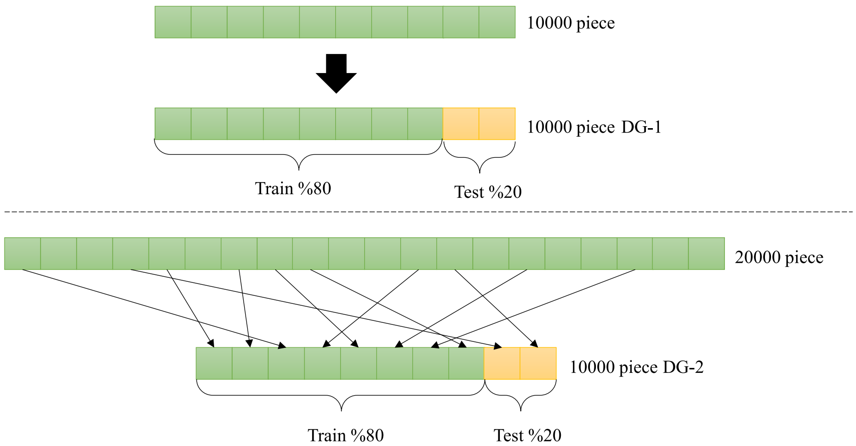



**FIGURE 6.** Grouping of the sets of training and test data.

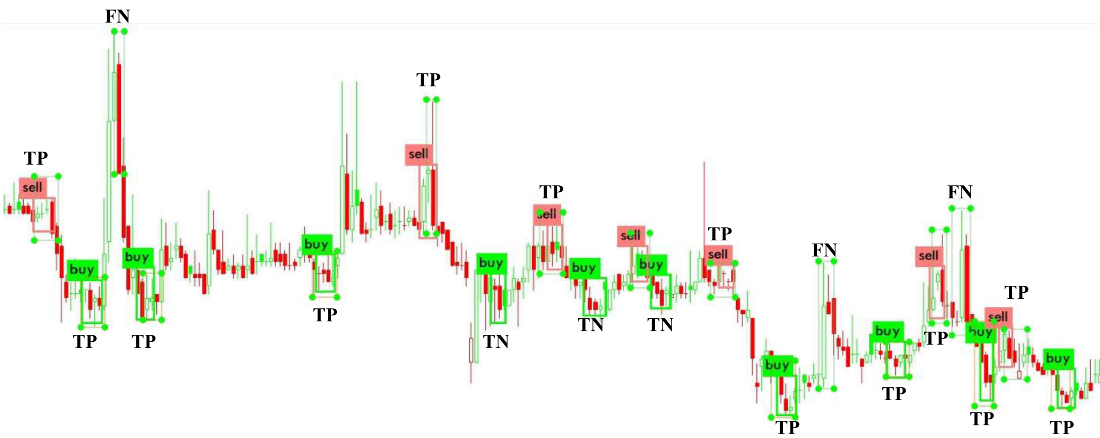



**FIGURE 7.** Assessment of the YoloV3 DG-2 detection results.

At another phase of assessment of the study, 5 different stocks listed on BIST-100 were randomly selected. The chart images of the candlestick image of the aforementioned stocks over the course of the past six months, were recorded. At this phase, the test processes were implemented for the stock chart images selected between the months of January-July, using four different models (YoloV3 DG-2, YoloV4 DG-2, SSD DG-2, Faster R-CNN DG-2), as well as YoloV3 DG-1. For testing purposes, a detection-decision output was created on the chart images of the closing time, and the *"Trading"* transactions were carried out based on the output results. The *"Trading"* decision labels produced by the models, were distributed on the image, as exemplified in Figure 7. It is possible to see these decision labels at many points within the tendencies on the image. Nevertheless, for real-time investment transactions, what matters is the detection of the last day decisions, which ensures that decisions are made actively for the next day, rather than the detection of the decisions produced at any point on the image. Thus, the last day/days, along with the *"Trading"* decisions forming on the candlestick/candlesticks, must be taken into account to make investment decisions. In this context, Figure 9 gives the chart images of the decisions made for *"Trading"* purposes, with the detection points marked with arrow symbols.

Initially, a specific amount of cash was determined for each stock, and a profit-loss analysis was carried out based on this cash amount. Table 3 gives elaborate information regarding the profit-loss data obtained as a result of the six-month testing processes.

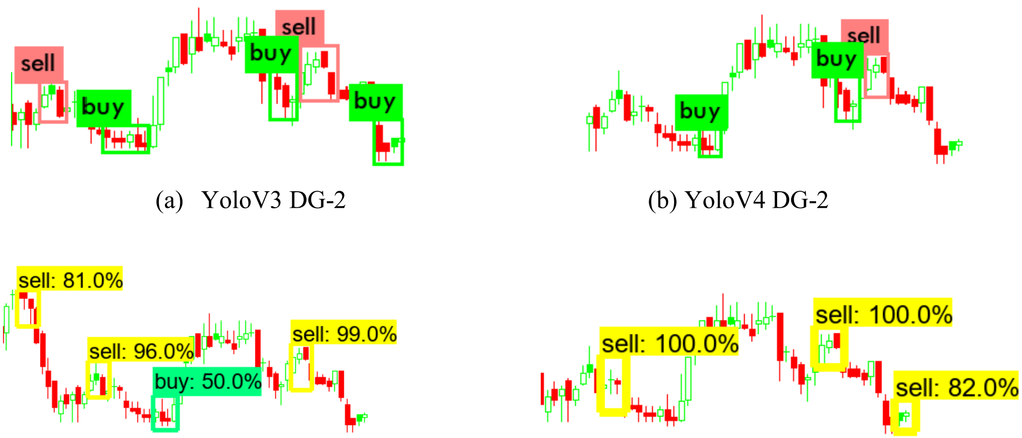
As is seen in the Table, a capital amount of \$100 was allocated for each stock, and the amounts of loss-profit obtained by the models at the end of 6 months were determined. It must be mentioned that YoloV3 DG-2 was the model that yielded the highest amount of profit at the test phase. The YoloV3 DG-1 model, named "initial version" in the chart, was the model with the lowest amount of profit. As it can be understood from this point, it is clearly visible that the model success improved, compared to the initial study, by implementing a training with different labels taken from a large pool of labels. Furthermore, another significant issue to mentioned is the fact that all models yielded profits. Consequently, it is possible to say that all models tested at this phase, yielded profits.

**TABLE 1. Model assessment of test data set.**

| MODEL | Data Size | TP | TN | FP | FN | Prediction | Precision | Recall | AP |
|---|---|---|---|---|---|---|---|---|---|
| YoloV3 | 1,948 | 1,323 | 589 | 0 | 625 | 1,912 | 1.00 | 0.69 | 1.00 |
| YoloV4 | | 1,100 | 305 | 0 | 848 | 1,405 | 1.00 | 0.57 | 1.00 |
| Faster R-CNN | | 1,325 | 488 | 234 | 623 | 1,813 | 0.84 | 0.61 | 0.96 |
| SSD | | 792 | 1.199 | 224 | 1,156 | 1,324 | 0.78 | 0.51 | 0.89 |

**TABLE 2. Prediction values of test data set.**

| MODEL | Size of Test Data Set | Prediction Percentage | Prediction Accuracy Rate |
|---|---|---|---|
| YoloV3 DG-2 | 1,948 | 98% | 100% |
| YoloV4 DG-2 | | 72% | 100% |
| Faster R-CNN DG-2 | | 93% | 96% |
| SSD DG-2 | | 68% | 89% |




(a) YoloV3 DG-2

(b) YoloV4 DG-2

(c) Faster R-CNN DG-2

(d) SSD DG-2

**FIGURE 8. Sample representation of test outputs.**

Ultimately, the model testing processes were carried out using the basket model, which is known in the literature as one of the most lucrative methods of the investment system. These testing processes were carried out between the YoloV3 DG-1, which took place in the first study, [1] and the YoloV3 DG-2 that yielded the most successful results in the tests so far. The concept of basket is known as a concept that minimizes the loss through the possession of multiple stocks in investment transactions. In other words, it stands for having multiple stocks in one's portfolio. Transactions were carried out to buy and sell based on daily *"Trading"* decision signals between August 31, 2018 - February 28, 2019, for YoloV3 DG-1. As a result of these transactions made to buy and sell, the success of the model was assessed based on the level it took the specified capital to. In this study, the testing processes were carried out on the same dates as the YoloV3 DG-2, which was the most successful model, based on the previous assessments. The initial assessment regarding the testing processes carried out based on the basket logic, as well as the comparative summary of the assessment results within the scope of this study, are given in Table 4.

The table serves as a summary in general. It provides information about the status of total profit-loss, and about the processes of this formation. The number of baskets specified in the table gives the number of groups of stocks created within the monthly testing process. The transactions were carried out based on the assumption that the initial capital was $10,000. Subsequent to these transactions that were carried out with an initial capital of $10,000, it can be seen that the capital reached $15,925.21 for the YoloV3 DG-1 tests, and $18,984.42 for the YoloV3 DG-2 tests.[1] When considered in terms of success, it is possible to say that a model was designed, which was capable of yielding quite successful results compared to many other methods related to issue of financial prediction mentioned in the related studies

[1]This profit calculation did not include any possible commission rates (0.02%) that would emerge in the case of "*Trading*".

**TABLE 3.** Assessment of models regarding the select BIST-100 stocks.

| Stock | Capital $ | MODEL | | | | |
|---|---|---|---|---|---|---|
| | | 10,000 data sets 10,000 labels (DG-1) | 20,000 data sets 10,000 labels (DG-2) | | | |
| | | **YoloV3 DG-1** | **YoloV3 DG-2** | **YoloV4 DG-2** | **Faster-RCNN DG-2** | **SSD DG-2** |
| Alark | 100 | 166.14 | 201.22 | 100.00 | 120.25 | 133.61 |
| Arclk | 100 | 127.30 | 118.82 | 154.12 | 128.74 | 96.91 |
| Ecilc | 100 | 96.94 | 111.33 | 113.20 | 103.94 | 110.19 |
| Gubrf | 100 | 92.13 | 114.34 | 75.02 | 101.21 | 101.75 |
| Parsn | 100 | 100.33 | 135.58 | 185.74 | 165.54 | 167.99 |
| **Total** | **500** | **582.84** | **681.29** | **628.08** | **619.68** | **610.44** |
| **Loss/Profit $** | | **82.84** | **181.29** | **128.08** | **119.68** | **110.44** |

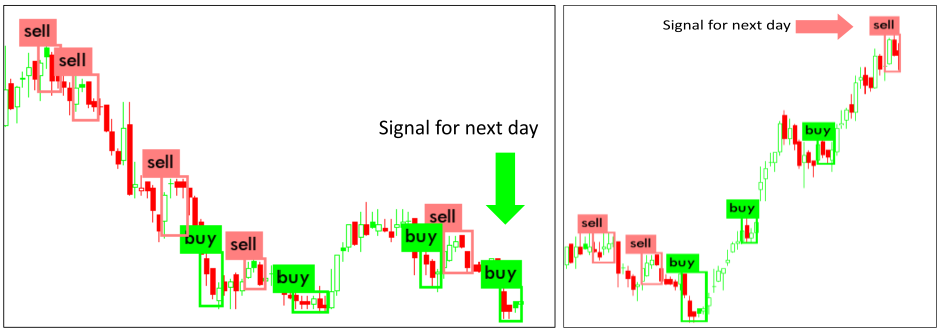



**FIGURE 9.** Examples of decisions to "Buy" and "Sell".

section. Moreover, when assessed in general, out of 8 basket groups, the models finalized a total of 6 periods with profits, and 2 periods with losses. These losses are of quite low percentages.

In order to measure the loss-profit data throughout these testing processes, the price and date-related information of the stocks for which a "*Buy*" signal was created, and the price and date-related information of the stocks for which a "*Sell*" signal was created, were registered in the table. Figure 10 gives a representation of the basket chart that was created and exemplified following the transactions.

The table in Figure 10 was created with the use of a total of 7 different stocks for DG-1, and 8 different stocks for DG-2. While the signals for *"buying"* were created on same days in a specific manner for virtually all basket groups, the creation of the signals for "*selling*" coincided with different times. This was caused due to the period of waiting until the creation of the final signal for "*Sell*" following the signal for "*Buy*" that were formed as a strategy. In the event that the results of any of the stocks included in our portfolio signalled "*Sell*", the monitoring process was finalized by assessing the results. The *% profit* column in the table stands for the status of profit/loss calculated for each stock. Consequently, following the calculation of the profit percentages of the stocks in Basket 1, this rate was determined to be 10.71% for YoloV3 DG-1, and 4.58% for YoloV3 DG-2. Here, the YoloV3 DG-1 was observed to be more successful for Basket 1. Nevertheless, this situation occurred at the beginning of the table, and it applies to Basket 1 that covered the 28-day period. When the profit chart in Figure 9 is analyzed, it can be clearly seen that the profit success of YoloV3 DG-2 separated from YoloV3 DG-1 in a positive, upward direction. 7 different basket group tests were conducted as well in the six-month period, in a similar manner. The Table gives the data regarding the profit-loss statuses in the baskets. This chart functions as a brief table used to express the real profit statuses of the models within a period of six months. The basket numbers on the chart indicate that there are a total of 8 baskets, numbered as 1, 2, ......, 8 with the new basket that was created following the latest transaction through which a stock was sold. The number of transactions, however, indicates the number of stocks included in the basket using a signal to *"Buy"* within a basket. As is seen in the total amount, 73 pieces of stocks were *"Bought"* in YOLOV3 DG-1, and 78 pieces of stocks in YoloV3 DG-2, and the same numbers of stocks were *"Sold"* for both.

The profit/loss percentage of each period was determined, and this profit/loss percentage was calculated as a return yielded by the previous capital. The calculation included the distribution of the capital in equal numbers to the number of stocks in the basket, and the valuation was performed

**TABLE 4.** Summarized chart of basket transactions.

| Test | YoloV3 DG-1 | | YoloV3 DG-2 |
|---|---|---|---|
| Starting Date | | August 31, 2018 | |
| End Date | | February 28, 2019 | |
| Total Days/Months | | 181 / 6.03 | |
| Number of Baskets | | 8 | |
| Total Transactions (Trading) | 73 | | 78 |
| Total Profit | 52.16% | | 71.23% |
| Initial Capital | | $10,000 | |
| **Final Capital** | **$15,925.21** | | **$18,984.42** |

YoloV3 DG-1

| Order | Stock | Buy Suggestion Date | Buy Suggestion Price | Sell Suggestion Date | Sell Suggestion Price | Result % Loss/Profit |
|---|---|---|---|---|---|---|
| 1 | AKSGY | 31.8.18 | 1.69 | 7.9.18 | 1.75 | 3.55 |
| 2 | AKSUE | 31.8.18 | 6.50 | 25.9.18 | 8.92 | 37.23 |
| 3 | DOGUB | 31.8.18 | 2.43 | 13.9.18 | 3.09 | 27.16 |
| 4 | INDES | 31.8.18 | 5.48 | 11.9.18 | 5.79 | 5.66 |
| 5 | KERVT | 31.8.18 | 1.92 | 10.9.18 | 1.93 | 0.52 |
| 6 | KLMNA | 31.8.18 | 3.26 | 6.9.18 | 3.21 | -1.53 |
| 7 | SEYKM | 31.8.18 | 3.90 | 28.9.18 | 3.99 | 2.31 |
| 8 | | | | | | |
| | Basket Avarage Loss/Profit | | | | | 10.70 |

YoloV3 DG-2

| Stock | Buy Suggestion Date | Buy Suggestion Price | Sell Suggestion Date | Sell Suggestion Price | Result % Loss/Profit |
|---|---|---|---|---|---|
| AKSGY | 31.8.18 | 1.69 | 11.09.2018 | 1.71 | 1.18 |
| AKSUE | 31.8.18 | 6.50 | 26.09.2018 | 8.63 | 32.77 |
| ARSAN | 31.8.18 | 1.90 | 6.09.2018 | 1.86 | -2.11 |
| INDES | 31.8.18 | 5.48 | 12.09.2018 | 5.61 | 2.37 |
| KERVT | 31.8.18 | 1.92 | 11.09.2018 | 1.86 | -3.12 |
| LİNK | 31.8.18 | 8.81 | 7.09.2018 | 9.25 | 4.99 |
| SEYKM | 31.8.18 | 3.90 | 28.09.2018 | 3.99 | 2.31 |
| TURGG | 31.8.18 | 30.80 | 4.09.2018 | 30.26 | -1.75 |
| Basket Avarage Loss/Profit | | | | | 4.58 |

**FIGURE 10.** Sample Basket-1 Table of formation.

**TABLE 5.** Assessment of total basket portfolio of models.

| | Basket No. | Number of Transactions YOLOv3 DG-1 | Number of Transactions YoloV3 DG-2 | Periodical % Profit YOLOv3 DG-1 | Periodical % Profit YoloV3 DG-2 | Capital $10,000 YOLOv3 DG-1 | Capital $10,000 YoloV3 DG-2 | |
|---|---|---|---|---|---|---|---|---|
| | **Basket 1** | 7 | 8 | 10.70 | 4.58 | 11,069.90 | 10,458.04 | |
| | **Basket 2** | 7 | 8 | 4.87 | 15.45 | 11,609.10 | 12,073.41 | |
| | **Basket 3** | 4 | 5 | -8.92 | -0.38 | 10,573.46 | 12,027.69 | |
| | **Basket 4** | 7 | 8 | 30.98 | 35.06 | 13,848.96 | 16,244.78 | |
| | **Basket 5** | 9 | 8 | 0.49 | 13.29 | 13,917.10 | 18,403.94 | |
| | **Basket 6** | 12 | 9 | -0.35 | -2.27 | 13,867.74 | 17,986.37 | |
| | **Basket 7** | 10 | 12 | 10 | 1.13 | 15,254.60 | 18,189.48 | |
| | **Basket 8** | 17 | 20 | 4.40 | 4.37 | **15,925.21** | **18,984.42** | **Capital** |
| **CONCLUSION** | **TOTAL** | 73 | 76 | **Total Profit %** | | 59.25% | 89.86% | |

accordingly. Subsequently, the profit or loss calculated, and the remaining capital were divided by the number of stocks, which were set to be bought in the next basket, and they were allocated equally for each stock. This situation is not specific to this study only, and it is expressed as the common basket logic. As mentioned in the result lines of the table, the success rate of the models is at quite high levels. While YoloV3 DG-1 achieved a profit success of 59% as a result of the "*Trading*" that took place within a period of 180 days, the YoloV3 DG-2 model was observed to have achieved a profit of 89%. Consequently, the YoloV3 DG-2 model structured within the scope of this study, was determined as the final model, as it yielded successful results in all tests. Table 5 gives the model chart representations of the profits acquired as a result of the six-month testing processes.

## V. CONCLUSION

Firstly, our approach involves advanced algorithms capable of observing changes in stock trends through graphical representations to make investment decisions. By accurately identifying turning points in stock trends and providing timely information, our approach can significantly enhance the financial decision-making process for investors. Providing the opportunity to make informed decisions based on reliable forecasts can increase profitability for investors and minimize losses.

Additionally, our approach addresses the issue of investment risk. By considering various risk factors such as market volatility and asset correlations using advanced modeling techniques, our approach can help investors evaluate and manage investment risks more effectively. Preventing further financial losses and time wastage due to erroneous decisions, our approach introduces 'sell' signals, discouraging long-term reliance on a single investment instrument.

In summary, our study not only presents a new approach to support investment decisions but also emphasizes its potential impact on financial decision-making and investment risk management. Leveraging advanced analytics and modeling techniques, our approach provides valuable tools for investors to navigate complex financial markets with greater confidence and success.

Having been designed as an innovative financial decision support model within the scope of this study, this model was trained with four different deep learning-based object detection algorithms. The models created were tested using three different scenario methods. At the first testing phase, the models were subjected to a test set performance assessment within the data set created. This assessment process was carried out in the form of comparison of the number of decision detections produced by the models using the number of labels, as well as the determination of the accuracy of the decision detections. The YoloV3 DG-2 and YoloV4 DG-2 algorithms achieved a rate of success of 100% in these test assessments. Of the stocks listed on BIST-100, five different stocks were selected randomly for the second assessment scenario. Tests were carried out regarding the "Trading"-oriented object detection of the models on the candlestick charts, which were selected within a period of six months. Similarly, the YoloV3 DG-2 model, which was created within the scope of the thesis, yielded the highest amount of profit, achieving the most successful result. Finally, a comparison was made between YoloV3 DG-2, which was the most successful model, and YoloV3 DG-1. As is known, DG-1 consisted of a set of 10,000 pieces of data, and this data set was allocated as the training-test. In DG-2, however, an additional 10,000 labeling processes took place, reaching a total of 20,000 labels. Subsequently, out of the 20,000 pieces of labels, a mixed data set was selected for DG-2, in a way that would be completely different from the initial labels. This final comparison process can actually be expressed as the assessment of the results of the data improvement process. Considering the test results obtained for the six-month period, it is possible to say that YoloV3 DG-2 certainly yielded more profitable results, compared to YoloV3 DG-1, which means that the data improvement affected the profits. Consequently, the modeling process was carried out with four different algorithms for a solution regarding the field of problems determined. Considering the general literature, this modeling has quite a different perspective, and it is quite an innovative approach. Separate tests were carried out with all models, and a final model success was achieved at the end. This final model functions as a model that is applicable for the detection of the *"trading"* decision on 2D candlestick charts of an investment instrument having the closing data of the day.

Training processes will be carried out using the augmented data set within scope of any further studies, and the results will be compared. In addition to the augmentation of the training data set, some improvement studies will be conducted. Subsequently, if deemed necessary, parametric changes will be imposed for the algorithms, and the training results will be assessed.

## ETHICAL APPROVAL

There is no conflict of interest in this study, and ethical approval is not required for this study.

## AUTHORS CONTRIBUTION

Gunay Temür: Preparation of the dataset, determination of algorithms, implementation, and writing of the paper.

Serdar Birogul: Determination of algorithms, analysis of the dataset, examination, and structuring of the paper for analysis.

Utku Kose: The analysis of algorithms and evaluation of the results obtained.

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## REFERENCES

[1] S. Birogul, G. Temür, and U. Kose, "YOLO object recognition algorithm and 'buy-sell decision' model over 2D candlestick charts," *IEEE Access*, vol. 8, pp. 91894–91915, 2020, doi: 10.1109/ACCESS.2020.2994282.

[2] Y. Taigman, M. Yang, M. Ranzato, and L. Wolf, "DeepFace: Closing the gap to human-level performance in face verification," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2014, pp. 1701–1708, doi: 10.1109/CVPR.2014.220.

[3] F. Schroff, D. Kalenichenko, and J. Philbin, "FaceNet: A unified embedding for face recognition and clustering," 2015, *arXiv:1503.03832*.

[4] Y. Sun, X. Wang, and X. Tang, "Deep learning face representation from predicting 10,000 classes," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2014, pp. 1891–1898.

[5] J. Salamon, E. Gómez, D. P. W. Ellis, and G. Richard, "Melody extraction from polyphonic music signals," *IEEE Signal Process. Mag.*, vol. 31, no. 2, pp. 118–134, Mar. 2014.

[6] C.-L. Hsu, D. Wang, J. R. Jang, and K. Hu, "A tandem algorithm for singing pitch extraction and voice separation from music accompaniment," *IEEE Trans. Audio, Speech, Language Process.*, vol. 20, no. 5, pp. 1482–1491, Jul. 2012.

[7] H. D. Huynh, L. M. Dang, and D. Duong, "A new model for stock price movements prediction using deep neural network," in *Proc. 8th Int. Symp. Inf. Commun. Technol.*, Dec. 2017, pp. 57–62, doi: 10.1145/3155133.3155202.

[8] M. Dixon, D. Klabjan, and J. H. Bang, "Classification-based financial markets prediction using deep neural networks," *Algorithmic Finance*, vol. 6, nos. 3–4, pp. 67–77, Dec. 2017.

[9] Z. Hu, Y. Bao, T. Xiong, and R. Chiong, "Hybrid filter–wrapper feature selection for short-term load forecasting," *Eng. Appl. Artif. Intell.*, vol. 40, pp. 17–27, Apr. 2015, doi: 10.1016/j.engappai.2014.12.014.

[10] H. Chung and K.-S. Shin, "Genetic algorithm-optimized long short-term memory network for stock market prediction," *Sustainability*, vol. 10, no. 10, p. 3765, Oct. 2018, doi: 10.3390/su10103765.

[11] C. A. S. Assis, A. C. M. Pereira, E. G. Carrano, R. Ramos, and W. Dias, "Restricted Boltzmann machines for the prediction of trends in financial time series," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, Jul. 2018, pp. 1–8, doi: 10.1109/IJCNN.2018.8489163.

[12] R. Singh and S. Srivastava, "Stock prediction using deep learning," *Multimedia Tools Appl.*, vol. 76, no. 18, pp. 18569–18584, Sep. 2017, doi: 10.1007/s11042-016-4159-7.

[13] W. Bao, J. Yue, and Y. Rao, "A deep learning framework for financial time series using stacked autoencoders and long-short term memory," *PLoS One*, vol. 12, no. 7, 2017, Art. no. e0180944, doi: 10.6084/m9.figshare.5028110.

[14] H. Gündüz, Z. Çataltepe, and Y. Yaslan, "Stock daily return prediction using expanded features and feature selection," *TURKISH J. Electr. Eng. Comput. Sci.*, vol. 25, pp. 4829–4840, 2017, doi: 10.3906/elk-1704-256.

[15] H. Li, Y. Shen, and Y. Zhu, "Stock price prediction using attention-based multi-input LSTM," in *Proc. Mach. Learn. Res.*, vol. 95, 2017, pp. 454–469.

[16] C.-A. Brust, C. Käding, and J. Denzler, "Active learning for deep object detection," in *Proc. 14th Int. Joint Conf. Comput. Vis., Imag. Comput. Graph. Theory Appl.*, 2019, pp. 1–12.

[17] A. S. Temür, M. Akgün, and G. Temür, "Predicting housing sales in Turkey using ARIMA, LSTM and hybrid models," *J. Bus. Econ. Manage.*, vol. 20, no. 5, pp. 920–938, Jul. 2019, doi: 10.3846/jbem.2019.10190.

[18] O. Sezer and A. Ozbayoglu, "Financial trading model with stock bar chart image time series with deep convolutional neural networks," *Intell. Autom. Soft Comput.*, vol. 26, no. 2, pp. 323–334, 2020, doi: 10.31209/2018.100000065.

[19] Ç. Orçun, "Finansal piyasalarda alim satim kararlarinda teknik analiz ve IMKB uygulamasi," M.S. thesis, Social Sci. Inst., Dokuz Eylul Univ., Izmir, Turkey, 2010.

[20] M. Everingham, S. M. A. Eslami, L. Van Gool, C. K. I. Williams, J. Winn, and A. Zisserman, "The PASCAL visual object classes challenge: A retrospective," *Int. J. Comput. Vis.*, vol. 111, no. 1, pp. 98–136, 2015, doi: 10.1007/s11263-014-0733-5.

[21] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A. C. Berg, and L. Fei-Fei, "ImageNet large scale visual recognition challenge," *Int. J. Comput. Vis.*, vol. 115, no. 3, pp. 211–252, Dec. 2015, doi: 10.1007/s11263-015-0816-y.

[22] R. Girshick, J. Donahue, T. Darrell, U. C. Berkeley, and J. Malik, "Rich feature hierarchies for accurate object detection and semantic segmentation," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2012, pp. 580–587.

[23] K. He, X. Zhang, S. Ren, and J. Sun, "Spatial pyramid pooling in deep convolutional networks for visual recognition," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 37, no. 9, pp. 1904–1916, Sep. 2015.

[24] R. Girshick, "Fast R-CNN," in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, Dec. 2015, pp. 1440–1448, doi: 10.1109/ICCV.2015.169.

[25] P. Sermanet and D. Eigen, "OverFeat: Integrated recognition, localization and detection using convolutional networks," 2014, *arXiv:1312.6229v4*.

[26] Z. Alom, M. Hasan, C. Yakopcic, T. M. Taha, and V. K. Asari, "Improved inception-residual convolutional neural network for object recognition," 2017, *arXiv:1712.09888*.

[27] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 39, no. 6, pp. 1137–1149, Jun. 2016.

[28] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2016, pp. 779–788.

[29] W. Liu, D. Anguelov, D. Erhan, and C. Szegedy, "SSD: Single shot MultiBox detector," in *Proc. Eur. Conf. Comput. Vis.*, 2016, pp. 21–37.

[30] J. Redmon and A. Farhadi. (2018). *YOLO V.3*. [Online]. Available: https://pjreddie.com/media/files/papers/YOLOv3.pdf

[31] A. Bochkovskiy, C.-Y. Wang, and H.-Y. Mark Liao, "YOLOv4: Optimal speed and accuracy of object detection," 2020, *arXiv:2004.10934*.

[32] (2016). *Intersection Over Union (IoU) for Object Detection—PyImageSearch*. Accessed: Nov. 18, 2020. [Online]. Available: https://www.pyimagesearch.com/2016/11/07/intersection-over-union-iou-for-object-detection/

[33] L. Jiao, F. Zhang, F. Liu, S. Yang, L. Li, Z. Feng, and R. Qu, "A survey of deep learning-based object detection," *IEEE Access*, vol. 7, pp. 128837–128868, 2019, doi: 10.1109/ACCESS.2019.2939201.

[34] (2020). *GitHub—Tzutalin/LabelImg: LabelImg is a Graphical Image Annotation Tool and Label Object Bounding Boxes in Images*. Accessed: Nov. 11, 2020. [Online]. Available: https://github.com/tzutalin/labelImg

[35] A. H. Moghaddam, M. H. Moghaddam, and M. Esfandyari, "Stock market index prediction using artificial neural network," *J. Econ., Finance Administ. Sci.*, vol. 21, no. 41, pp. 89–93, Dec. 2016, doi: 10.1016/j.jefas.2016.07.002.


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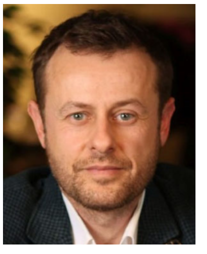

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