IFA
Iranian Journal of Finance
Print ISSN 2676-6337
Online ISSN 2676-6345

Predicting the trend of the total index of the Tehran Stock Exchange using an image processing technique

Roxane Pooresmaeil Niaki *

*Corresponding Author, MSc, Department of Accounting and Management, Allameh Tabataba'i University, Tehran, Iran. (Email: roxane.psn@gmail.com)

Moslem Peymany Foroushani

Assistant Prof., Department of Finance and Banking, Allameh Tabataba'i University, Tehran, Iran. (Email: m.peymany@atu.ac.ir)

Seyed Morteza Amini

Associate Prof., School of Mathematics, Statistics and Computer Science, University of Tehran, Tehran, Iran. (Email: morteza.amini@ut.ac.ir)

Iranian Journal of Finance, 2025, Vol. 9, No.1, pp. 1-31.
Publisher: Iran Finance Association
doi: https://doi.org/ 10.30699/ijf.2024.426626.1442
Article Type: Original Article

Received: December 27, 2023
Received in revised form: September 22, 2024
Accepted: September 29, 2024
Published online: January 01, 2025

Abstract

This study explores the considerable significance of candlestick chart patterns as a foundational asset within the realm of stock market analysis and prediction. As a graphical representation of historical price movements and patterns, Candlestick charts offer a distinct and valuable perspective for understanding how the financial market operates. This perspective assists us in accurately pinpointing the most advantageous times for making decisions to buy or sell financial securities, such as stocks or bonds. These charts provide insights into market trends and potential trading opportunities. We adopt an innovative approach by harnessing image processing techniques to extract and analyze patterns from Candlestick charts systematically. Our findings underscore the pivotal role of visual data in financial analysis, particularly in times of market volatility and uncertainty. Investors often resort to technical analysis strategies when confronted with erratic market trends, often relying on insights derived from chart-based analysis to guide their decision-making processes. By meticulously extracting essential insights from candlestick charts, our study aims to provide investors with more efficient and less error-prone tools. Ultimately, this endeavor contributes to the enhancement of decision-making precision and the mitigation of risks inherent in participating in the dynamic stock market landscape.

Keywords: Tehran Stock Exchange, Image processing, Market trend prediction, Machine learning.

Introduction

Investors are always looking for a solution to maximize capital and minimize risk, which has led to the development of many approaches to investigate the market trend. Studies emphasize two main approaches: fundamental analysis and technical analysis (see, e.g., Peymany Foroushany et al., 2020). Fundamental analysts measure intrinsic values by considering economic, industry, and company-specific factors (Saghafi & Mortazavi, 2016). In contrast, technical analysis is based on the efficient market hypothesis and relies on careful examination of price movements to detect new information (Sullivan et al., 1999). The information reflected in Candlestick charts can indicate the direction of investors' decisions and strengthen people's interest in using candlestick charts as an analytical tool (Lo & MacKinlay, 1990). In addition, they have examined the integration of content-based image processing methods in financial research and emphasized their importance in managing image data sets. Quan (2013) has tried to examine the patterns in candlestick charts to predict future price trends and evaluate the effectiveness of content-based image processing techniques in the field of financial analysis.

John and Coupland (2007) performed a comprehensive review of stock price forecasting and market trends and focused on the Tehran stock market. Jamshidi and Galibaf Asl (2018) have evaluated the effectiveness of repeating patterns by using candlestick charts as trading indicators. Recognizing the intertwining of behavioral finance perspectives and trading decisions, emphasizing the influence of individual characteristics and emotions on trading outcomes, their study needs to include the inherent limitations of traditional numerical data analysis methods. To reduce emotional biases, they have proposed the integration of artificial intelligence while at the same time supporting the adoption of image processing as a viable alternative.

The use of image processing not only overcomes the challenges associated with traditional numerical data processing but also reduces the possibility of errors in data entry and validation (Quan, 2013). Their findings emphasize that image processing methods provide higher predictive accuracy for analysts and investors involved in stock market valuation and identifying investment opportunities. Consequently, their emphasis is on improving image retrieval systems, with a special focus on extracting modified texture features to improve content-based image retrieval. Unlike the conventional text-based search methods popular in previous research, their study advocates for a content-based approach that integrates diverse image features, including color, texture, and shape, optimizing the precision and efficiency of image extraction from databases.

Literature Review

Fegheh Majidi and Shahidi (2018) emphasized the pivotal role of indices, with special emphasis on the widespread use of stock market indices as a standardized measure to assess global market conditions. Analysis of trading portfolios depends heavily on such indicators and provides an overview of market dynamics. Investors' informed decisions in buying and selling stocks are facilitated by accurately understanding the behavior of the index, examining its historical patterns, and predicting its future trends. Empirical research performed by Jahangiri Rad et al. (2012) showed that the total index reflects the impact of political and economic variables. It is also possible to find the thought process of investors in the direction of the index.

In numerous research studies on achieving abnormal returns in the stock market, two main issues have been investigated. First, fundamental analysis has been evaluated as a method of predicting future market returns. However, the results show that, despite the undeniable effect of this method, it needs to be sufficiently important due to the inefficiency of the Iranian market and the differences in the behavior of investors under the same conditions. Second, the impact of emotions on traders' decisions has been studied, and the results show that, in some cases, stock price changes are not determined by fundamental reasons, and investors' emotions have played an important role in this process.

Furthermore, Azizi et al. (2021) have shown that the news also has a direct effect on price trends, which indicates the significant influence of fundamental factors. In order to better understand these multiple effects, they have used the candlestick chart as an efficient tool to study the effects of all such factors. Candlestick patterns are drawn according to price information from various aspects of the indices, and due to their higher accuracy and lower error compared to data mining methods, they have been evaluated as an effective tool for predicting future trading trends. They have also shown that candlestick charts can be used as a reliable solution to eliminate systematic errors related to data mining methods.

In order to predict the future behavior of a variable, examining its historical behavior can be the first step in finding useful solutions. In technical analysis, it is assumed that the trend is continued and the past behaviors are repeated. Emamverdi and Safarzade Bijar Beneh (2016) have also shown that the stock price index in the Tehran stock market follows a nonlinear trend. As a result, its behavior can be predicted in the short term. It has been pointed out that there is a repeating pattern in certain months or days of the year, and according to their repetition, unusual returns can be obtained by using such patterns. Also, in Shabahang and Hassani (2003), the profitability of some technical patterns has been investigated, and the information related to the companies admitted to the Tehran Stock Exchange has been examined, and the head and shoulders, symmetrical triangle, and rectangular technical patterns have been evaluated. The results showed that the head and shoulders and symmetrical triangle patterns result in greater returns in the prediction of future prices.

In recent years, image processing techniques, particularly those utilizing Convolutional Neural Networks (CNNs), have garnered considerable attention for their ability to extract intricate patterns from visual data, such as financial charts. Unlike traditional statistical methods that primarily handle numerical and linear data, CNNs excel in processing multidimensional and nonlinear information, making them highly effective for complex data analysis (LeCun et al., 2015). The following table provides a comparative overview of the advantages of image processing methods over conventional statistical approaches in stock index prediction.

In summary, the reasons for the superiority of image processing over traditional statistical methods are presented in the table below:

Table 1. Comparison of Image Processing Method Advantages Over Statistical Methods

Statistical Method	Advantages of Image Processing Compared to Each Statistical Method	Scientific References
Linear Regression	1. Ability to analyze nonlinear and complex data 2. Extracting hidden patterns from images that linear regression cannot identify 3. Less sensitivity to outliers	(Huang et al., 2020)
Artificial Neural Networks	1. Specialization in processing visual data like charts and market patterns 2. Requires less data to extract visual features compared to general neural networks	(LeCun et al., 2015)
Decision Trees	1. Better at analyzing complex and nonlinear visual data 2. Reduced sensitivity to noise and small data changes 3. Prevention of overfitting with CNNs	(He et al., 2016)
Time Series Methods (ARIMA)	1. Analyzing visual trends in financial charts without requiring stationarity 2. Capable of extracting long-term trends and complex temporal patterns	(Bollerslev, 1986)
Traditional Statistical Methods	1. Ability to analyze multidimensional visual data 2. Flexibility in modeling complex and diverse data 3. Extracting detailed features from visual data and charts	(Krizhevsky et al., 2012)

Image processing techniques include a set of algorithmic activities that are used to examine and analyze images. Image processing has the following steps:

1. Collecting images.
2. Image preprocessing: It includes operations such as determining the color range of the image, removing noise, de-blurring, correcting brightness and contrast, etc.
3. Image analysis: This step involves detecting objects and various features in the image, such as color, shape, size, and resolution.
4. Image processing: It includes operations such as image segmentation, object detection and positioning, face detection, motion detection, etc.
5. Examining and interpreting the results: This step includes operations such as generating reports, displaying them graphically, and interpreting them if necessary.

Wavelets

Discrete wavelet transform is a mathematical technique used to analyze signals and extract information from them. This technique is based on the use of wavelets, which are small and local functions that can be used to represent a signal in a compact form and analyze signals in both the time and frequency domains. It has been widely used in signal processing, image compression, and data analysis.

This conversion consists of dividing a signal into different frequency sub-bands, each of which corresponds to a different scale. Wavelet functions are used to filter the signal at any scale, and the resulting coefficients to represent the signal that is used in a compact way can be done using different types of wavelets, each of which has its own properties and advantages. One of the main advantages of the wavelet transform is its ability to analyze signals with non-constant characteristics, such as signals that have sudden changes in frequency or amplitude. Another advantage is its ability to perform multi-resolution analysis, which allows signal analysis at different levels of detail. This can be useful in applications such as image compression, where the details of an image can be compressed to a greater extent than the overall structure.

There are several algorithms that can be used to implement wavelet transformation, and each of these algorithms has its own advantages and disadvantages. The algorithm that is chosen depends on the specific application and signal characteristics.

In summary, the discrete wavelet transform is a powerful mathematical tool that can be used to analyze signals in both the time and frequency domains. Its ability to perform multi-resolution analysis and detect non-stationary properties makes it useful in a wide range of applications.

In 1910, Haar established a comprehensive orthogonal system of functions, subsequently termed Haar functions. This seminal system possesses a characteristic whereby any continuous function delineated within the interval [0, 1] can be uniformly and convergently approximated as a series composed of the system's elements. Contemporary scholarship has introduced several alternative definitions of Haar functions, which diverge based on their assigned values at discontinuities. A prototypical example of the Haar basis is delineated as follows:

$$\psi(0,t) = 1, \text{ for } \ t \in [0,1); \quad \psi(1,t) = \begin{cases} 1, & \text{for } t \in [0,\frac{1}{2}) \\ -1, & \text{for } t \in [\frac{1}{2},1) \end{cases} \tag{1}$$

In the discrete domain, Haar functions are defined through the process of sampling continuous Haar functions at 2N distinct points. These discrete counterparts can be succinctly represented in matrix notation, known as Haar matrices, denoted by H(n). Such matrices are examined in both natural and ordered sequences, differing primarily in the permutation of their rows. Each row of H(n) encapsulates a discrete Haar sequence, expressed as $\psi(w,t)$, where the parameter w designates the sequence number of the Haar function, and t represents the discrete point within the function's interval of determination. The construction of Haar matrices for any given dimension can be systematically achieved through the application of the subsequent equation:

$$H(n) = \begin{bmatrix} H(n-1) & [1 \quad 1] \\ 2^{\frac{n-1}{2}} I(n-1) & [1 \quad -1] \end{bmatrix}, \qquad H(0) = 1 \tag{2}$$

Analysis of equation (2) elucidates that, in contrast to the Fourier transform, the Haar matrix H(n) comprises solely real elements. The matrix is characterized by its asymmetry and contains elements valued at 1, -1, or 0, each scaled by powers of √2. Derived from equation (2), the discrete and orthogonal Haar basis functions are delineated within the interval [0,1).

The Haar function is distinguished by its hierarchical structure: barring the initial ψ(0,t) function, each i-th Haar function is derived by imposing constraints on the (j-1)-th function. This recursive characteristic has garnered interest in Haar functions due to their foundational role in wavelet theory, where they represent the simplest form of wavelets as pairs of odd rectangular pulses. The impetus for employing discrete wavelet transforms lies in their ability to delineate information with varying resolutions across the time-frequency plane, offering detailed insights into the signal's time-spectral content. Such transforms facilitate the partitioning of the time-frequency domain into non-uniform segments, each correlating to specific signal characteristics. The classical basis of Haar functions is intrinsically linked to wavelet methodologies; scaling and dilating a base wavelet yields various Haar functions. The definition of a Haar wavelet function is as follows:

$$\Psi(t) = \begin{cases} 1, & \text{for } t \in [0, \frac{1}{2}) \\ -1, & \text{for } t \in \left[\frac{1}{2}, 1\right) \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

Attributable to its efficient computational characteristics, the Haar transform is extensively applied in the fields of image processing and pattern recognition. This efficiency renders it particularly advantageous for applications in two-dimensional signal processing, where its wavelet-like structure can be effectively utilized. In the context of two-dimensional spectral analysis, the coefficients are determined by the product of pairs of Haar functions, showcasing the transform's adaptability to various signal processing tasks.

Given that the output of the Haar transform is the product of an image matrix, this resultant matrix functions as a unique feature extractor, enabling the delineation of salient features within the actual image. Specifically, it facilitates the localization of latent linear discontinuities, or edges, within the image. A comprehensive examination of all coefficients within the spectral domain allows for the identification of significant edge orientations throughout the image. This critical information is subsequently instrumental in advanced image analysis and object recognition tasks.

At this stage, the characteristics of the images are extracted using the Haar wavelet. Haar wavelet divides the image into four parts, each of which has a different frequency. In this research, the part that has the lowest frequency has been selected because the image information is located in that part. After selecting the part with the lowest frequency, this part is again divided into four new parts, and the lowest frequency is selected in this stage. After three Haar wavelets, the estimation section of the third stage of LL3 is selected for the next stage (Porwik & Lisowska, 2004).

Artificial neural networks are known as deep learning models that are inspired by the structure and function of the brain. By learning from large data, these networks have the ability to learn complex patterns and process continuous and discrete inputs. They are used in many applications, such as imaging, natural language processing, face recognition, machine translation, etc. The advantages of these networks include the ability to learn without the need for precise definitions of features, to process high-dimensional data, and to adapt to nonlinear problems. However, to improve performance and accuracy, there is a need to pay attention to issues such as feature selection and parameter setting, use optimization methods, and increase network depth.

A multilayer neural network is one of the most popular deep learning models, and it is used as a powerful tool in the fields of machine learning and artificial intelligence. These networks are inspired by structures documented in brain function and are able to learn complex patterns and connections using training data.

A single-layer neural network is the simplest type of neural network that has only one output, and all inputs are connected to it. By considering the weights as input features, this network can predict the output from the input data. In a multilayer neural network, by adding layers and creating an architecture, information is taken and processed from layer to layer. Each layer includes input, processing, and output. The purpose of learning in this network is to optimize the weights by reducing the error and adapting the model to new data.

Supervised algorithms are one of the main methods of machine learning. These algorithms build a model based on training data to predict the output for new data. Examples of these algorithms include K-nearest neighbor, decision tree, support vector machine, neural network, and linear regression.

As a result, the multilayer neural network is recognized as one of the vital tools in the field of deep learning. These networks benefit from the ability of accurate prediction, complex data processing, and application in various problems such as face recognition and machine translation. In this article, we have used the k-nearest neighbor algorithm and the neural network. Considering that we explained the neural network algorithm earlier, we will describe the KNN algorithm in the following section (Hastie et al., 2009).

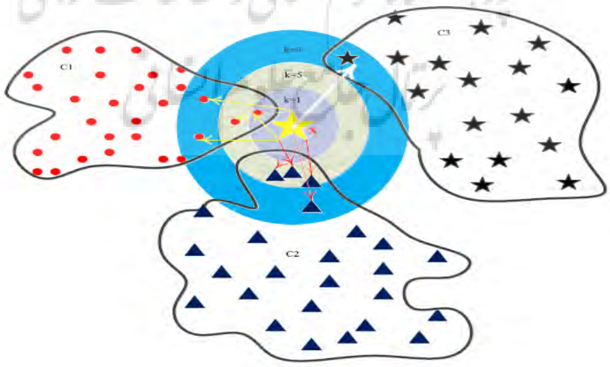

Figure 1. KNN algorithm (Xing & Bei, 2019)

The K-nearest neighbor (KNN) algorithm stands as one of the most fundamental algorithms in supervised machine learning, utilized extensively for both classification and regression tasks. Characterized as an instance-based or lazy learning model, KNN diverges from typical methodologies by not constructing an intrinsic model nor learning discriminatively from training data. Instead, it retains the training samples, employing them as a repository of 'knowledge' during the prediction phase. For classification problems, the algorithm determines the class of a given input by identifying the k nearest neighbors and adopting a majority vote mechanism for prediction (Figure 1).

The underlying principle of the K-nearest neighbor algorithm is straightforward: a given test sample is assigned to the category of its closest training sample. Provided that both the training set and the distance metric remain consistent, the outcome of the nearest neighbor rule is uniquely determined for each test sample under consideration (Xing & Bei, 2019).

Empirical studies

In the following section, we review the latest research in the context of CSR. Stock Price Forecasting Using ARIMA and LSTM Models by Ho et al. (2021) is another article on stock price forecasting in the US market. In this article, the authors have compared the performance of two different machine learning models, ARIMA and LSTM, in predicting the stock prices of four different companies: Apple, Amazon, Facebook, and Google. They used the historical data of the stock prices of these companies in the period from 2012 to 2019 and concluded that the LSTM model performed better than the ARIMA model in forecasting accuracy. This article provides a detailed description of ARIMA and LSTM models and how they are used in stock price forecasting. Also, the limitations of this model and potential research areas for future research are discussed. Finally, stock price forecasting using ARIMA and LSTM models is a useful resource for those interested in using machine learning techniques to forecast stock prices in the US market.

Samanta et al. (2017) discuss the importance of a company's stock value as a key indicator of its success and the challenges investors face in predicting future stock prices due to market volatility. In response to this, the paper highlights the popularity of stock market forecasting in the corporate sector and proposes a solution using machine learning algorithms, particularly focusing on the application of Python and linear regression for stock price forecasting. The goal is to create a website that uses historical data to increase the accuracy of linear regression models and emphasizes the feasibility of tuning the training dataset for improved results. The purpose of this research is to establish linear regression as the most effective technique for stock market analysis, dealing with the limitations of current technologies such as deep learning and neural networks. This research also emphasizes the importance of dataset selection in achieving accurate predictions and points to academic studies that show the superiority of the linear regression method in terms of accuracy compared to other machine learning strategies.

Saeidi and Amiri (2009) conducted research on the data of the total stock market index between 1380-1386; an attempt was made to examine the relationship between macroeconomic variables of the consumer index, such as the free-market exchange rate and oil prices, with the total stock market index. In this article, seasonal data, econometric methods, the OLS model, the linear regression model, the F test, Dickey Fuller and Phillips-Proon unit root test, and the White test are used. Research results have shown that there is an inverse and significant relationship between the price of crude oil and the total stock market index, but using these methods, no significant relationship was found between the consumer index, the free-market exchange rate, and the total stock market index.

Zarei et al. (2018) conducted research with the aim of investigating and comparing the ability to predict the stock prices of banks in the Tehran Stock Exchange using fuzzy neural networks and fuzzy wavelet neural network methods. The time period used in this research was 1390 to 1395. In this research, the fuzzy logic system, as well as a multilayer neural network using error back-propagation optimization and maximum overlap of the discrete wavelet transform, was used on the variables of gold, exchange rate, total stock index, trading volume, and OPEC oil. The results of this research, after updating by the cost function, have shown that the percentage of confidence in the prediction results by the fuzzy wavelet neural network is above 90%, and the percentage of confidence in the prediction results by the fuzzy neural network is above 80%.

The research conducted by Seif et al. (2021) has been examined on a daily basis on the data of the total index as a thermometer of the economy and indicates the general situation of the Iranian stock market from 2008 to 2020. Then, using the Elliott waves and movement strength index, kinetic and corrective movements are found and labeled into three categories: buying, selling, and holding. Next, the output of this step is given to three machine learning algorithms, including simple Bayes, decision tree and support vector machine, to be tested on the test data for learning and then predicting the process. The results showed that it is possible to identify Elliott waves in the

Tehran Stock Exchange index, and decision tree and support vector machine algorithms can predict the trend of the total index for the future with an accuracy of over 90%.

In Aminimehr et al. (2021), an attempt has been made to investigate the behavior of Tehran Stock Exchange index data. In this paper, by taking a statistical look at the data of the main stock market of Iran, an attempt has been made to identify the behavior and the process of generating daily return data of Iran's primary stock exchange, and after conducting many tests, by identifying the statistical behavior of the data, a new model has been developed to predict it. The research model in this article consists of two artificial neural networks of combined probability and short-term and long-term permanent memory, which, considering the number of different behavioral regimes, explains the daily movements of the return of the Tehran Stock Exchange index between 2008 and April 2021. The results of the research reject different tests of weak market efficiency and show the nature of chaos in the return behavior of the total index of the Tehran Stock Exchange. By using the Diabold Mariano test in the model presented in this research, it has been able to obtain better accuracy than the model without considering the regime.

In the research conducted by Karbalaei Mirzaei et al. (2022), neural network and time series models have been compared to investigate the effect of macro variables on the total index of the main stock market of Iran in the period from April 2012 to March 2018. In this regard, the multilayer Prospertronic neural network model and VAR regression model have been investigated. The results, which have been analyzed using root mean square error, mean absolute value of percentage error, mean absolute value of error, and coefficient of determination, have shown that the neural network model has less error than the VAR series model in terms of error criteria.

The subject investigated in this paper is forecasting the trend of the stock market index for the future using artificial intelligence methods. The area of this research is the Tehran Stock Exchange, where the data was collected. By examining the research that has been done so far on the data of the Tehran Stock Exchange and forecasting the index, several points can be seen. The first thing is that the data set used in previous works is numerical data. Numerical data is prone to error and even their values may need to be clarified on some days, which is called missing data. It is true that there are methods (such as deletion or filling with mean, minimum value, maximum value, etc.) to deal with missing data, but these methods have an impact on the final result and prediction accuracy. However, in our proposed method, the collected data set involves images. The characteristics of the candles can be extracted from the images and in this case, there is no data error.

The next point of interest is that some previous works have used statistical methods that perform weaker than machine learning methods in cases similar to the subject under review. In this matter, we are dealing with dynamic data and conditions, and it is necessary to train a model that can observe and learn different states based on their characteristics so that he can make predictions based on what he has learned and with higher accuracy when the data is slightly different.

Among the aforementioned reviewed papers, some have used machine learning methods, while they have used numerical data sets. Here, we use images as input data and image processing methods are used for feature extraction.

Research Methodology

This study is conducted within the context of the Tehran Stock Exchange, an organized and self-regulating market where securities are traded by brokers or traders in adherence to legal regulations. Operating as a public joint-stock company, the Tehran Stock Exchange serves as a crucial platform for securities transactions, embodying a structured and law-abiding environment for trading activities. In temporal scope, this study encompasses the comprehensive analysis of the total index of the Tehran Stock Exchange, spanning from March 2016 to March 2022.

The method proposed in this thesis comprises four distinct steps. Initially, the collection of the input dataset is imperative. Subsequently, the dataset undergoes preprocessing, and features are extracted to prepare the data for model input appropriately. Following this, the chosen machine learning model is applied to the data, culminating in the acquisition of prediction results. The intricacies of each of these steps are elucidated in the following sections.

The collected dataset is the image obtained in the following way:

A broker has been selected from the Rahvard 365 site and the photos of the candles have been provided. In the following, each image has been enlarged so that all 40 candles are placed on one page. A picture was taken of every 40 candles, and the 41st candle was chosen as a label, which needs to be clarified in the picture.

An example of the image data in the dataset is shown in Figure 2. In each image, the bottom line of the candle, which is considered the lowest point, is where the price is seen. The beginning of the rectangle is where the price is opened, and the top of the rectangle is where the price is closed. The shadow or line above the rectangle is where the price is seen from above. In this image, you can see 40 candles; the ascending and descending of each one is indicated by white or black color, respectively. The horizontal axis of Figure 2 shows the days.

Each candlestick in the data set represents one day's volatility. There are 40 candles in each image, which show a total of 40 days of fluctuations. Seven features are extracted from each candle, and for each image, a 7x40 matrix of candles and their features is created.

A total of 1402 dataset images have been collected.

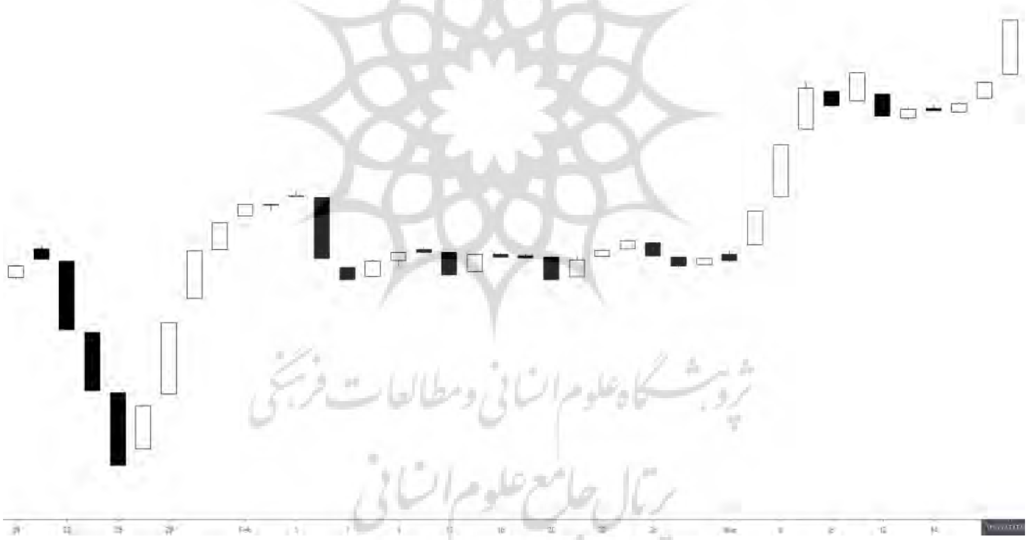

Figure 2. Sample image in the dataset

A method called wavelet transformation is used, which will help us analyze the general features by converting the photo scale to different sizes. In general, the goal of this method is to choose the band that gives us the most information about the photo by decomposing the photo of the graphs into several different frequency bands. This will also help us to reduce the dimension and remove unnecessary data. The discrete wavelet transform method is used. This method is one of the most popular image processing algorithms, which divides candlestick signals into high-frequency and low-frequency parts. After these changes, the image is divided into four parts: LL1, LH1, HL1, and HH1. So that the upper LL is placed on the left side of the new image, and its frequency is the lowest, which makes the most information remain in this part of the image. In each step of this transformation, to enlarge the image again, we will transform the LL part of the image into LL2, LH2, HL2, and HH2, and this process can be repeated p times to reach LLp, LHp, HLp, and HHp. Finally, we can choose the most suitable conversion stage by using appropriate statistical tests. For example, the image in Figure 3 is the enlarged image of the part containing the most information in the third layer.

Figure 3. Enlarged image of section LL3

As is clear in Figure 3, by using this color conversion, each pixel is removed from the state that has only two values of black (0) and white (255), and each pixel has a value between 0 and 255. It is possible to extract the information related to the color of the pixels of each candle, which is called texture-based information (TBFs). In addition, the information related to the length of the shadows and the length of the body of each candle is also important and indicates the fluctuation in that trading day, which is called location-based information (LBFs).

Haar wavelet is used in addition to wavelet transform, which divides the image into four parts, each with a different frequency. Here, the part that has the lowest frequency has been selected because the image information is located in that part. After choosing the part with the lowest frequency, this part is again divided into four new parts and the lowest frequency is selected at this stage.

Therefore, in the first step to extract features, using discrete wavelet and rabid wavelet transform, each image is divided into four parts; the LL part with the lowest frequency is kept, and the rest of the image is removed. This step is the first step of using a wavelet basis. In the continuation of this existing LL part, which we call LL1, it is again divided into four parts and its LL is kept, which is called LL2 because it is the second implementation of the wavelet. In the third stage of Violet's implementation, LL2 is again divided into four parts, and in this stage, the lowest frequency is kept, which is called LL3. After three implementations of the Haar wavelet, the estimation section of the third stage of LL3 is selected for the feature extraction stage.

Since our goal is to predict it for use in short-term transactions in the coming days, we use the information related to the next day of the index in labeling the images.

Note that 40-day candles are given in each image, which are collected as data. The index of the next day, which is day 41, is selected as a label. The way candle 41 is labeled is that if this candle is bullish, the label is one and if it is bearish, the label is zero. The data labeling is as follows. The images are placed in two classes, zero and one, which contain 538 and 864 images, respectively. There are a total of 1402 images in the datasetEClass “zero” hasm a descending label and class “one” has an ascending label. It should be noted that the color of the candlestick is considered to determine whether it is bullish or bearish and to determine the label. If the color of the candle is black, the indicator of candle 41 will be bearish and its label will be zero. If the color of the candle is white, the indicator will be bullish.

For example, considering the 41st trading day of the year, the image containing the candlestick chart of the first 40 trading days of 2015, for the index growing or falling compared to the 40th trading day, ascension and descent labels are used, respectively.

After collecting the data set, preprocessing the images is necessary. At this stage, the images are segmented and the candles are detected. An example of such a process is shown in Figure 4.

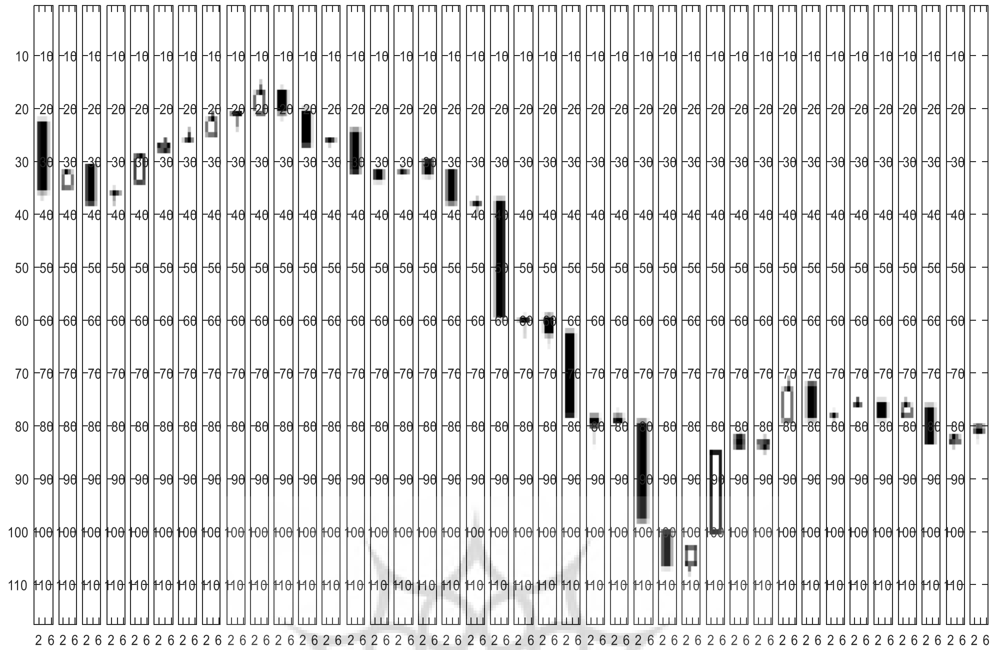

Figure 4. The result of image segmentation

Here, we intend to use the information in candlestick chart images. It is necessary to extract this information in the best way in the preprocessing stages. The main data is the image of the candlestick chart, the shape, color, and content of charts, and the text-based methods are not used. As a result, we use the content-based image retrieval method to read and extract information from candlestick charts automatically.

In order to determine the identity of an image from the patterns, a series of general or specific features must be extracted from the image. At this stage, the characteristics of the images and basically the characteristics of each candle are extracted. The following features are extracted from each candle:

1. The location of the highest point of the candle
2. The location of the lowest point of the candle
3. The brightness of the highest point of the candle
4. The light intensity of the lowest point of the candle
5. The brightness of the middle point of the candle
6. Candle length
7. The average light intensity of each candle

The lowest point of the candle is where the price has been seen, and the highest point of the candle is where the price has been seen above. Candle length is the difference between the location of the highest point of the candle and the location of the lowest point of the candle.

With the abovementioned seven features, the feature vector of each image can be formed for input to the machine learning model. Each image has 40 candles and seven features are extracted from each candle. Therefore, each image has 40*7 features and a feature vector of 280 is created for each image, which can be used to train the model.

The purpose of this research is to provide a model for predicting the stock index in the next day. In order to use machine learning algorithms and build models, it is first necessary to divide the collected data into two main parts: training data and test data. The training data is the data that is used to train the model. The test data is used to evaluate the performance of the built model. The label predicted by the model is compared with the actual label in the dataset. It should be noted that the dataset for training this model is divided into 70% training, 15% evaluation and 15% testing.

Here, a multilayer neural network and K-nearest neighbor have been used for classification. As shown in Figure 5, a multilayer neural network takes the feature vector of size 280 as input. Three hidden layers are considered, with 60 neurons in the first layer, and 15 and 5 neurons in the second and third layers, respectively. This architecture is obtained by trial and error during cross-validation. The sigmoid function is used as the activation function. The output of the model is binary, which predicts the rise or fall of the index.

In the K-nearest neighbor method, the number of neighbors is considered to be one and the Euclidean distance is used.

In the evaluation stage, the four most famous criteria, accuracy, precision, sensitivity, and F-measure, are used.

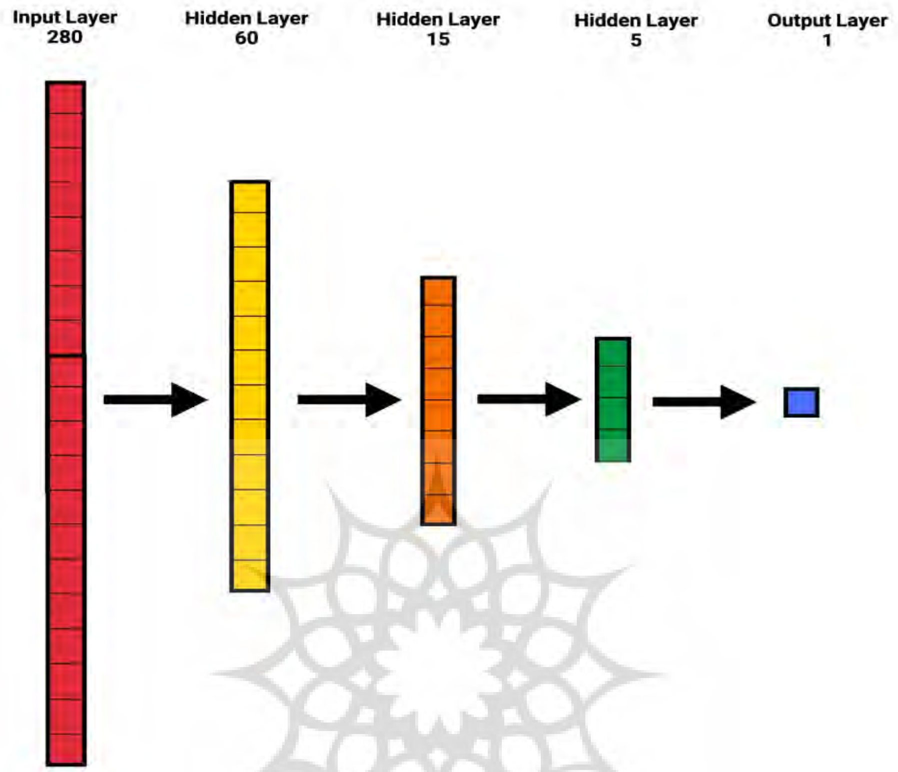

Figure 5. The architecture multilayer neural network

Results

To implement the proposed method, we have utilized MATLAB 2017 software, and the employed functions are delineated below. For Haar wavelet calculation, the dwt2 function is utilized with the input parameter "haar." This function computes the single-level discrete 2D wavelet transform, a widely applied technique in image processing and compression. Following wavelet transformation and feature extraction, the multilayer neural network model is deployed. MATLAB provides several functions for learning hidden layers, including trainlm, known for its speed; trainbr, which is more time-consuming but advantageous for challenging problems; and trainscg, requiring less memory and thus suitable for low-memory situations. The trainscg function, employed in this study to address the memory constraint when dealing with image features as input, employs the scaled conjugate gradient algorithm.

Unlike other conjugate gradient algorithms, trainscg does not necessitate a linear search in each iteration, enhancing efficiency. This MATLAB function updates weight and bias values according to the scaled conjugate gradient method, offering robustness and independence from user-defined parameters (Babani et al., 2016). Figure 6 illustrates the proposed multilayer neural network structure within the MATLAB software.

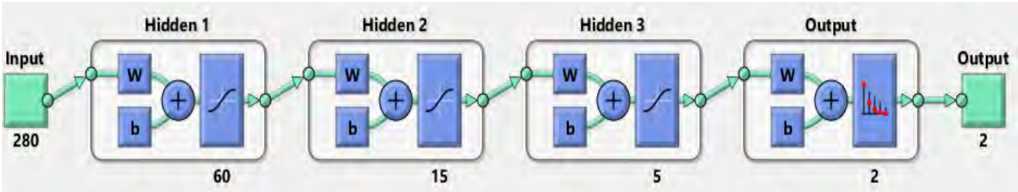

Figure 6. Proposed multilayer neural network

Two algorithms, a multilayer neural network and K nearest neighbor, have been used to create the prediction model, and the results of each are analyzed below.

To evaluate the model based on a multilayer neural network, the input data set is divided into 70, 15, and 15, where 70% of the data are used for training the model, 15% for evaluation, and 15% for testing. The confusion matrix is shown in Table 1. As one can see, the model has placed 71+48 = 119 samples out of 161 samples in the correct class.

Table 2. Confusion matrix for multilayer neural network

	positive	negative
positive	71	27
negative	15	48

Table 2 presents the outcomes of the review, accompanied by the evaluation criteria.

Table 3. Evaluation results of multilayer neural network

Accuracy	0.73
Precision	0.82
Sensitivity	0.72
specificity	0.76
F-measure	0.77

Table 3 shows the confusion matrix for the K-nearest neighbor model, which was able to place 122 samples out of 191 samples into the correct class.

Table 4.Confusion matrix for the KNN

	positive	negative
positive	56	19
negative	20	66

The results of the evaluation of the K-nearest neighbor model with evaluation criteria are given in Table 4.

Table 5. The KNN evaluation results

Accuracy	0.75
Precision	0.73
Sensitivity	0.74
specificity	0.76
F-measure	0.74

By comparing the two models, the following results (Table 5) are obtained:

- The accuracy of the K-nearest neighbor model is higher than that of the multilayer neural network.
- The accuracy of the K-nearest neighbor model is lower than that of the multilayer neural network.
- The sensitivity of the K-nearest neighbor model is higher than the multilayer neural network.
- The specificity of the K-nearest neighbor model and multilayer neural network is almost the same.
- The F1 score of the K nearest neighbor model is lower than the multilayer neural network.

Table 6. Results

Evaluation criteria	Multilayer neural network (percentage)	K nearest neighbor (percentage)
Accuracy	73	75
Precision	82	73
Sensitivity	72	74
specificity	76	76
F-measure	77	74

Two key prerequisites must be ensured to facilitate a meaningful comparison between the proposed method and other models or prior studies. First, the datasets utilized in both studies need to be identical to enable a direct comparison of the prediction outcomes of each model. Secondly, it is crucial to establish uniform evaluation criteria for both methods. The dataset employed in this research comprises candlestick images from the years 2016 to 2022 of the Tehran Stock Exchange, specifically collected for this study and not utilized in prior works. To enable a fair comparison, an extensive review of previous articles pertaining to Tehran stock market forecasting was conducted to identify a dataset closely aligned with the research subject. However, it was observed that the evaluation criteria in these prior articles needed to be more consistent and differed from those employed in this research. Furthermore, many of these articles, albeit related to the thesis's subject matter, relied on statistical methods for predictions. Given these disparities, a direct comparison with previous works was deemed unfeasible. Consequently, a competitor model has been defined within this research for the explicit purpose of comparison.

The competing model is the numerical dataset collected from 2016 to 2022. This time interval is the same interval at which the dataset of images was collected. However, these data are numerical. This dataset was collected from the gold, coin, and currency information network website. There are four features in the data set: the lowest candle interval, the highest candle interval, the point at which the price opened, and the closing number. Then, like the image dataset, these data are also labeled in two classes (ascending or descending). In the following section, this data set is divided into training, evaluation, and test data. Neural network and K-nearest neighbor models are trained and evaluated with test data (similar to the image dataset).

Figure 6 shows the proposed multilayer neural network structure in MATLAB software. In the first step, four features per data are entered as input to the network. After that, three hidden layers are placed with 60, 15, and 5 neurons, respectively. The activation function of these layers is sigmoid. In the last layer, there is a linear function that defines the output. The problem is that it is two classes, and the output can be ascending or descending.

The confusion matrix is shown in Table 6. As can be seen, the model has placed 53 samples out of 161 samples in the correct class.

Table 7. Confusion matrix for multilayer neural network

	positive	negative
positive	52	70
negative	38	1

The results of the review with evaluation criteria are given in Table 7.

Table 8. Evaluation results of multilayer neural network

Accuracy	0.67
Precision	0.98
Sensitivity	0.57
specificity	0.97
F-measure	0.72

Table 8 shows the confusion matrix for the K-nearest neighbor model, which was able to place 44+63 = 107 samples out of 161 samples in the correct class.

Table 9. Confusion table for the KNN

	positive	negative
positive	63	21
negative	33	44

The results of the evaluation of the K nearest neighbor model with evaluation criteria are given in Table 9.

Table 10. The KNN evaluation results

TAccuracy	0.66
Precision	0.65
Sensitivity	0.75
specificity	0.57
F-measure	0.70

By comparing the two models (Table 10), the following results are obtained:

- The accuracy of the K-nearest neighbor model is slightly lower than that of the multilayer neural network.
- The accuracy of the K-nearest neighbor model is lower than that of the multilayer neural network.

- The sensitivity of the K-nearest neighbor model is higher than that of the multilayer neural network.
- The specificity of K-Nearest Neighbor and Multilayer Neural Network models is less.
- The F1 score of the K nearest neighbor model is lower than the multilayer neural network.

Table 11. Results

Evaluation criteria	Multilayer neural network (percentage)	K nearest neighbor (percentage)
Accuracy	67	66
Precision	98	65
Sensitivity	57	75
specificity	97	57
F-measure	72	70

Table 11 compares the results of the proposed method with the competing model. In this table, it is clear that for many evaluation criteria, the proposed method that uses the image dataset has performed better than the competing model that uses index numbers.

Taking a look at the accuracy, the proposed method performed better with both the multilayer neural network algorithm and K nearest neighbor than the competing model, and the accuracy was higher in both models. K nearest neighbor performed best with the image dataset.

The accuracy of the multilayer neural network in both data sets is higher than K nearest neighbor. Therefore, according to the accuracy value, the multilayer neural network is more suitable for prediction in both datasets. Using the data set, the index numbers have reached 98%, which is a very high accuracy. Therefore, the multilayer neural network has performed very well for the data set with index numbers and has more accurate predictions.

The sensitivity in both data sets is higher for the K-nearest-neighbor model than for the multilayer neural network. K nearest neighbor has almost similar sensitivity for both image and index numbers.

The specificity criterion in the image dataset is the same for both models, and both models have similar performance based on this criterion. However, when using index numbers as input to the model, the multilayer neural network performed very well and was very different from other results.

The F1-score for the multilayer neural network model has the highest value in the image data.

Based on the results and evaluation criteria, it can be concluded that the multilayer neural network model predicts better than the K-nearest neighbor model in both image data sets and index numbers.

Table 12. Comparison of the results of the proposed method with the image data and the results of the competing model

	Proposed method with image data		Competitor model	
Evaluation criteria	Multilayer neural network (percentage)	K nearest neighbor (percentage)	Multilayer neural network (percentage)	K nearest neighbor (percentage)
Accuracy	73	**75**	67	66
Precision	82	73	**98**	65
Sensitivity	72	**74**	57	**75**
specificity	76	76	**97**	57
F-measure	**77**	74	72	70

Discussion and Conclusion

In this research, we encountered some limitations, which we mention as follows.

- The first step in using machine learning methods is data collection. In this research, data collection was a challenging task. There are usually ready-made datasets for work in different areas that can be downloaded and used. However, for the Tehran Stock Exchange, there was no ready dataset of images of candlesticks. Therefore, the dataset was prepared manually. First, a broker was selected, and then the images of 40 candles, which is equivalent to 40 days, were taken. Then, it was necessary to select and label a number of data as training data, which included 70% of the data for the multilayer neural network model and 85% of the data for the K nearest neighbor. So, the labeling process was time-consuming.
- In machine learning methodologies, data features form the basis of predictive models. However, external factors like economic and political decisions significantly influence the stock market indices, with even singular political remarks capable of instigating notable shifts.

Consequently, the likelihood of model inaccuracies escalates due to the impact of these unpredictable variables.

- Since the dataset of images is collected and the ready dataset is not used, the results cannot be compared with those of previous works. Therefore, another data set of numbers was collected and the model was trained with those data to compare the results of the research with them.

Predicting stock market trends remains a paramount yet challenging objective within capital market analysis. Accurate forecasts promise the potential for more secure investments. Accordingly, this research aims to propose a model that leverages artificial intelligence and machine learning techniques to anticipate the trajectory of the Tehran Stock Exchange index. The following novel approaches and innovations were undertaken in this study:

- Collecting images of stock market candles from 2016 to 2022 and creating a labeled data set with 1402 images.
- Image preprocessing methods were used, and seven features were extracted from each candle, with a total of 280 = 40*7 from each image.
- Creating a multilayer neural network to predict the trend of a stock market index
- Creating a model based on K nearest neighbor to predict the trend of the stock market index
- Collecting a numerical data set of stock index information related to the years 1395 to 1400 and labeling them (therefore 2 data sets have been collected)

The focus of this research is forecasting the Tehran Stock Exchange index. For this purpose, the data set was collected between the years 2016 and 2022, and this data set is from the images of candles. In each image, 40 candles are shown and the 41st candle is selected as the label. This label indicates the upward or downward trend of the index in the next step, which is the purpose of creating a machine learning model to predict this step.

Since the data set used is the image, it is necessary to perform preprocessing on it so that the data is suitable for the input of the machine learning model. In this regard, first, the candles were separated, and wavelet transformation was applied to them. Then, seven features were extracted from each candle. As mentioned, there are 40 candles in each image, each for one day. Therefore, the input of the machine learning model has a size equal to 40 x 7 = 280.

Two models based on machine learning were created to predict the stock index. The first model uses a multilayer neural network that has three hidden layers. The second model based on K is the nearest neighbor with a radius of one.

The results show that both methods for index prediction can be effective but still need to be improved to achieve more accuracy.

In the following, we provide suggestions for future research.

- In this research, a method for predicting the trend of the stock market index was presented, which predicts whether it will rise or fall for a future day. In future research, a model can be presented to predict the stock market index number using the image data set.
- There are other deep learning and machine learning methods that can be checked on the dataset, and the results can be compared with the methods described in this research. In this research, only two methods, a multilayer neural network and a K-nearest neighbor, were used. Further, machine learning methods such as support vector machines, decision trees, random forests, and even group learning algorithms can be used. Deep learning methods can also be used. In machine learning methods, we have a feature extraction stage, which requires features to be extracted before training the model (as was done in the third chapter). However, the deep learning methods of feature extraction are done automatically and by the model. Therefore, for example, the CNN network can be used for feature extraction. After that, the LSTM method can be used to train the model since the data is a time series. Of course, it should be noted that deep learning methods require a lot of data and the need to collect more data is clearly felt.
- A dataset of images was collected using a broker. For training machine learning models, the more data there is, the higher the accuracy of the model. Therefore, more data can be collected, and the model can be trained to improve the results.
- Image features were used in the proposed method. Other features of the stock market index can be given as input to the model in addition to image features to obtain more accurate results.

- In the proposed method, 40-day candles were used, and the 41st-day candle, which is the next day, was predicted. Therefore, the proposed method can only be used to predict a future day. In future works, the forecast can be made for more days.
- In this research, a method for predicting the trend of the stock market index was presented, regardless of the type of the previous trend; in the future, the upward and downward trends can be examined separately, and the forecast can be made for each one separately.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest concerning the research, authorship and, or publication of this article.

Funding

The authors received no financial support for the research, authorship and, or publication of this article.

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Bibliographic information of this paper for citing:

Pooresmaeil Niaki, Roxane, Peymany Foroushani, Moslem & Amini, Seyed Morteza (2025). Predicting the trend of the total index of the Tehran Stock Exchange using an image processing technique. *Iranian Journal of Finance*, 9(1), 1-31.