
GAZİ ÜNİVERSİTESİ
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DEEP LEARNING BASED STOCK MARKET PREDICTION USING TECHNICAL INDICATORS

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
GAZİ UNIVERSITY

BY

Halil RAŞO

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
COMPUTER ENGINEERING

APRIL 2019

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(M. Sc. Thesis)

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April 2019

ABSTRACT

Stock market prediction is the focus of interest of the traders and the economic practitioners since long time. They used in their prediction process some technical and fundamental indicators calculated from historical data of market indices. But all these indicators stand helpless because of the high non-linearity nature and high change rates of index historical data. Machine learning techniques especially deep learning methods have proved themselves in such high volatility environments and for time series forecasting problems. The thesis addressed in this paper deals with this problem in details and proposes a deep neural network model to predict possible future values and so directions that BIST 30 the most well-known index of Turkish stock market may take. The dataset used in training our deep model has been gathered from a famous website followed by most of the investors and the traders www.investing.com for 36 months' period from 01.01.2016 to 31.12.2018. Our model has proved itself through the experiments done on this dataset by outperforming other proposals where MSE or mean squared error got by it is 0.0302, 0.1009, 0.0930, 0.1075 and 0.2781 in forecasting BIST 30 index movements and prices for the next five trading days respectively.

Science Code	:	92431
Key Words	:	Stock market index prediction; Deep learning; Artificial Neural Network; Stock index; BIST 30.
Page Number	:	52
Supervisor	:	Assist. Prof. Dr. Mehmet DEMİRCİ

TEKNİK GÖSTERGELERİ KULLANARAK DERİN ÖĞRENME İLE HİSSE SENEDİ PİYASASI TAHMİNİ GERÇEKLEŞTİRME

(Yüksek Lisans Tezi)

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GAZİ ÜNİVERSİTESİ

FEN BİLİMLERİ ENSTİTÜSÜ

Nisan 2019

ÖZET

Borsa tahmini, hisse alım-satımı yapan kişilerin ve ekonomistlerin ilgi odağıdır. Tahmin sürecinde piyasa endekslerinin geçmiş verilerinden hesaplanan bazı teknik ve temel göstergeler kullanılmaktadır. Ancak bu göstergelerin başarısı, endeks hareketlerinin öngörülemez yapısı ve geçmiş verilerdeki yüksek değişim oranlarından dolayı kısıtlı kalmaktadır. Makine öğrenmesi teknikleri, özellikle derin öğrenme yöntemleri, yüksek değişkenliğe sahip ortamlarda ve zaman serisi tahmin problemlerinde kendilerini kanıtlamıştır. Bu tezde borsa endeks tahmini problemi ayrıntılı olarak ele alınmış ve BIST 30'un gelecekteki değerlerini tahmin etmek için bir derin sinir ağı modeli önerilmiştir. Derin öğrenme modelimizin eğitiminde kullanılan veri seti, 01.01.2016 - 31.12.2018 tarihleri arasındaki 36 aylık dönem için www.investing.com sitesinden toplanmıştır. Bu veri setiyle yapılan deneylerde modelimizin ulaştığı ortalama kare hata oranı (MSE) gelecekteki beş işlem günü için sırasıyla 0.0302, 0.1009, 0.0930, 0.1075 ve 0.2781 olarak tespit edilmiştir. Önerilen modelin literatürdeki diğer çalışmalardan daha iyi sonuç verdiği ve borsa endeks fiyatlarını tahmin etmede başarılı olduğu görülmüştür.

Bilim Kodu	:	92431
Anahtar Kelimeler	:	Borsa endeksi tahmini; Derin öğrenme; Yapay Sinir Ağı; Hisse senedi endeksi; BIST 30.
Sayfa Adedi	:	52
Danışman		Dr. Öğr. Üyesi Mehmet DEMİRCİ

ACKNOWLEDGMENTS

First of all, I would like to thank Allah for giving me the chance of getting master degree from high reputed university like Gazi University. Then, I would like to give this thesis as a gift to my father's soul and ask my Allah to bless his soul and also for my mother as they deployed themselves for my success in my life. My life parter, my wife she deserves more than thanks because she did not stop her support and she did her best to make me achieve my goals. To my brothers and sisters who prayed for me so much. To my friends who always tried to raise my morals and advised me in my decisions. My teachers at Gazi and especially my supervisor Dr. Mehmet DEMİRCİ for his patience and support. Finally, I would like to give this thesis as a gift to Turkey and Turkish people.

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SYMBOLS AND ABBREVIATIONS

The symbols and abbreviations used in this thesis are given below with their descriptions.

Symbols	Descriptions
%D	3-period moving average of %K.
%K	The current market rate for the currency pair
EMA_t	The current EMA value
EMA_y	The previous EMA value
OBV_C	The current on-balance volume,
V_{PN}	The positive-negative volume
closing, C	Stock closing price in the trading unit
H_14	The highest price traded in14-day period
HH	The highest high price
high	Stock highest price in the trading unit
L_14	The lowest price traded in 14-day period
LL	The lowest low price
low	Stock lowest price in the trading unit
open	Stock open price in the trading unit
t	Trading unit: day in our case
volume	Stock trading volume in the trading unit
N	The length of the EMA

Abbreviations	Descriptions
%R	Williams %R indicator
AI	Artificial Intelligence
ANN	Artificial Neural Network
BB	Bollinger Band indicators
BIST100	Turkish stock market index containing 100 companies
BIST30	Turkish stock market index containing 30 companies
BIST50	Turkish stock market index containing 50 companies

Abbreviations	Descriptions
CCI	Commodity Channel Index indicator
CNN	Convolutional Neural Network
DL	Deep Learning
EMA	Exponential Moving Average
KNN	K Nearest Neighbors
MACD	Moving Average Convergence Divergence indicator
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
MSE	Mean Squared Error
OBV	On-Balance Volume indicator
R2 Score	Popular Error Calculation Metric
RNN	Recurrent Neural Network
ROC	Price Rate of Change indicator
RSI	Relative Strength Index indicator
SMA	Simple Moving Average indicator
STOCH	Stochastic oscillator
STOCHRSI	STOCHRSI indicator
SVR	Support Vector Machine

1. INTRODUCTION

Turkey like any other country has its own stock market composed of companies which have shares traded in this market. Every stock market is represented by one or more indices that reflects the volume of trading by individuals and organizations on such companies' shares. Turkish stock market has three important indices that are followed by all traders and investors: BIST 30, BIST 50 and BIST 100. We deal through this thesis with BIST 30 as it represents the most powerful companies in the Turkish stock market and it is followed not only by national investors but also by foreign investors. On the other hand, BIST 100 and BIST 50 represent more companies and this leads to lower predictability compared with BIST 30 because some of these companies have small trading volumes and do not show good performance in their productivity and economically.

Traders and economic practitioners care about the future possible values and directions of stock market indices by analyzing their historical data such as close, open, highest and lowest values or prices during the trading days. They use in their analysis many factors and indicators that can be categorized into two main groups of indicators: Technical and fundamental indicators, besides other influencing factors such as country politic and economic news and investors' moods. What makes this prediction process a difficult task is not only the vast amount of trading data of indices but also the very frequent and high inlinear changes and movements that take place over indices in addition to the diversity of influencing factors on them such as general investment atmosphere.

Technical analysis is a kind of analysis that most traders and investors use to build their investment and strategies and helps them to make consistent decisions for buying or selling of a company's shares. Mainly, the core of this analysis is building charts, patterns and oscillators from stock index historical data. According to technical analysts, there is a strong relationship between this historical data and possible future values or directions. These patterns help reveal such relationships and hidden information about the next possible values or directions that indices may take in short or medium terms.

Another school of economic practitioners believe in different kinds of factors when building their investment strategies and portfolios. This school is called fundamental analysis school where its proponents argue that you would not invest in any company shares if you are not

making fundamental analysis about the company itself besides other issues. The main idea behind this analysis is that in order to build strong investment strategies and powerful portfolios, you should strongly analyze the long term factors which involve looking at revenue, expenses, assets, liabilities and all the other financial aspects of a company you wish to invest in.

There is another camp or school of analysts who consider investors' moods in their investing analysis. They strongly believe that these sentiments have big impacts on the next possible directions and values that an index may take such as positive moods will lead to increase trading volume of an index and so increase the demands on it and its stock prices.

Also, some economic analysts analyze economic and politic breaking news and decide their next actions in building their investment strategies. For example, good news about politics or economy will relax both national and foreign investors to invest more and more leading to increasing stock shares prices. On the other hand, bad news will make them feel afraid and pull back their investments, hence decreasing the trading volume and this opens the way to lose the shares their prices and directions.

Stock market prediction is in its essence a time-series problem where there is a series of historical data of an index and it is required to predict the next possible values and directions. But the high frequency and high non-linearity of changes in index data as well as the wide range of impacting factors cause this prediction to be difficult to solve properly by traditional time-series methods. Machine Learning techniques such as support vector machines, variant decision trees, k-nearest neighbors and artificial neural networks have been applied and gave good empirical results in this direction. Deep learning is a leading technique in machine learning which has proved its effectiveness and showed high performance in highly volitale environments and for time series forecasting problems. Since stock markets suffer from such stability issues, we think that deep learning is a promising solution for stock market prediction.

Stock market prediction can also be expressed as prediction of the future directions that an index may take according to the possible future prices that it may close on. Our thesis tries to achieve the price prediction and so the next directions for the next five trading days. For this purpose, we collected historical data of BIST 30 for a long enough period; 36 months

from well-known investing portal called www.investing.com followed by most traders and investors from 01.01.2016 to 31.12.2018. Our deep neural network model was fed with technical indicators extracted from BIST 30's historical data.

Technical indicators contain tens or even hundreds of indicators, but we chose only 11 indicators after investigating their effectiveness and relations with index next prices and directions. Our indicator choice process is proved by www.investing.com and other well-known investing portals. Experiments achieved by our deep model show the power of deep learning as a promising solution for such problems where we have got 0.0302, 0.1009, 0.0930, 0.1075 and 0.2781 as mean squared error in predicting BIST 30 values for the next five trading days.

The main contribution of this thesis can be summed up in the following three points:

- We have investigated the stock market of a developing country like Turkey. This is important as there are few works in this direction.
- We have applied feature selection engineering of technical indicators to pick the most important ones to be used among many other options. We have chosen the ones that have the most impact over stock index performance.
- We have used deep learning methods, which have proved their effectiveness in problems which involve tens of features, big volume of training set and data with unstable nature.

The rest of the paper is organized as follows. A detailed background of stock market prediction, deep learning techniques and technical indicators and oscillators used in our proposal have been described and given in Section 2. Related works are categorized and described in section 3. Our proposal and the walkthrough of our method have been explained in detail in Section 4. Section 5 describes our experiments and presents the evaluation results. Finally, we conclude our work in Section 6.

2. BACKGROUND

The problem we address through this thesis is stock market prediction using deep learning techniques. So, to better understand our problem we try to explain it in this section by formalizing it and later we give a background about machine learning techniques in general and deep learning in special. Stock market prediction is in its essence a time series problem where every index or stock of a company traded in Turkish stock market BIST has trading data such as open, high, low, trading volume and close price besides to trading date. So, we try to predict the close prices of an index or stock for the next trading days using this historical data. Prediction process could be done for the next trading minutes or hours. As our dataset contains trading data of BIST 30 on daily basis, so our prediction function predicts prices for the next five trading days. We formalize our problem in mathematic terms in the following equation:

$$close = f(open, high, low, volume, t) \tag{2.1}$$

The next closes prices are related with previous data as expressed in Eq. 1 but what does make this prediction so difficult is the huge amount of stock's historical data as well as this data changes very frequently and in non-linearity manner. According to technical analysis school, technical indicators reveal important hidden information from these historical data and help investors or traders making proper decisions.

2.1. Technical Analysis and Indicators

Technical analysis helps investors extract hidden information from historical data by building patterns or indicators which represent as decision making points. In other word, the close prices of an index are related with historical data and this can be expressed as the following equation:

$$closing = f(tech_{time-period}) \tag{2.2}$$

There are more than 150 technical indicators, but we will talk about the most important ones which noted by the most famous investing portal www.investing.com. The following subsections are dedicated for these indicators which are also used as input into our deep model.

2.1.1. Relative Strength Index – RSI

RSI comes in the leading momentum technical indicators. It is developed by noted analyst J. Welles Wilder Jr and explained in (Welles, 1978). This indicator analyzes the corresponding stocks or the indices and in order to measure speed and change of stock price movements, it observes the magnitude of recent losses and gains over a specified time period and identifies two important regions: overbought and oversold regions. The traders use these two regions to give sell or buy orders. The default time period considered by RSI is 14 trading units (days in our case because our samples are daily basis). RSI is calculated by the following formula:

$$RSI = 100 - \frac{100}{HH-LL} \tag{2.3}$$

RSI draws two important levels: (70, 30). The region which is above the upper level is called oversold region and the region resides under the lower level is called overbought region. Now sell signal is raised when the value of RSI exceeds 70 as the price becomes overvalued. On the other hand, a buy signal is generated when the RSI value falls under 30. This is the standard version of RSI and there is extreme version which considers (80, 20) levels. Some investors use extreme version of the RSI indicator where these two levels are (80, 20).

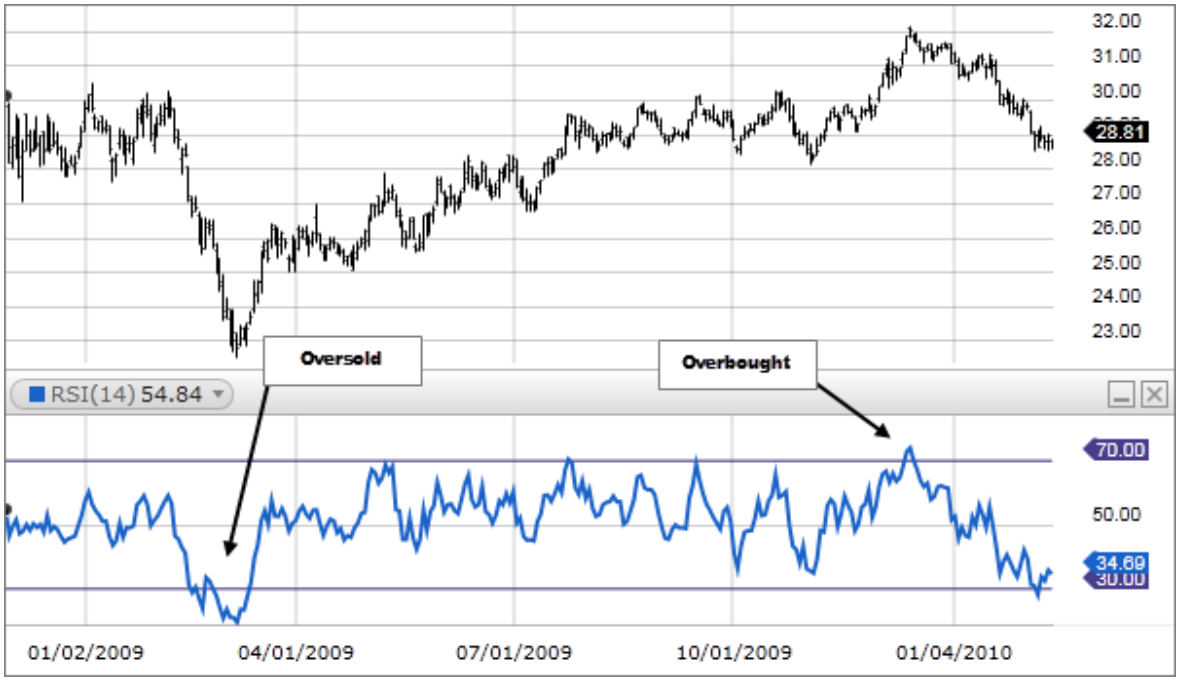


Figure 2.1. RSI, oversold and overbought regions [website 1].

2.1.2. Bollinger Band – BB

The famous technical trader John Bollinger (1980) developed a momentum indicator or chart called Bollinger bands or BB. There are three bands in this chart: Upper, middle and lower bands. The upper and lower bands are two standard deviations (positively and negatively) away from 20-day simple moving average (middle band). The default time period considered here is 21 trading units). According to Bollinger, there are two important points to generate buy and sell signals: Sell signal when the price exceeds the upper band as it becomes overvalued and there will be a correction. Conversely, when the price goes below the lower band, it becomes undervalued and it should be corrected, so a buy signal is raised.

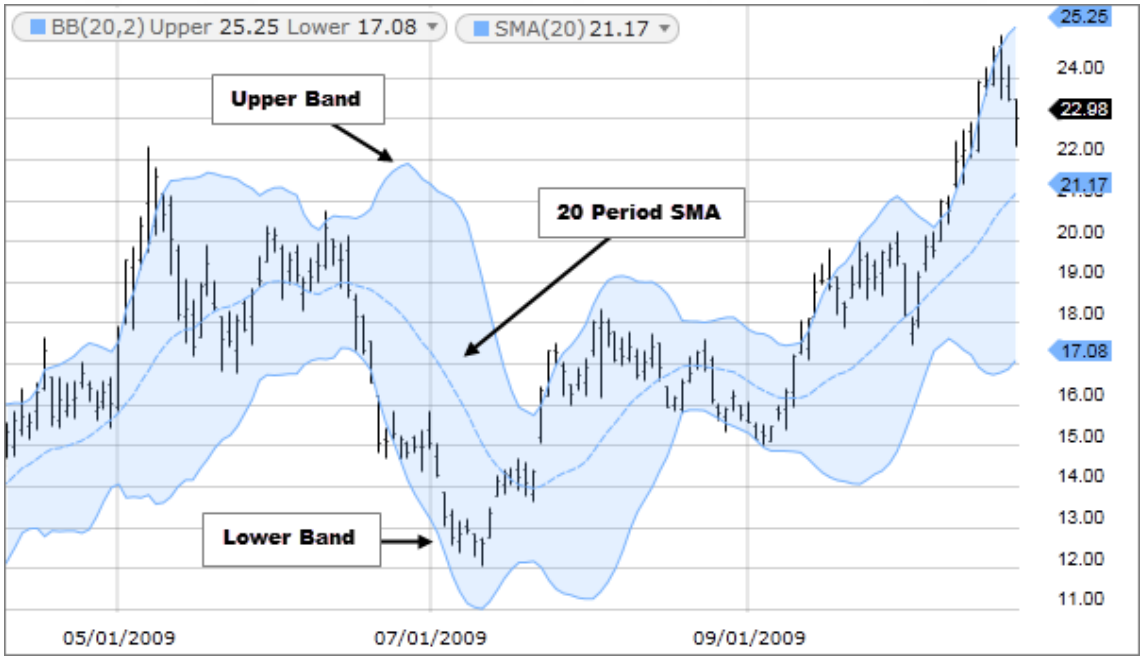


Figure 2.2. Bollinger Bands: Upper, middle (20-day SMA) and lower bands. [website 1]

2.1.3. Stochastic Oscillator – STOCH

The trader George Lane developed a momentum indicator or oscillator called STOCH which compares the stock price to the range of its prices over a certain period of time (The default time period is 14 trading units). The stochastic oscillator is given by the following formula:

$$\%\boldsymbol{K} = \mathbf{100} * \frac{(\boldsymbol{C}-\boldsymbol{L_{14}})}{(\boldsymbol{H_{14}}-\boldsymbol{L_{14}})} \qquad (2.4)$$

Where:

C is the most recent closing price,

L_{14} is the low of the 14 previous trading sessions,

H_{14} is the highest price traded during the same 14-day period,

$\%K$ is the current market rate for the currency pair,

$\%D$ is 3-period moving average of $\%K$.

According to Lane, prices in the up-trending market will close near the high, and close near the low in down-trending market. Transaction signals are created when the %K crosses through a three-period moving average, which is called the %D.

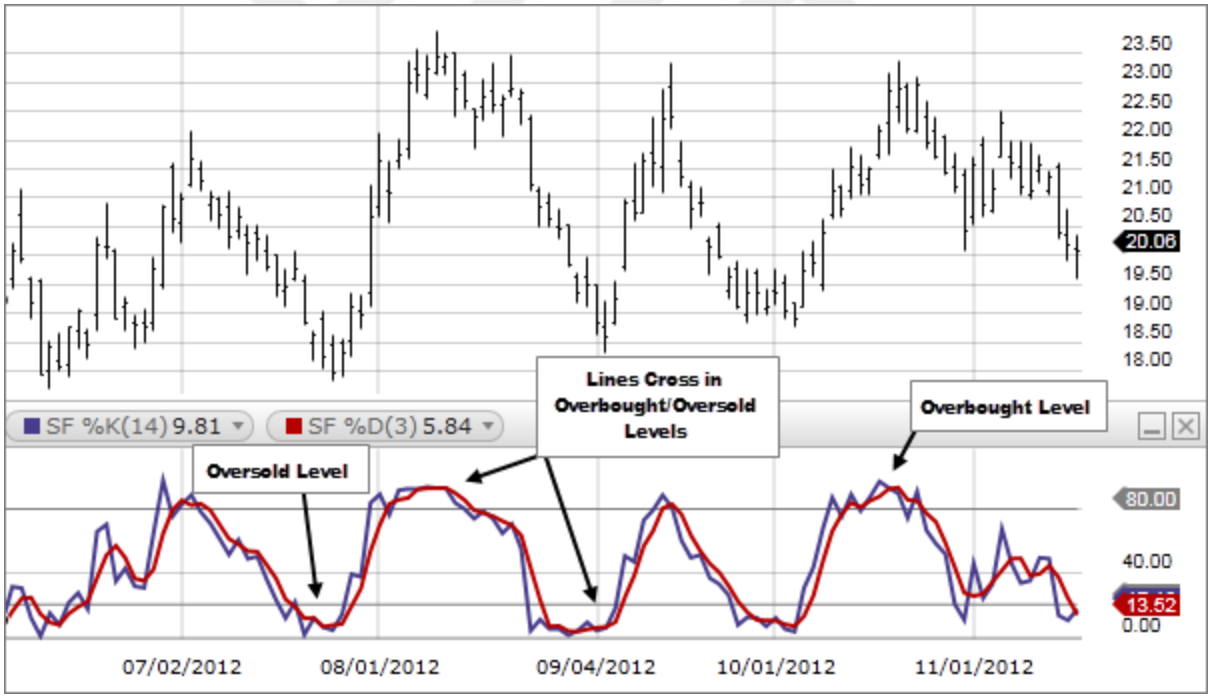


Figure 2.3. Stochastic Oscillator – STOCH [website 1]

2.1.4. Williams %R

The famous technical analyst Larry Williams developed a technical momentum indicator called Williams %R (1973). The time period considered in Williams %R calculation is 14 trading days. It is the inverse of the Fast-Stochastic Oscillator. While Williams %R indicator

compares the stock closing price to the highest price for the look-back period, the Stochastic Oscillator compares it with the lowest price in the same time period. Williams %R is given in the following formula:

$$\%R = \frac{HH-C}{HH-LL} * -100 \quad (2.5)$$

Where:

HH is the highest high,

C is the closing price,

LL is the lowest low.

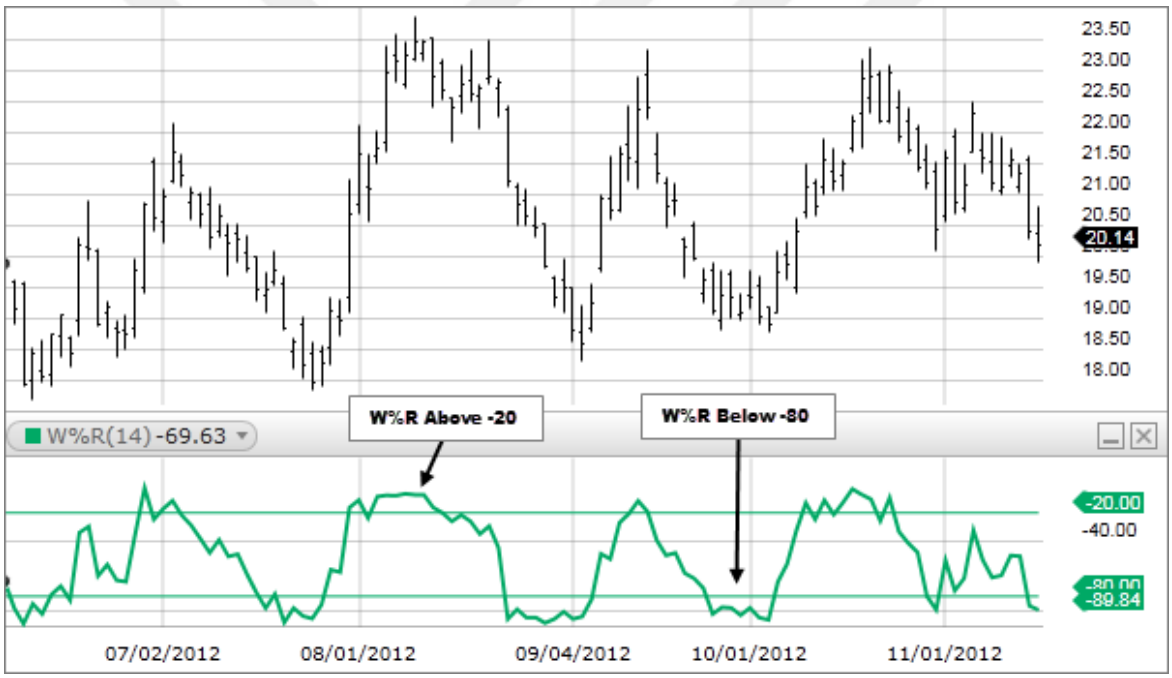


Figure 2.4. Williams %R indicator. [website 1]

2.1.5. Price Rate of Change – ROC

As its name implies, it is a technical momentum that calculates the percentage change in stock price between the current price and the price of n periods in the past. It is calculated by using the following formula:

$$ROC = \frac{C-C_n}{C_n} * 100 \quad (2.6)$$

Where

C is the most recent closing price,

C_n is the closing price n periods ago.



Figure 2.5. Rate of change ROC indicator. [website 1]

2.1.6. Simple Moving Average – SMA

SMA is the simplest technical momentum indicator used by many traders and investors. As its name implies, it could be calculated by getting the sum of the stock prices during a time period (The time period considered here is also 14 trading days) and then dividing this sum by the number of considered time periods as it expressed in the following formula:

$$SMA = \frac{\sum_{i=0}^{n} C}{n} \tag{2.7}$$



Figure 2.6. SMA with 200 trading days as window. [website 1]

2.1.7. Exponential Moving Average – EMA

An exponential moving average (EMA) indicator is the exponential variation of the standard simple moving average indicator. EMA is like SMA except that in the former we give more importance to the latest stock prices and so it reacts faster to recent price changes than SMA. It can be calculated by using the following formula:

$$EMA_t = (C * K) + (EMA_y * (1 - K)) \tag{2.8}$$

$$K = \frac{2}{(N+1)} \tag{2.9}$$

Where:

EMA_t is the current EMA value,

EMA_y is the previous EMA value,

N is the length of the EMA.

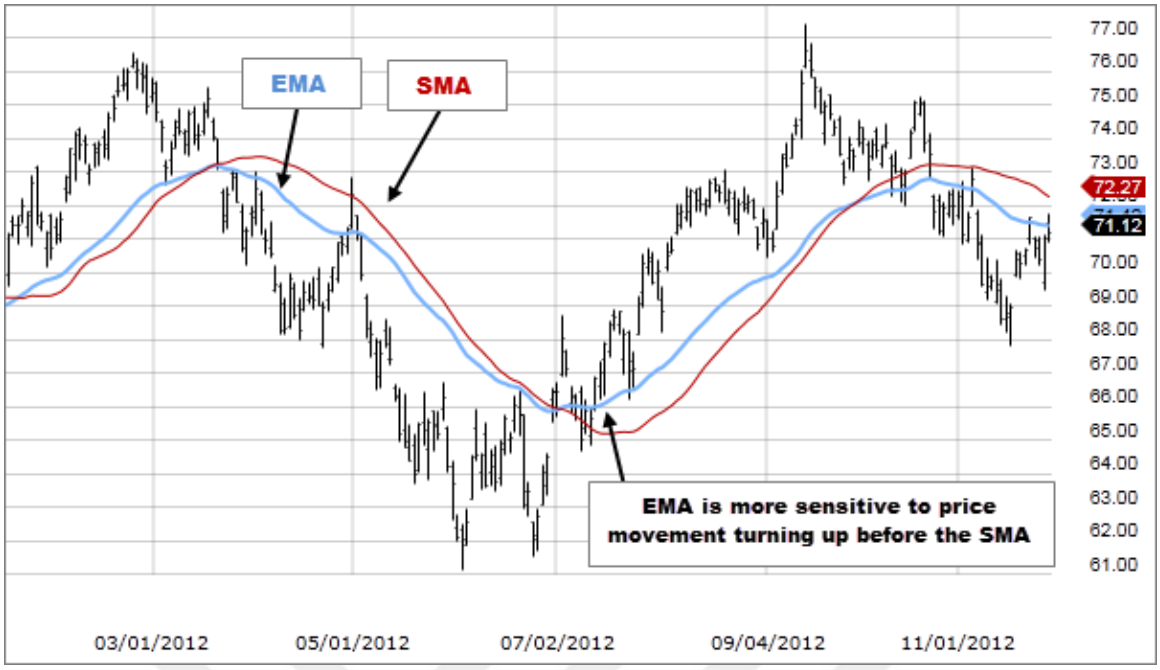


Figure 2.7. EMA and SMA indicators. [website 1]

2.1.8. Commodity Channel Index – CCI

The trader Donald Lambert developed a momentum indicator called Commodity Channel Index or CCI. it measures the current price level of a stock relative to an average price level over a given period of time (14 trading days). CCI is relatively high when prices are far above their average, and low when prices are far below their average. In this manner, CCI can be used to identify overbought and oversold levels which are important levels considered by traders to make buy and sell orders. It is calculated by using the following formula:

$$CCI = \frac{(C - SMA_{20})}{0.15 * Mean\ deviation} \tag{2.10}$$



Figure 2.8. CCI indicator. [website 1]

2.1.9. On-Balance Volume - OBV

Joseph E. Granville (1976) developed an important momentum technical indicator called On-balance volume or OBV by which considers index volume flow to predict changes in its price. According to Granville, the stock price will eventually jump upward when volume increases sharply without a significant change in it and vice versa. It is given by using the following formula:

$$OBV_c = \sum V_{PN} \tag{2.11}$$

Where:

OBV_C in the current on-balance volume,

V_{PN} is the positive-negative volume (volume is positive if current volume is bigger than previous volume).



Figure 2.9. On-Balance volume technical indicator. [website 1]

2.1.10. Moving Average Convergence Divergence - MACD

Moving average convergence divergence MACD or as most traders call it a trend-following indicator is momentum indicator that shows the relationship between two moving averages of stock prices. The MACD is calculated by subtracting the 26-day exponential moving average (EMA_{26}) from the 12-day EMA (EMA_{12}). A nine-day EMA of the MACD, called the "signal line", is then plotted on top of the MACD, functioning as a trigger for buy and sell signals. MACD is calculated by the following formula:

$$MACD = (EMA_{26} - EMA_{12}) \tag{2.12}$$

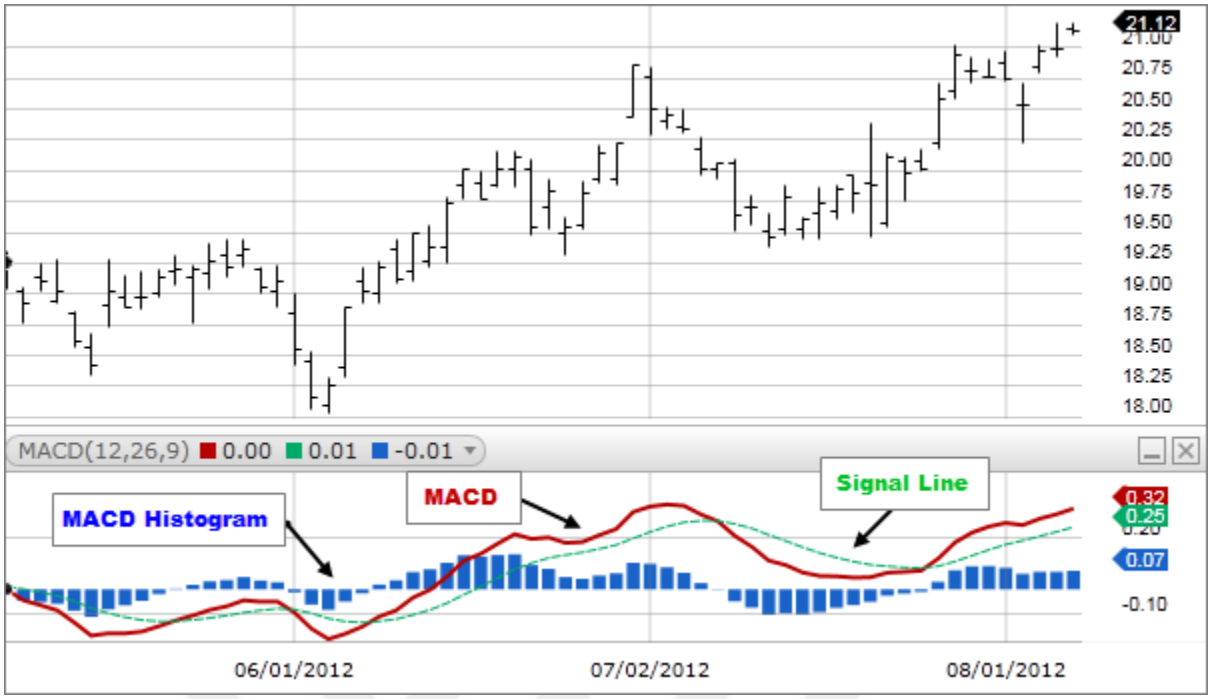


Figure 2.10. Moving average convergence. [website 1]

2.1.11. STOCHRSI

Some momentum indicators show better performance when they are attended by other indicators. STOCHRSI is one such indicator that combines two important indicators: STOCH and RSI indicators and it ranges between zero and one. It is created by applying the Stochastic Oscillator formula to a set of Relative Strength Index (RSI) values rather than standard price data. Using RSI values within the stochastic formula gives traders an idea of whether the current RSI value is overbought or oversold - a measure that becomes specifically useful when the RSI value is confined between its signal levels of 20 and 80.

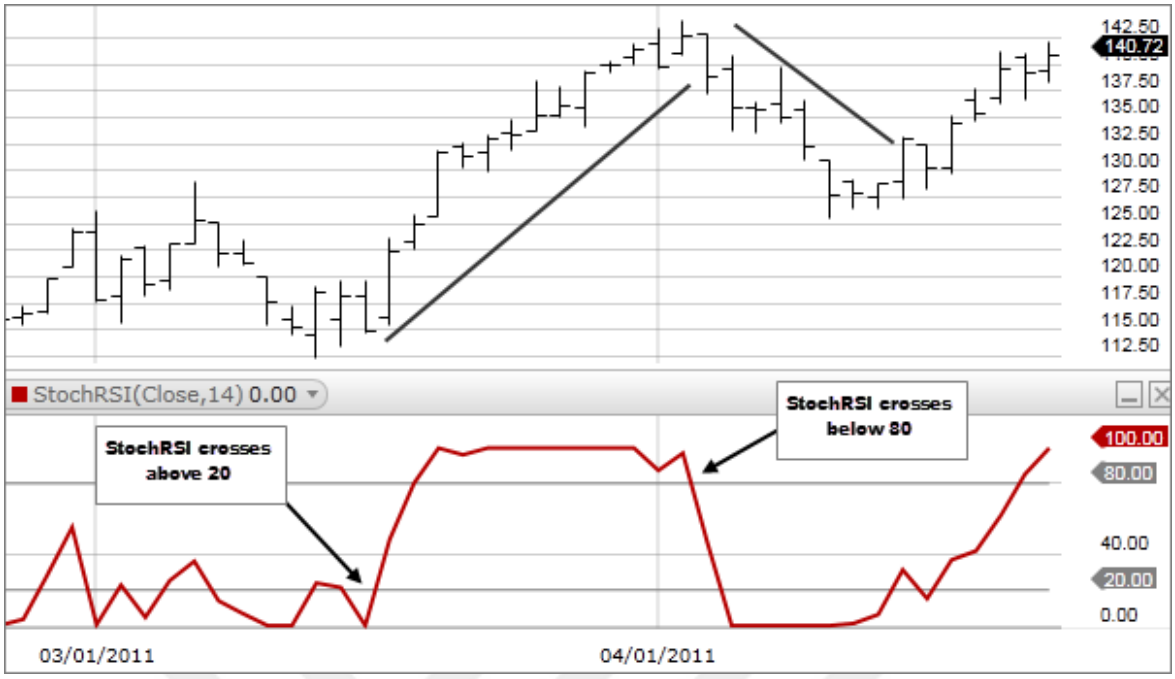


Figure 2.11. STOCHRSI indicator. [website 1]

2.2. Machine Learning

Machine learning is a set of algorithms or techniques that increases the systems' the ability to achieve tasks and solve problems without human intervention. In other words, these systems and by aid of these techniques learn solving tasks by themselves. Machine learning has been applied in many applications from computer vision and robotics to driving driverless cars and making medical operations. Whatever the problem that machine learning trying to solve and whatever the technique used, there are steps followed and in the following subsections we will mentions these steps.

2.2.1. Gathering data

The first step in any machine learning application is collecting data phase. This data is collected from the target environment and called dataset. The system analyst after analyzing the environment identifies the interested features and starts getting samples by observing these features from the target environment. Sometimes sampling process is done automatically by systems and the system analyst selects only interested features and eliminating the others.

2.2.2. Data manipulation

The data gathered in the previous section may suffer from many problems that makes the systems learn incorrectly and so affects the system performance. To name few of these problems:

- Missing data:

Sometimes this sample data contains missing data for any reason and this missing data should be either filled by proper values or the samples containing them should be dropped from the dataset.

- Redundant data:

Redundant data should be detected and dropped from the dataset as they are redundant and affect on the system performance in terms of time and may lead the system to be learnt incorrectly.

- Correlated features:

Every feature represents specific aspect of the environment and carries important information about it. But sometimes some of these features are correlated with each other. The correlated features lead to many problems such as overfitting and so prevent the system from learning well. These correlated features should be dropped so that the remaining features should be not correlated with each other.

2.2.3. Choosing model or algorithm

This is the most important step in any machine learning application and it depends on the application kind whether it is classification, regression or clustering problem. Some of machine learning techniques has proved their power in classification problems more than others and so on.

2.2.4. Training

In the beginning the system does not have any prior information or knowledge about the problem and need to be learned and this be done by training phase. This step is done by applying the steps of the chosen algorithm on the dataset. The dataset should be divided into training and test sets. Most popular ratio of training and test sets is 80/20 and sometimes machine learning engineers use 70/30 and so on.

2.2.5. Evaluation

Now and in order to verify that whether the system learned well or not, it should be evaluated and here the test set of the dataset is used. In most cases the machine learning engineers use cross validation by which the model first is learned by the first 80% portion of dataset and the validated by the last 20% of it, later the training set is shifted with 20% and the model is trained with this new shifted portion and so on.

2.2.6. Hyperparameter tuning

Many of machine learning techniques depend on some parameters during learning phase and these parameters have default values but in some cases and in order to increase the system performance they should be readjusted and the learning phase should be restarted until reaching to the desired results.

2.2.7. Prediction and visualization

Now the model is trained, evaluated and ready to be tested over real data. In this case we can say that our system is learned. Some applications use visualization tools to visualize the results and so on.

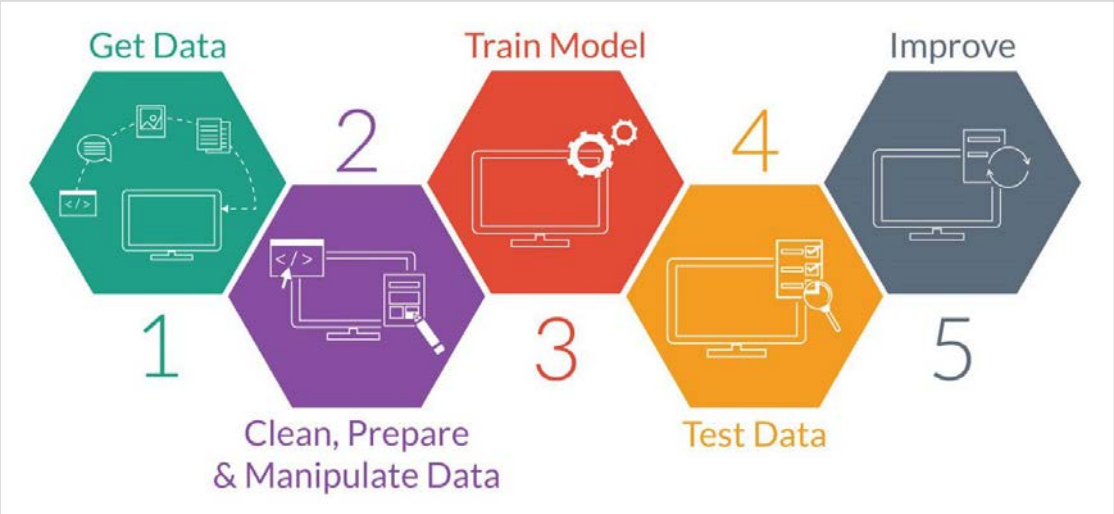


Figure 2.12. Machine Learning Steps. [website 2]

2.3. Artificial Neural Networks and Deep Learning

Before talking about deep learning, we will talk about artificial neural networks as the former is special kind of the second. Artificial neural network or ANN is one of the most AI and ML research area and it is inspired from neural network of the human nervous system where neurons are connected with each other through axons and dendrites. Each one participates in solving a part of the problem faced by a person and sends the result to another connected neuron through axons.

Generally, ANN is set of computing units (neurons) organized into layers connected with each other in form of network. Every neuron has multiple weighted inputs called synapse, summing junction which gets sums of these weighted inputs, an activation function which determines the output of it and one output. Some neurons have another input to the summing junction called bias. The simplest kind of ANN is perceptron which has only one neuron used in binary classification problems. Activation function used in perceptron called Step function or threshold unit function. Typical example of perceptron is logic gates such as ‘OR’, ‘AND’ and ‘XOR’ gates.

At the beginning ANN does not have any prior knowledge about the problem to be solved and needs to be trained. Training ANN is done by learning algorithm such backpropagation algorithm which is applied in general on Multilayer perceptron. Training algorithm’s core

function is adjusting neurons weights and bias to get the desired outputs in other words to minimize the error in the output layer.

Deep learning or deep neural network is the current trend of machine learning engineers which differ from normal neural network with hidden layers numbers. More hidden layers mean more ability to solve more complex problems and with vast advanced in computing power, deep learning could easily recognize objects and do very complex tasks in real time. Now and by aid of deep learning we could say that machine learning is closer to achieve its promising goal which is being smart.

There are many types of deep neural networks in terms of architectures but the most popular and widely used ones are as follows:

2.3.2. Convolutional neural networks CNNs

Convolutional neural network or CNN is a multilayer neural network that was inspired by the animal visual cortex and it is the most popular architecture used in computer vision and robotics tasks such as image recognition, video recognition and various tasks within natural language processing. The name “convolution” comes from a mathematical operation: convolution between functions. There are two main tasks done by CNNs: features selection or extraction and classification as shown in Fig. 2.13. The image is applied first on convolutional layer after being divided into receptive fields which extracts features from the input image such as edges. Then pooling layer comes directly after convolutional layer which its main function is reducing the dimensionality of the extracted features (through down-sampling) while retaining the most important information (typically through max pooling). There maybe more than one pair of convolutional and pooling layers in a CNN architecture to achieve higher performance and then the output from the last pair is feed into into a fully connected multilayer perceptron in which the output layer is used for classification.

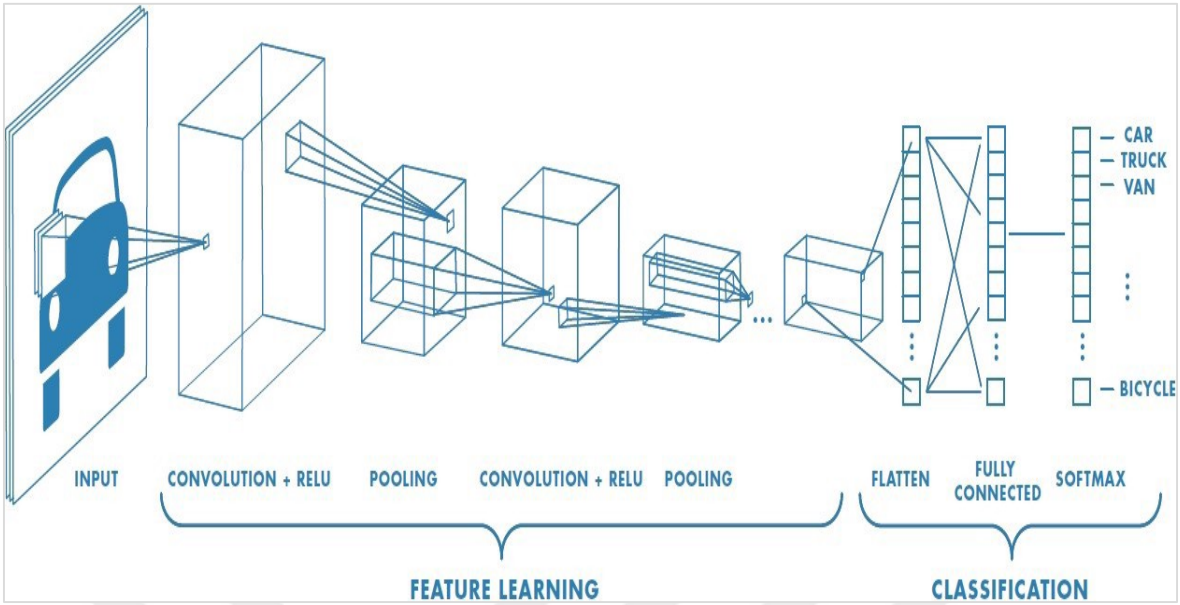


Figure 2.13. CNN architecture used in image recognition. [website 3]

2.3.2. Recurrent neural networks RNNs

Recurrent neural networks or RNNs is a popular architecture that other deep neural networks derived from and achieved a big progress in speech recognition, automatic music composition, sentiment analysis, DNA sequence analysis, machine translation. The core difference between a typical multilayer network and a recurrent network is that neurons in RNN beside of completely feed-forward connections may have feedback connections from either themselves or from the next layers. These layers which have feedback connection are called context layers. For training such networks standard back-propagation could be applied by unfolding in time or variant back-propagation for time involved networks.

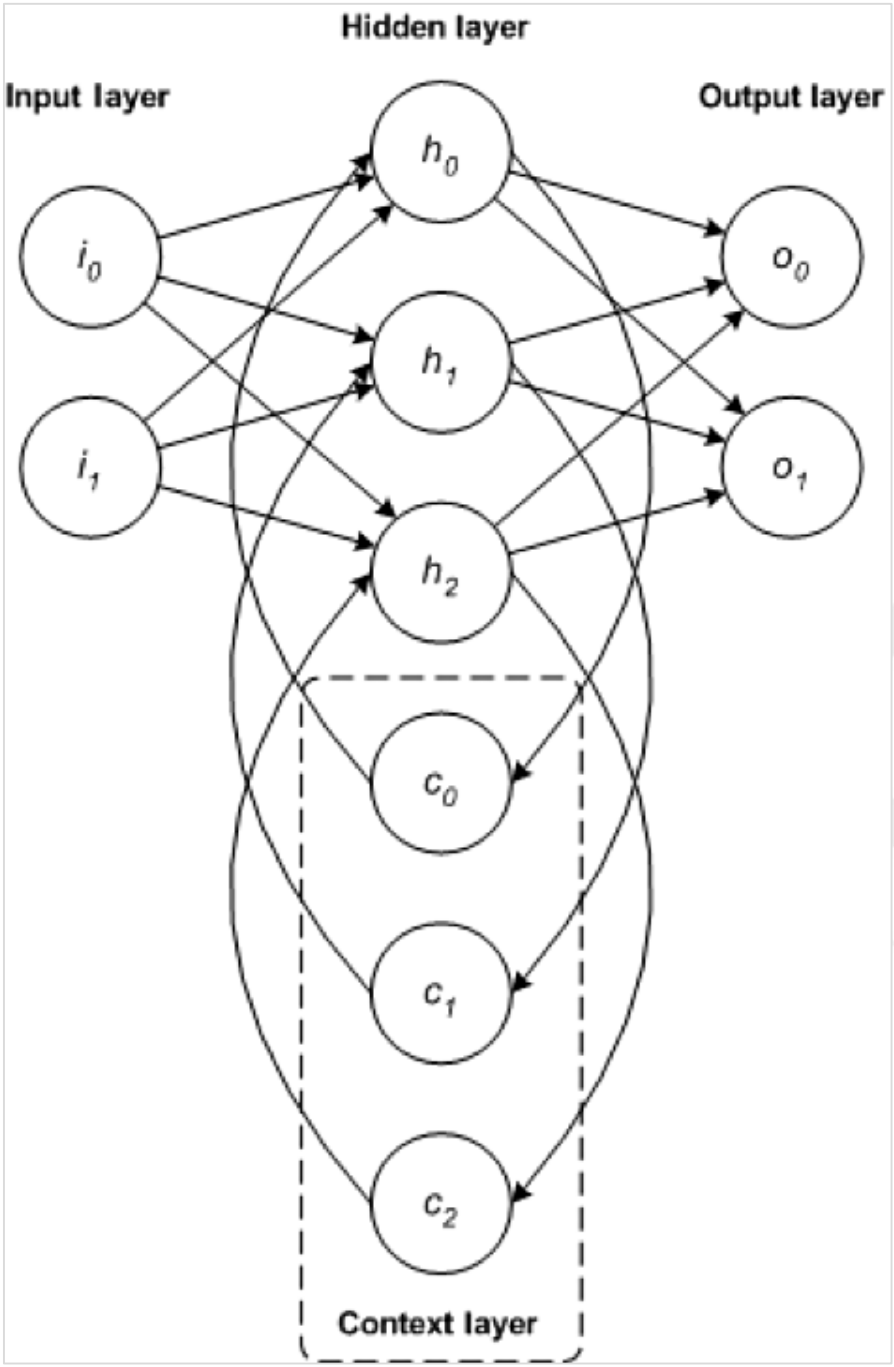


Figure 2.14. RNN architecture with context layer. [website 4]

2.3.3. Autoencoders

Autoencoder neural network is a popular ANN architecture applied mainly in unsupervised learning applications such anomaly detection. The most two applications that Autoencoders are applied for are fraud detection in bank transactions and dimensionality reduction like Principal Component Analysis. In other words, the core function of autoencoders is to teach the machines what constitutes “normal” data.

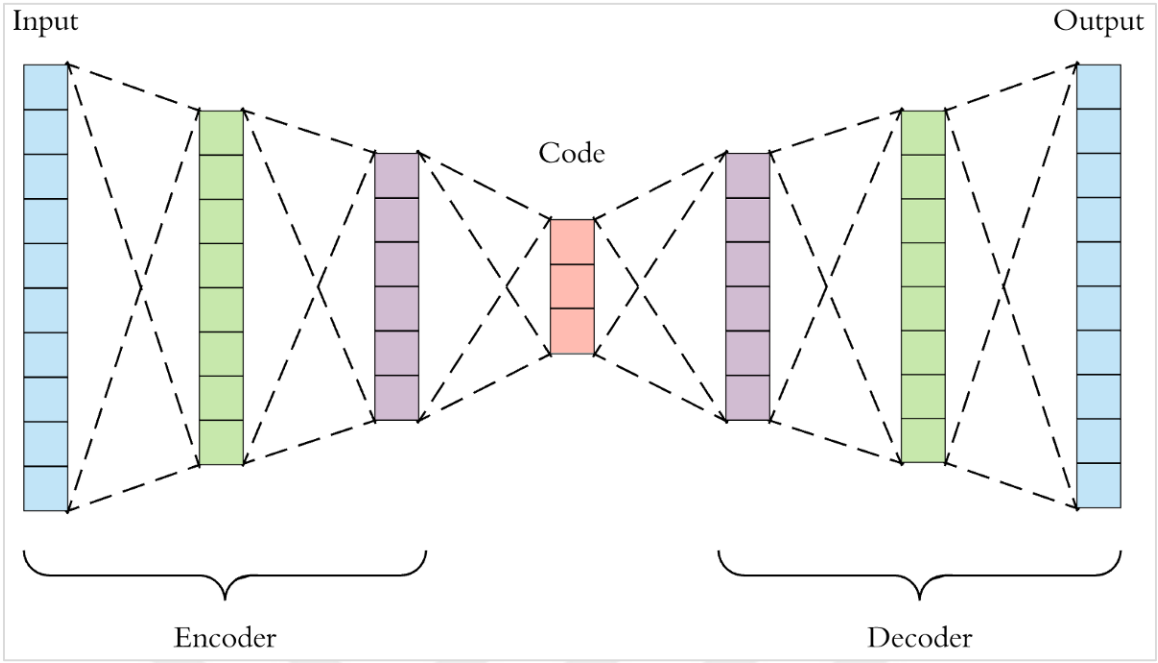


Figure 2.15. Autoencoders architecture. [website 5]

There are many other architectures of deep neural networks but these three are the most popular and widely-used ones besides to typical neural networks which have one input layer, multiple hidden layers and output layer. Our porposal as it is explained in details in section 4 follows the typical architecture of deep neuarl networks. The reason of chosing typical architecture is that our problem is regression problem so CNN is not be suitable for our case. CNN could be used in our case for extracting features from the dataset but we have applied features engineering by analyzing the most important technical indicators that have big impacts over the stock prices and our chosen features have been proved by the most well-known investing web portal www.investing.com and by the most popular economic traders. RNN is not suitable for our problem either because feedback connections in hidden layers leads to overfit in stock market prediction as the purpose is not remembering from old data but adjusting weights only. Finally we did not use Autoencoders as their main application is anomaly detecting and unsupervised learning but our case is supervised learning of regression type where in the training set we have label class representing the target stock price for the corresponding trading day.

3. RELATED WORKS

As stock market prediction is a time series forecasting problem, it has two main aspects: Time series aspect and forecasting aspect. It is a forecasting problem because we try to predict the next movements and prices that an index may take in the future using historical data directly or by generating indicators based on such data. And it is time series problem because the historical data used in the prediction process is sampled and acquired on the time basis where the input is such data and the output is the index value we try to predict for the next time periods. So, in order to do a thorough analysis of the problem we should divide related works and methods proposed in the literature into the following three categories:

3.1. Methods for Stock Market Forecasting

Stock market prediction is an old problem faced by traders and economic practitioners through which they try to infer the values that an index may take in the future and its next directions whether up or down to maximize their income by building investment strategies. The literature is full of with proposals to achieve this goal and in order to facilitate the problem, it is better to categorize these works into classes or categories. We prefer categorizing them according to what the traders do into their calculations. So, there will be three main work lines in analyzing stock market: Technical analysis, fundamental analysis and News and sentiments-based analysis.

News based analysis depends on analyzing financial, politic breaking news, market-based articles and their impacts on the index values and directions. While Shynkevich et al. analyzed industry-based articles to build model predicting index trends and prices, Nassirtouss, Aghabozorgi, Wah and Ngo (2015) dealt with financial breaking news headlines and proposed an approach to predict intraday forex currency-pair directions. Another work prepared by Oliveir, Cortez and Areal (2017) forecast the returns, volatility and trading volume of diverse indices and portfolios from microblogging data gathered from tweet messages and how this data has big impacts on investors' moods and so on their investment strategies. Ni, Wang and Xue (2015) investigated the relation between investors' moods and indices trends and prices. They carried out that such sentiments have considerable impacts on indices trends and prices for up to 2 years. While they are positive and large for stocks with high return in the short term, they are positive and small in the long term.

From technical school, Leigh, Purvis and Ragusa (2002) investigated the effectiveness of technical analysis in achieving high income rates. The authors emphasized through their study the importance of the “bull flag” price and volume pattern heuristic in getting high results. The indicators noticed by them and which participates in such results are used as feed to their prediction system.

Machine learning techniques are the primary methods used for predicting stock trends and prices. Gui, Wei, Shen, Qi and Guo (2014) suggested a different approach through which the prediction is not a specific value or volume but a limit instead. The authors used support vector machine feed by fuzzy particle sequences which are transformed from financial time series to build a regression model on the lower and upper bounds to decrease the estimation error.

Dechow, Hutton, Meulbroek and Sloan (2001) investigated how short-sellers build their portfolios and maximize their returns using those factors. Another work (Lewellen (2010)) analyzed the key factors of the fundamental analysis and their importance in building high return portfolio and suggested some improvements in empirical tests. Dechow Dechow, Ge and Schrand (2010) investigated the various measures of “earning quality” and how it is highly correlated with the company fundamental performance. Qian and Rasheed (2007) used the Hurst exponent to select highly predictable period, and used auto-mutual information and false nearest neighbors methods to generate training patterns or indicators. Trained by an ensemble of inductive machine learning approaches such as artificial neural networks, decision trees and k-nearest neighbors, the model achieved 60- 65% of accuracy.

Sands, Tayal, Morris and Monteiro (2015) used different classification proposals such as artificial neural networks, naïve Bayes classifier and two variants of support vector machine: SVM with least squares implementation and SVM optimized by particle swarm optimization to propose a model for building an investment portfolio with maximum return and minimum risk. They deduced that SVM optimized by particle swarm optimization can predict stock next prices and trends with high accuracy compared with other techniques. Another work (Ince and Trafalis (2017)) suggested a hybrid model for predicting stock market trends. This model is composed of ICA for selecting important features based on some technical indicators and then using kernel methods such as SVM, TWSVM, MPM, KFDA and random walk to build a model for predicting stock movements. According to their empirical

experiments on Dow-Jones, Nasdaq and S&P500 indices, the models like ICA-SVM, ICA-TWSVM, ICA-MPM and ICA-KFDA have achieved high accuracy. Basti, Kuzey and Delen (2015) investigated the most important factors affecting the short-terms performance of initial public offers for Turkish companies traded in Turkish stock market BIST using support vector machine and decision tree techniques for such purpose.

Another approach (Chen and Hao (2017)) proposed a hybrid model composed of feature weighted of both k-nearest neighbors and support vector machine. Their experiments applied on two well-known Chinese stock market indices, Shanghai and Shenzhen stock exchange indices. Teixeira and De Oliveira (2010) used k-nearest neighbors feed by technical analysis. Qian and Rasheed (2007), Zhang and Wu (2009), A. H. Moghaddam, M. H. Moghaddam and Esfandyari (2016), and Boyacioglu and Avci (2010) have investigated the use of artificial neural networks in stock market prediction.

3.2. Deep Learning for Time Series Problems

Time series prediction is an important research topic stopped over and handled by machine learning scientists. Its importance comes from that there are many important forecasting problems on time basis scuh as stock market, demand and energy load forecasting (J. Connor, Martin and Atlas (1991 and 1994)), speech recognition and robotics beside others. Deep learning is a leading technique used as proposal for such problems (Busseti, Osband and Scott (2012)) where they used deep learning architectures to predict short term electricity loads across different network grid areas, using only time and temperature data. Xueheng, Zhang, Ren, Suganthan and Amaratunga (2014) proposed an ensemble of deep learning belief networks (DBN) for regression and time series forecasting. They applied their proposal on on set of datasets of electricity load demand, artificial time series and regression datasets over other benchmark methods. (Yisheng Lv, Yanjie Duan, Wenwen Kang, Zhengxi Li, and Fei-Yue Wang, Fellow, IEEE) propsoed a novel deep-learning-based traffic flow prediction where a stacked autoencoders model is used in learning global traffic features flow and according to their experiments they have got superior performance in traffic flow prediction. Ma, Yu, Y. Wang, Tao and Y. Wang (2015) and Ma, Y.Wang , Yu and Y.Wang (2015) used deep learning approach in large-Scale transportation network congestion evolution prediction. Also an ensemble method composed of Empirical Mode

Decomposition (EMD) algorithm and deep learning method is proposed by Qiu, Ren Suganthan and Amaratunga (2017) for load demand time series forecasting.

3.3. Deep Learning for Stock Market Prediction

Deep learning as proved itself in many time series research areas such as traffic flow prediction, energy demand forecasting, it is also applied on stock market prediction. What makes deep learning approaches are more suitable for stock market forecasting is the ability of such networks to deal with huge amount of training data and extracting non-linearity models predicting the stock prices from thoses input features. Akita et al. (2016) proposed deep learning techniques for Tokyo stock market prediction. Ding et al. (2015) proposed a deep learning method for event-driven stock market prediction by extracting events from news text, representing them as dense vectors and training them by novel neural tensor network. They also used deep convolutional neural network to model the impact of both short-term and long-term events over stock price movements of S&P 500. Yoshihara et al. (2014) proposed an approach based on a recurrent deep neural network to market trend prediction using temporal effects of past events and their achievements on the the real-world data for ten Nikkei companies showed the validity of the proposed approach. Akita et al. (2016) proposed novel application of deep learning models, Paragraph Vector, and Long Short-Term Memory (LSTM) to financial time series forecasting.

Most of technical analysis-based proposals did not mention the reason behind of choosing the technical indicators used in their proposal and they chose such factors heuristically without any features engineering or what recently technical analysts prefer to use between such indicators. There are three important distinguishing aspects in our thesis; The first is using feature engineering in selecting technical indicators as features and showing their performance and validity on Turkish stock market index BIST 30. The second is using BIST 30 instead of BIST 100 or BIST 50 as BIST 30 represents the most powerful companies in the Turkish stock market and shows better performance than the other two indices. The third point in our thesis is analyzing the Turkish stock market as there are few works in this direction to the best of our knowledge. We have used have used deep learning because it proved itself in time series forecasting and our problem is another kind of time series forecasting.

4. PROPOSED MODEL

We go through this chapter to describe our model to predict directions and possible values of Turkish stock market well-known index BIST 30. We propose using deep learning technique as stock market prediction is a difficult task because of huge amount of data need to be handled, data changes rate is so high, and these changes are done in non-linearity manner. And because of our model is deep model in other words machine learning model, we should go through the steps described in Chapter 2 Section 2. In the following section we give walkthrough of developing our model.

4.1. Walkthrough

The following subsections are about machine learning steps achieved by us for developing our model.

4.1.1. Data collection and features selection

Every machine learning problem needs data or samples acquired from the target environment in order to train and validate its model and thanks to www.investing.com the most famous investing portal followed by most of traders and investors for providing historical data for most stock markets indices. We get our dataset for enough long period 36 months from 01.01.2016 to 31.12.2018. BIST 30 index is like any index or stock has the following attributes in each sample: open, low, high, close price besides to trading volume and trading date. I call them attributes not features because they are so simple and could not be used in such complex system. Table 4.1 Shows a portion of such dataset. In other words, this dataset could not be applied directly to our deep model and we need to extract features and here technical analysis comes to rescue us. Technical analysts believe strongly that this data contains useful hidden information about the future trends in short and middle terms and they developed indicators and oscillators to extract such useful information.

Table 4.1. Sample of our dataset

Date	Price	Open	High	Low	Volume
04.01.16	85,981.14	87,428.49	87,428.49	85,023.80	339.09
05.01.16	86,147.25	85,981.14	86,940.28	84,502.58	488.09
06.01.16	86,862.50	86,147.25	86,970.83	84,904.24	596.21
07.01.16	87,417.44	86,862.50	87,577.47	84,994.29	705.17
08.01.16	86,234.62	87,417.44	88,226.75	85,932.68	565.21
11.01.16	86,825.17	85,933.88	87,568.90	85,517.25	500.37
12.01.16	87,724.37	86,783.72	88,216.83	86,094.12	634.06

There are more than 150 indicators and we should select the most important ones and use them as features. For features selection, we apply feature engineering to select momentum indicators and those which give oversold and overbought regions so sell and buy signals. These indicators (11 technical indicators) are described in the chapter 2 Section 1 and given in Table 4.2. Some of these indicators have more than one output. For example, There are three outputs for Bollinger Bands indicator, one for RSI, two for STOCH, one for Williams %R, one for ROC, one for both SMA (will be droped because it is highly correlated with EMA) and EMA, three for MACD, one for CCI and one for STOCHRSI where OBV has one output but it is droped as it is highly correlated with Bollinger Bands. So Totally we have 15 outputs and they are used as inputs to out deep model. Our selection is proved and supported by most of investing portals and investors. Kim et al. (2000) used genetic algorithm to select technical indicators and the most selected features by their proposal are identical to our features. Tsai et al. (2010) also proposed combined methods: Union, intersection, and multi-intersection approaches for features selection and their work concluded to 14- 17 features and our features are among of them and so it confirmed our selection success.

Table 4.2. Technical indicators used in our proposal.

Technical Indicator Name	Considered Time Period
Relative Strength Index RSI	14 trading days
Bollinger Bands BB	21 trading days
Stochastic Oscillators STOCH	14 trading days
Williams %R	14 trading days
Price Rate of Change ROC	14 trading days
Simple Moving Average SMA	14 trading days
Exponential Moving Average EMA	14 trading days
Commodity Channel Index CCI	14 trading days
On-Balance Volume OBV	14 trading days
Moving Average Convergence Divergence MACD	14 trading days
STOCHRSI	14 trading days

4.1.2. Preparing data

The dataset which will be handled by machine learning model should be pure from some problems we mentioned them in Chapter 2. Let us start with them and make our dataset is clean from these problems.

- Missing data: This is handled by dropping them from our dataset and thanks to Python useful method called ‘dropna()’ which handle such problems.
- Correlated features: The best way to discover which features are correlated is calculating bitwise correlation between every pair of features. There is pretty method in python called corr() which calculates this bitwise correlation. Fig 4.1 shows the bitwise correlation between SMA and EMA indicators and how they are highly correlated, and this is expected case as these two features represent moving average, but one is simple and another uses exponential format.
- From Fig. 4.2 we see that OBV is highly correlated with Bollinger Bands BB, so we drop OBV and SMA indicators and continue building our model with 9 indicators i.e. 15 inputs as some indicators’ output is more than one output.

- Every indicator’s output values range differ from others and this flagged by machine learning terminology as issue, so we should normalize indicators output. Fig. 4.3 and Fig. 4.4 show histograms of features before and after normalization respectively.
- Still one issue with our dataset which is shifting issue. As our problem is time series problem in its essence, we should shift the close price y according to the target trading day. For example, if we need to predict the next trading day, we should shift y with once and twice for the second trading day and so on.

Now our dataset is clean and ready to be handled by the next steps of ML.

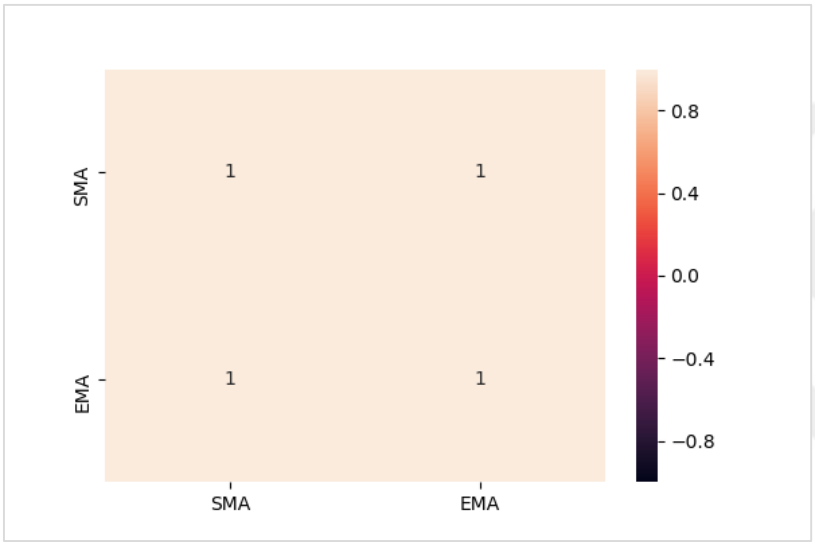


Figure 4.1. Correlation between SMA and EMA

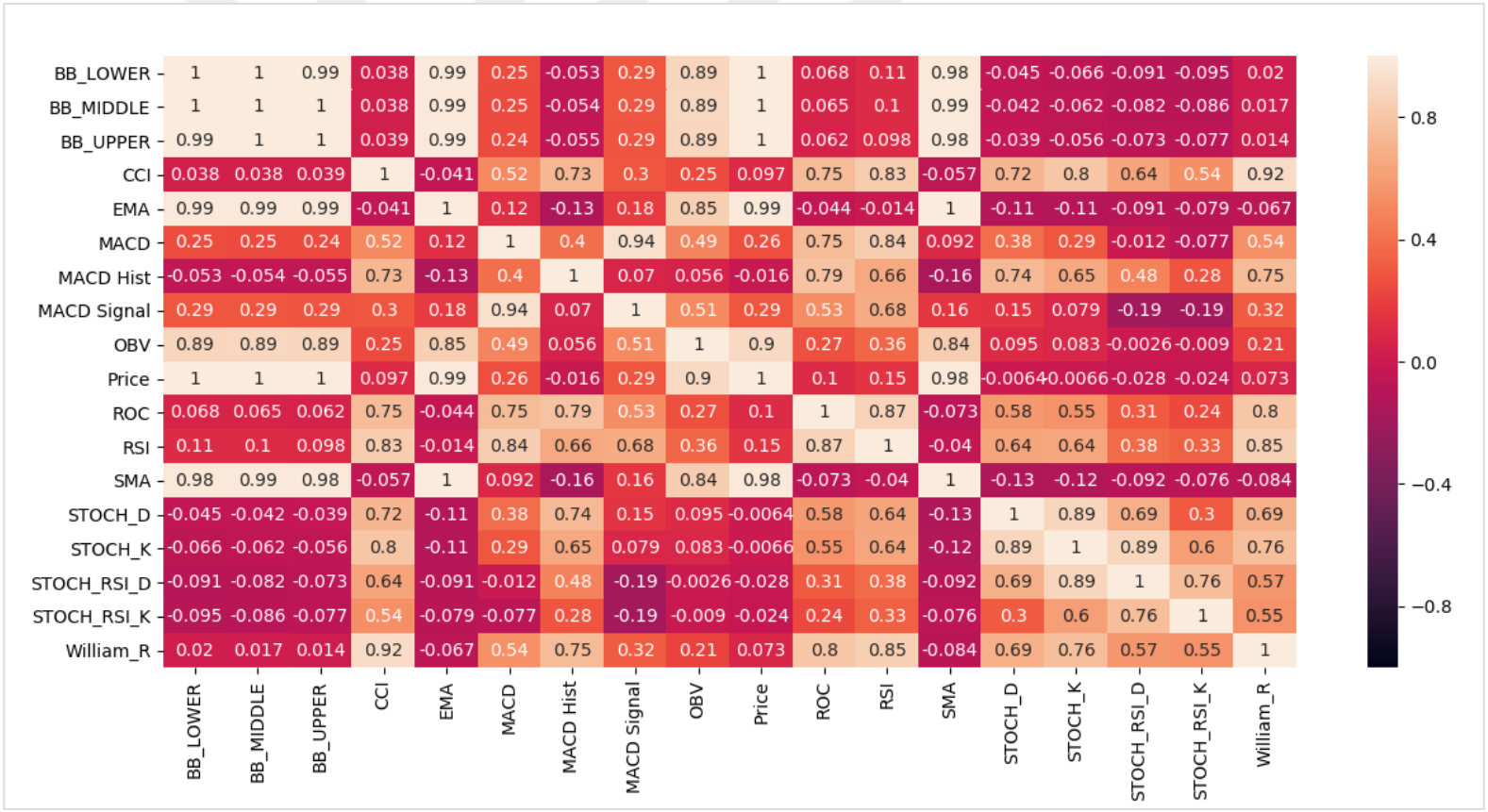


Figure 4.2. Bitwise correlation between every pair of features

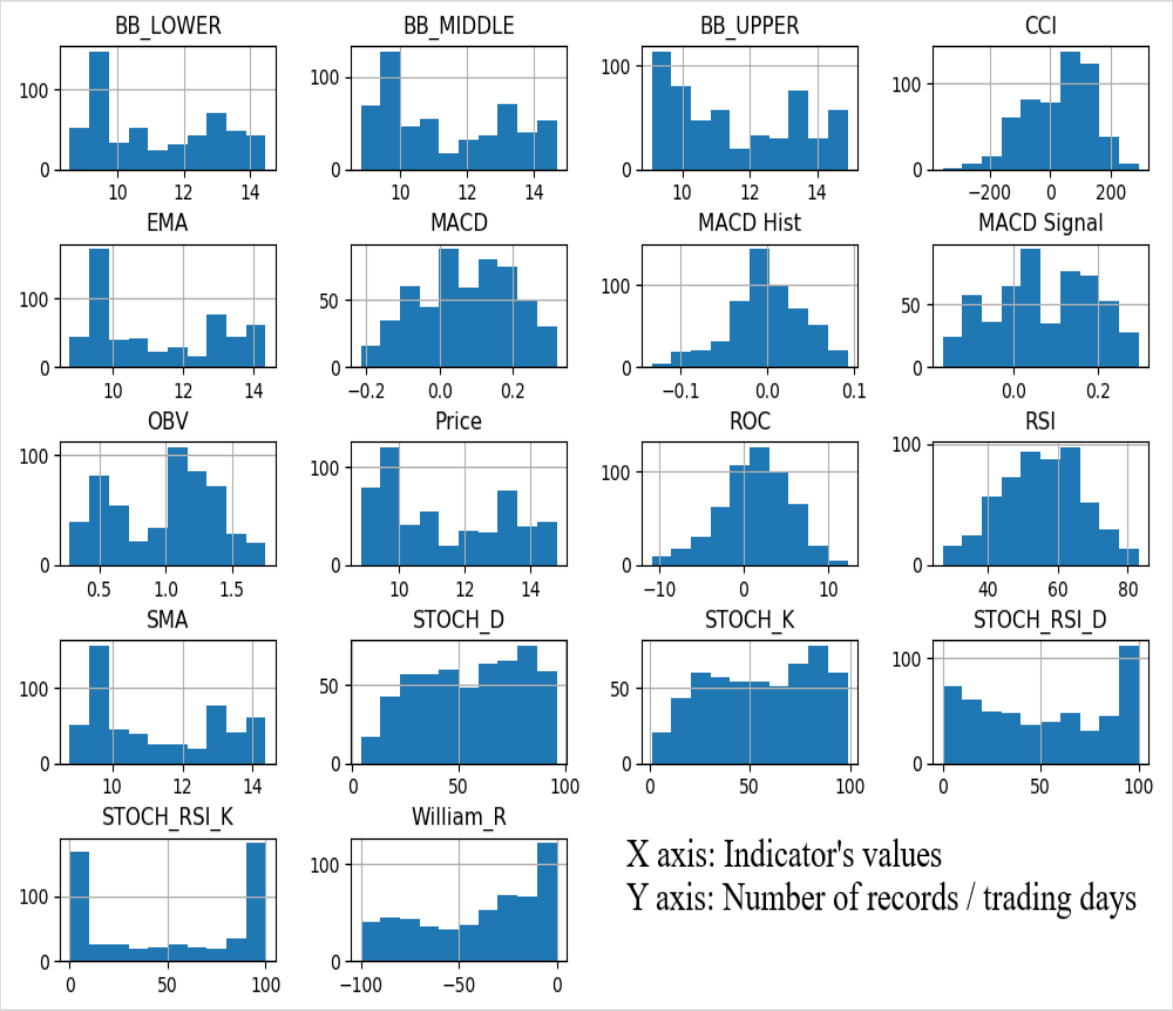


Figure 4.3. Histogram of features before normalization

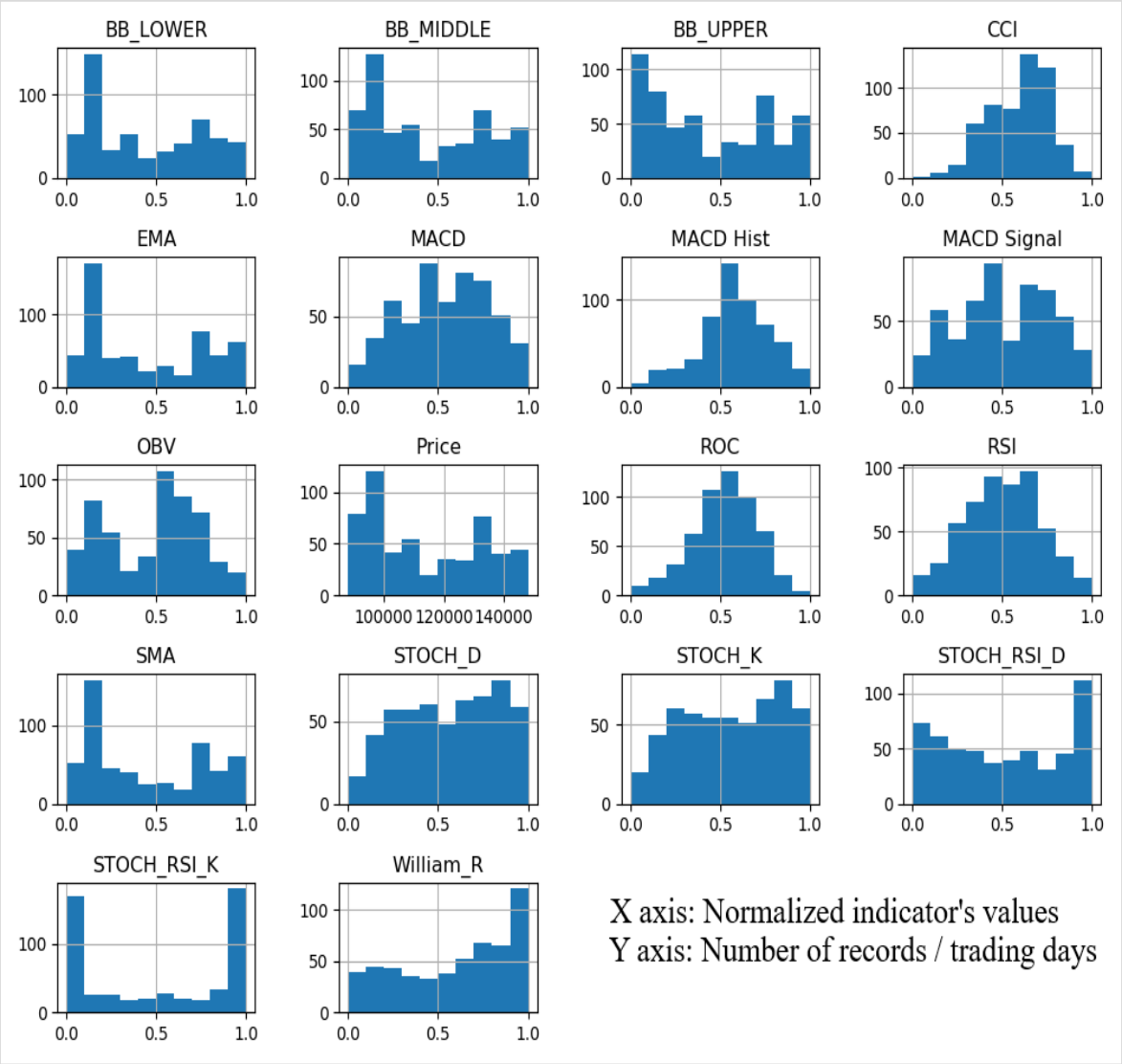


Figure 4.4. Histogram of features after normalization.

4.1.3. Choosing model

Our model is deep neural network feed with technical indicators as inputs and the output is the predicted index values. There are many architectures for deep neural networks but the most popular and widely-used ones are CNNs, RNNs, Autoencoders and typical fully foreword connected neural networks. Our deep neural network falls under the last one; typical deep neural network and the reason for choosing typical architecture is that our problem is a regression problem, so CNN would not be suitable for our case. CNN could be used in our case for extracting features from the dataset but we have applied features engineering by analyzing the most important technical indicators that have big impacts over the stock prices and our chosen features have been proved by the most well-known investing

web portal www.investing.com and by the most popular economic traders. RNN is not suitable for our problem either because feedback connections in hidden layers lead to overfit in stock market prediction as the purpose is not remembering from old data but adjusting weights only. Finally, we did not use autoencoders as their main application is anomaly detection and unsupervised learning but our case is supervised learning of regression type where in the training set we have label class representing the target stock price for the corresponding trading day.

4.1.4. Training

Our network does not have any prior knowledge about the problem we are going to solve so it needs to be learned in other words trained. Training Deep neural network means adjusting neurons weights and bias to get the desired outputs by minimizing the error in the output layer. We train our deep neural network using Keras API over the TensorFlow framework developed by Google. We have used Keras sequential model API with ReLU (Rectified Linear Unit) Activation Function for hidden layers. As our target model is a regression model, there is no need for an activation function in the output layer. The last point that we should mention is the optimizer algorithm which is responsible for adjusting weights and bias. We have used Adam adaptive moment estimation optimizer.

4.1.5. Evaluation

In this phase, we should identify the ratio of training and test set and it will be 80/20. As our problem is time series problem so there will not be cross-validation because the network could not be trained on recent data and devalued on older data. Another important point in this phase is time shifting because our problem is time series problem so the column represents the desired prices values should be shifted according to the corresponding trading day. In other words, when we train our deep neural network for the next trading day, the last column should be shifted by one before training process starts, by two for predicting the price for the next two days and so on.

4.1.6. Hyperparameter tuning

Typically, it is hard to generate a robust and highly accurate model on the first run of an algorithm. Thus, some parameters of the model should be readjusted to decrease the loss of the regression model. Possible changes include increasing or decreasing the number of hidden layers, number of the neurons in such layers, activation function and optimizer algorithm used for training the network. We have achieved the desired performance with 7 hidden layers and 2 dropout layers, Relu as an activation function and Adam as an optimizer. Fig. 4.5. shows our network where the input layer has 15 neurons (technical indicators after dropping SMA and OBV) and the output layer has only one neuron as we try to predict the index value (one value). In the other hand, there are 7 hidden layers with 512, 256, 128, 64, 32, 16, 8 neurons respectively. There are two dropout layers after the first and the second hidden layer with 30% and 25% as dropout rates respectively.

4.1.7. Prediction

After adjusting the parameters which helped to obtain an acceptable model, this model applied over the test set data to make predictions and evaluate the performance using various metrics. Performance evaluation metrics differ from one problem to another. For example for classification problem, generally we use confusion matrix by which we calculate true positive, true negative, false positive and false negative besides to accuracy, precision, recall and Sensitivity. In the other hand and because our problem is regression problem following metrics: mean squared error (MSE), mean absolute percentage error (MAPE), mean absolute error (MAE) and R2 score. It is important to mention here that there is an extra input represernts the trading day we are going to predict BIST30 value for, so we can say there are five different models in our case; one model for each trading day.

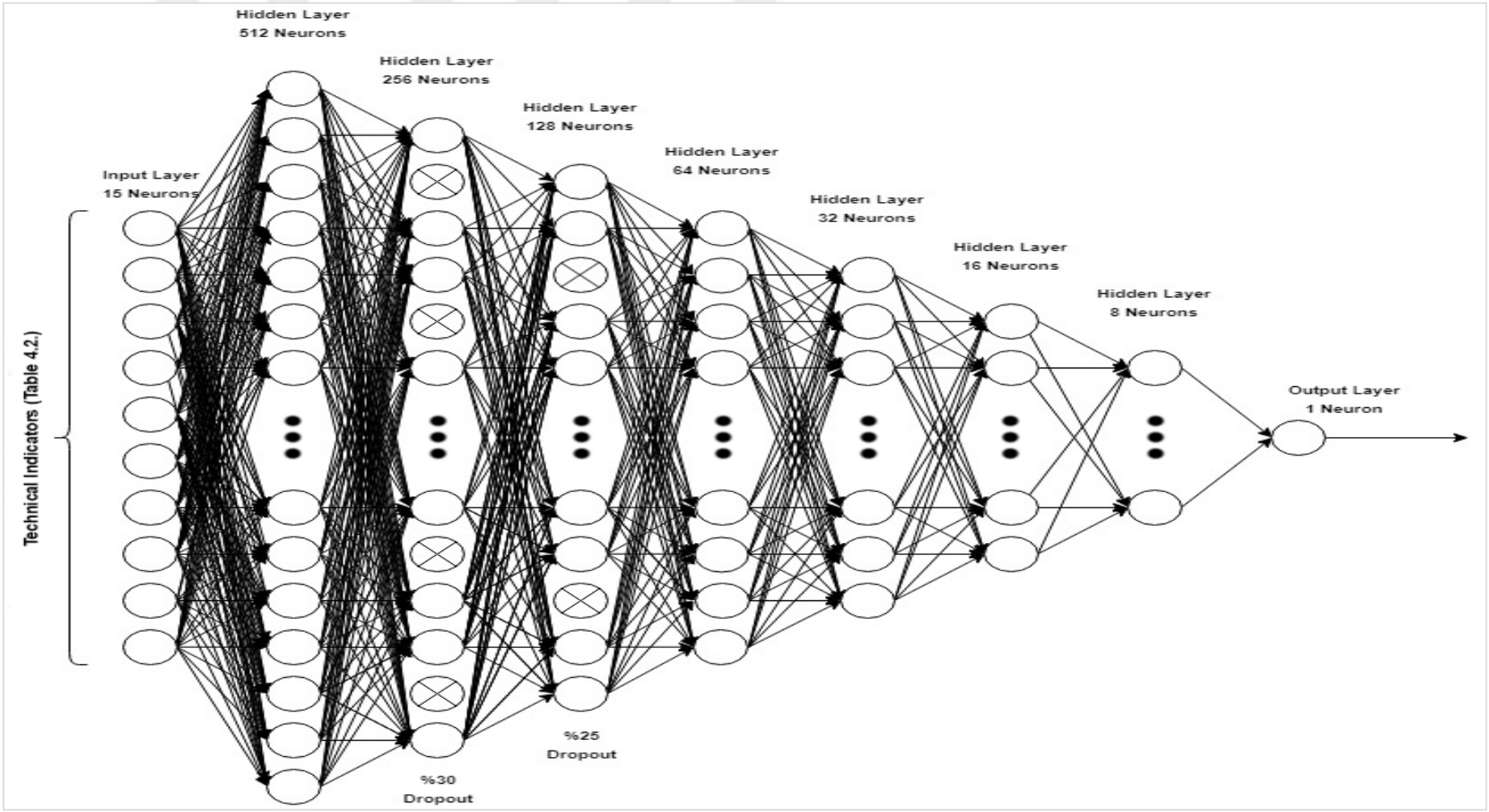


Figure 4.5. Deep neural network used in our work

5. EXPERIMENTAL RESULTS

We have proposed a deep learning network for predicting the close prices and directions for Turkish stock market well-known BIST 30 index for the next five trading days. Our experiments have been done over a dataset got from the most famous investing portal followed by the most traders and investors www.investing.com for 36 months from 01.01.2016 to 31.12.2018. We feed our deep network with technical indicators calculated from index historical data because this data contains simple information about the index such as open, low, high and close prices besides to trading volume and trading day. Another reasons for choosing technical indicators because they have revealed useful hidden information from such data and gives buy and sell signals that help traders to take actions when the prices come to specific region. Dataset is cleaned from some problems that paralyze the network from being learned well such as missing data by dropping them, detecting correlated features by checking bitwise correlation between every pair of features and dropping them, Normalizing technical indicators data as every indicator output ranges differ from others and last issue with dataset is shifting according the target trading day as our problem is time series problem in its essence.

Training and test ratio is 80/20 where 80% of dataset (80% of 36 months) is used for training our deep network and 20% of it used for evaluating its performance and accuracy. Cross validation could not be applied on our problem because it is time series problem, and in such problem, network could not be trained on recent data and evaluated with older data.

Predicting next possible close values of the index is regression problem so and in order to evaluate our model performance we should use the following metrics: mean squared error (MSE), mean absolute percentage error (MAPE), mean absolute error (MAE) and R2 score. We compared our model with two works like (Patel et al., 2015) and (Sakarya et al., 2015). The reason of using multiple metrics in our performance comparison because each one gives different valuable information not given by other metrics. When R2 score is negative and MSE value is very low this means the model is arbitrary and did not train well. R2 score considers good when its value so close to zero and its best value is 1.

Fig. 5.1. shows the loss achieved by our model. Our model is trained well because the loss value is close to zero as it is depicted in fig. 5.1. Table 4.2 provides the performance metrics

achieved by our deep learning model for the first five trading days and compare them with two other methods: regular ANN (artificial neural network) and SVR (support vector regression). Our deep learning model clearly outperforms and gives better results than ANN for the first five trading days and SVR for the first four trading days, whereas SVR gives better results for the fifth trading day. Also, our deep neural network model outperforms the proposal presented by Patel et al. (2015) where MSE values of our model for the first five days are 0.0302, 0.1009, 0.0930, 0.1075 and 0.2781 vs. 0.4427, 0.8748, 1.3556, 1.8445 and 2.3455 for the other work as it is given in Table 5.2. Another comparison between our deep learning model with an ANN-based proposal by Sakarya et al. (2015) given in Table 5.3. shows that our proposed model produces 1.6743 as MAPE while the other proposal produces 2.015 for the next trading day when using their dataset and gives 1.0676 on our own dataset. Fig. 5.2, Fig. 5.3, Fig. 5.4, Fig. 5.5 and Fig. 5.6 plot predicted closing prices vs. real closing prices for the five next trading days. We observe that the predicted prices closely follow the actual trends in the first five trading days, where the our deep model gives better results in the first four days compared to SVM and ANN but for the fifth trading day, SVM exceeds our model and gives better result.

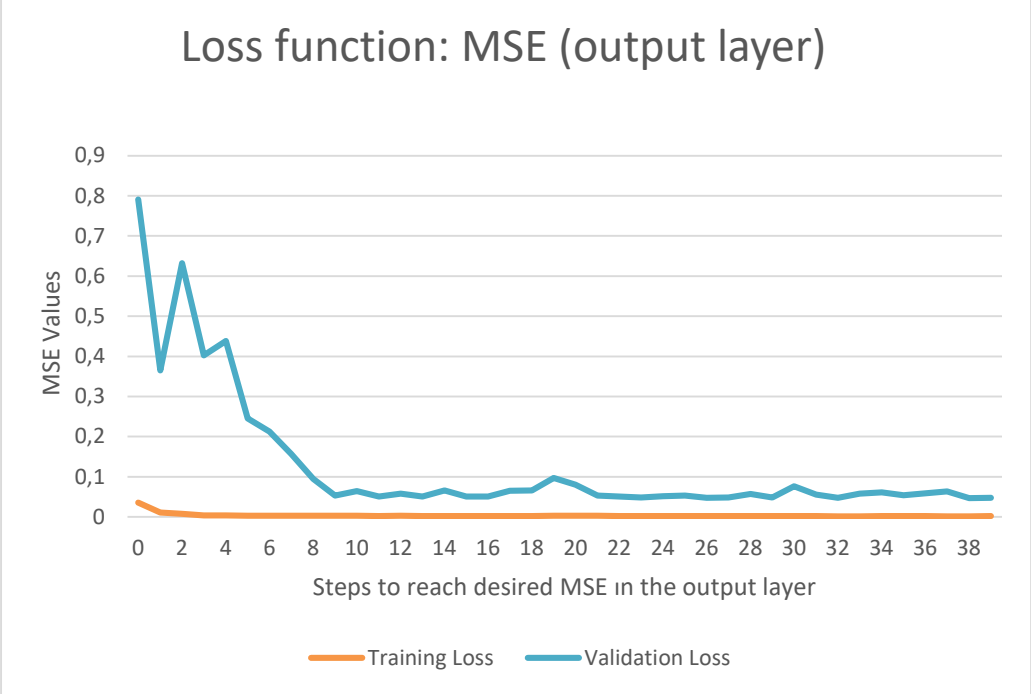


Figure 5.1. Loss achieved by our model for the next trading day

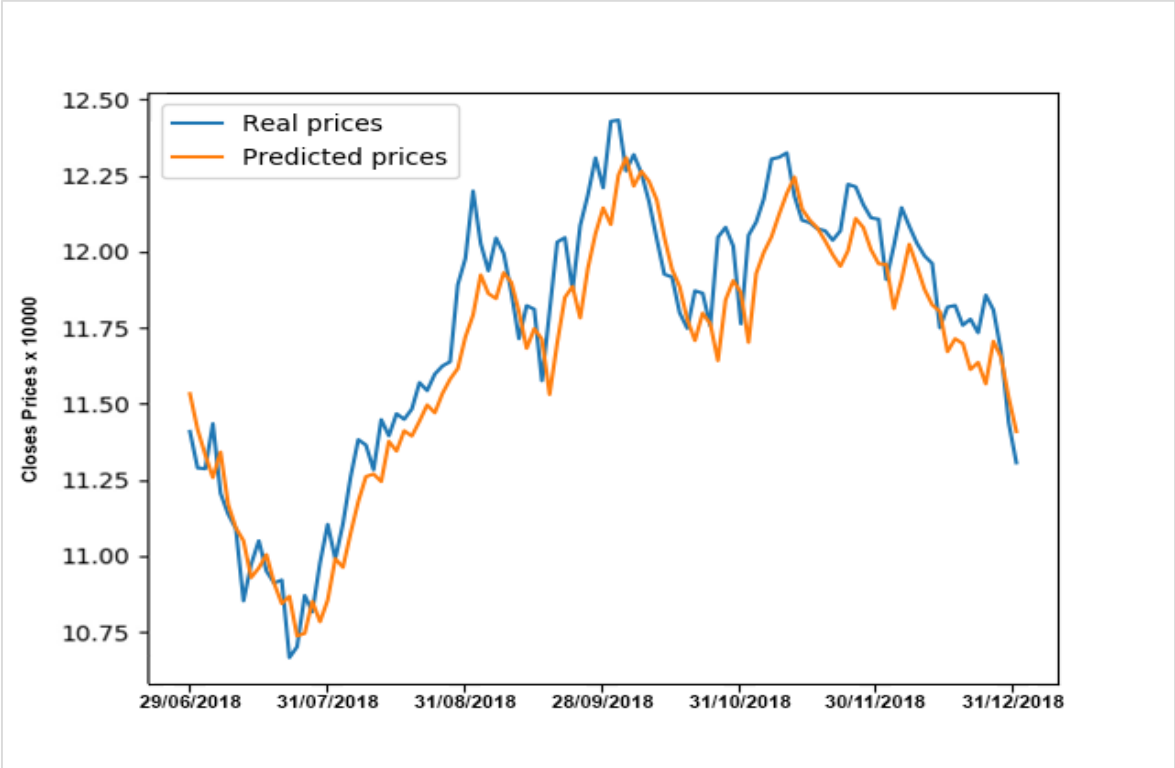


Figure 5.2. Actual vs. predicted prices for the next trading day

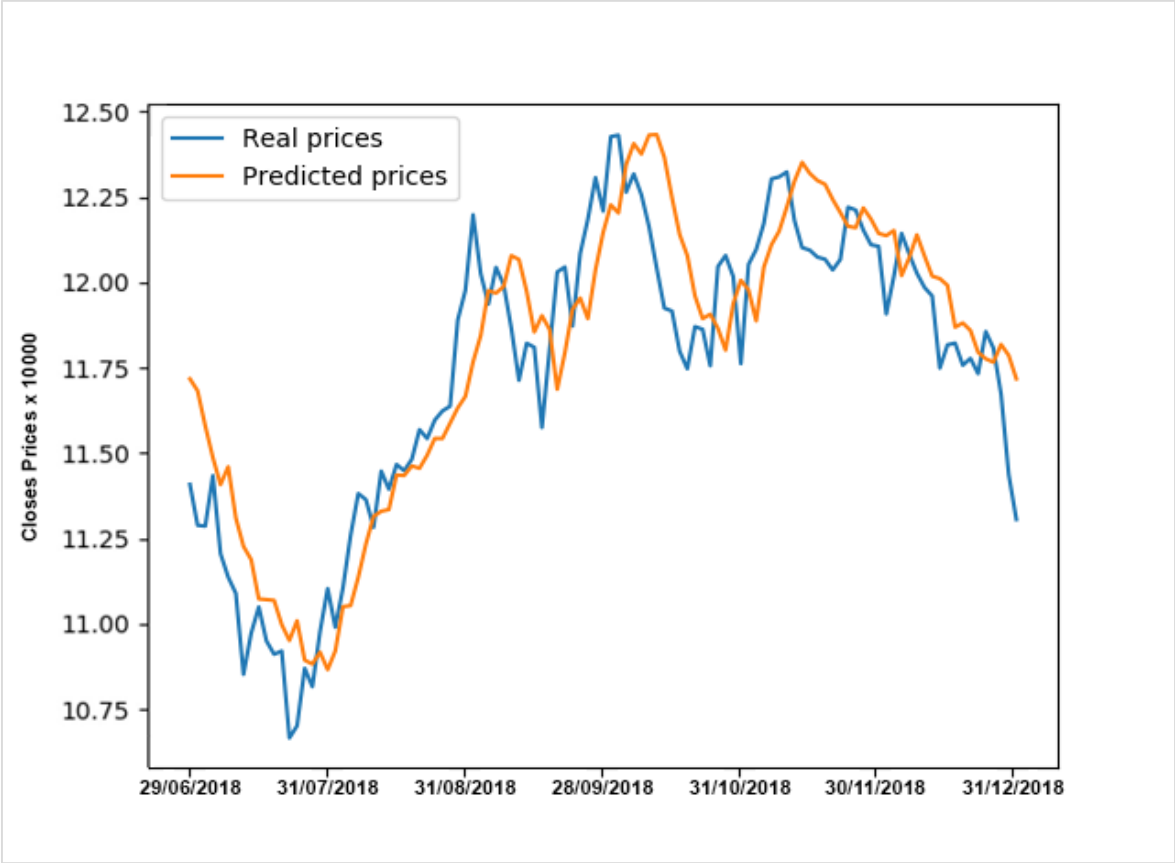


Figure 5.3. Actual vs. predicted prices for the next second trading day

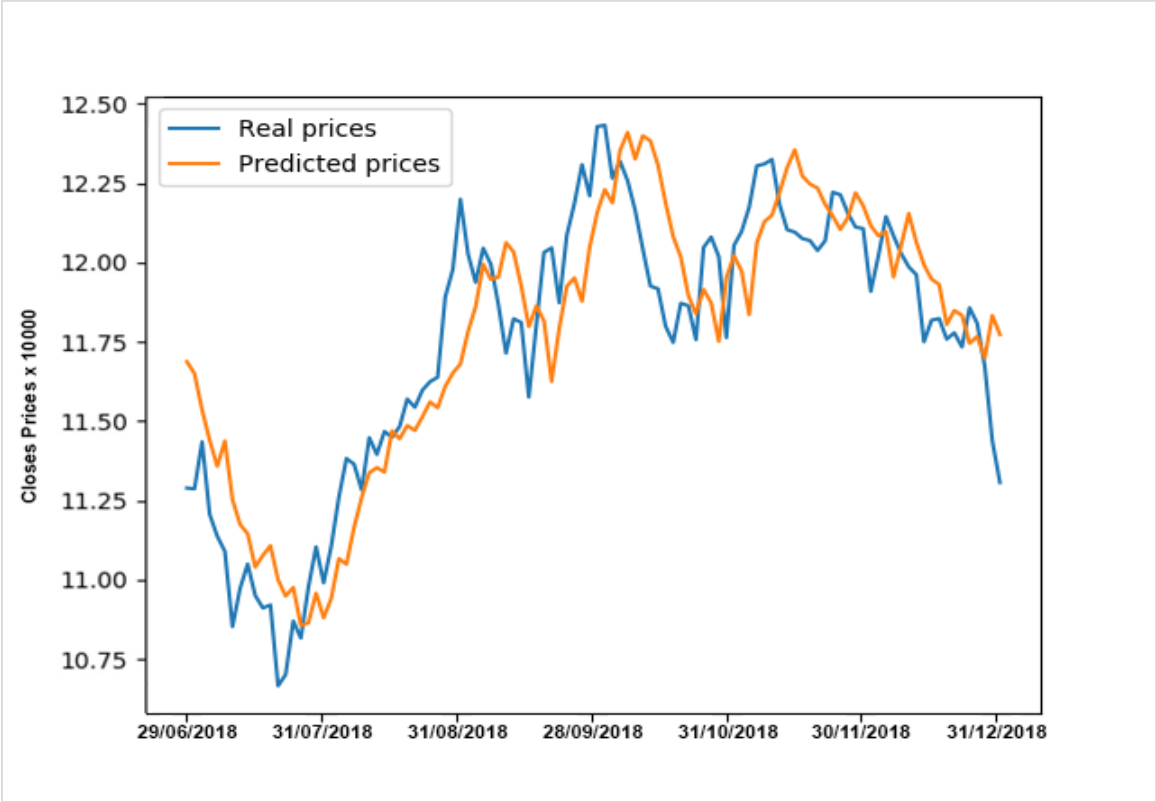


Figure 5.4. Actual vs. predicted prices for the next third trading day

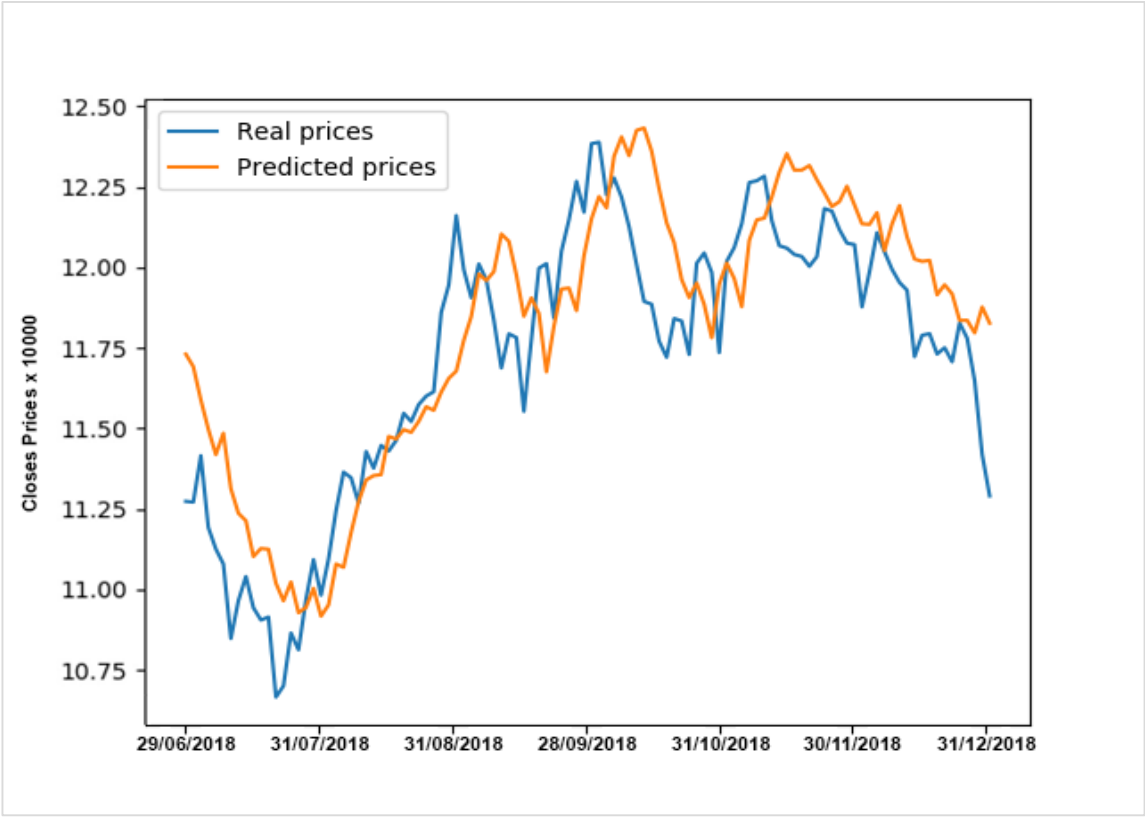


Figure 5.5. Actual vs. predicted prices for the next fourth trading day

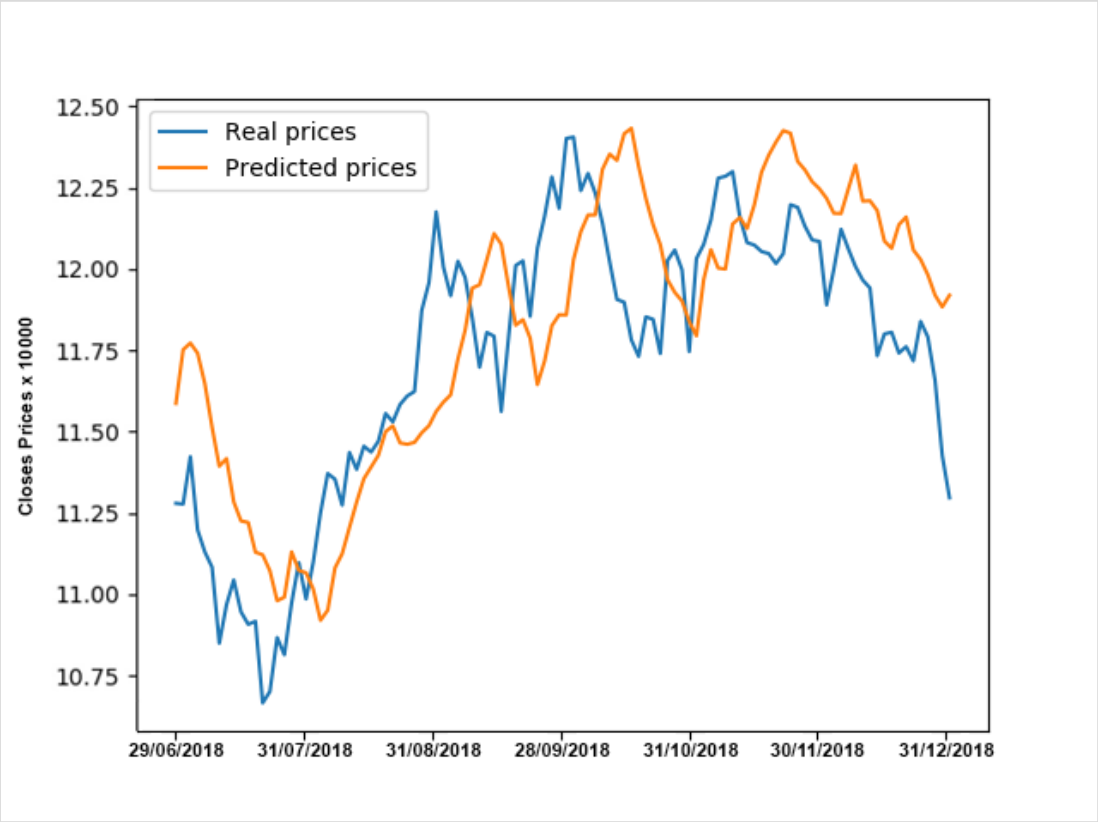


Figure 5.6. Actual vs. predicted prices for the next fifth trading day

Table 5.1. Performance comparison for the next five trading days

		MSE	R2 Score	MAE	MAPE
1st Trading Day	Deep Model	0.0302	0.8927	0.1455	1.0643
	SVR	0.1846	0.422	0.3844	2.7585
	ANN	0.8866	-1.8311	0.7703	5.537
2nd Trading Day	Deep Model	0.1009	0.6518	0.2714	1.6726
	SVR	0.1448	0.5374	0.3188	2.2634
	ANN	0.5971	-1.301	0.7747	4.5565
3rd Trading Day	Deep Model	0.0930	0.7105	0.2732	1.7052
	SVR	0.1009	0.6789	0.2580	1.8394
	ANN	0.4554	-0.4488	0.5635	4.0630
4th Trading Day	Deep Model	0.1075	0.6598	0.2669	1.6103
	SVR	0.0996	0.6831	0.2609	1.8694
	ANN	5.9874	-16.545	2.4313	14.9569
5th Trading Day	Deep Model	0.2781	0.1737	0.4215	3.1046
	SVR	0.1496	0.5240	0.3160	2.2551
	ANN	2.9015	-8.6205	1.6230	10.5003

Table 5.2. Comparison between our proposal and work by Patel et al. (2015) using MSE as metric

Trading Day	Our proposal	Patel et al. (2015)
1st trading day	0.0302	0.4427
2nd trading day	0.1009	0.8748
3rd trading day	0.0930	1.3556
4th trading day	0.1075	1.8445
5th trading day	0.2781	2.3455

Table 5.3. Comparison between our proposal and work by Sakarya et al. (2015) using MAPE as metric

	Our Proposal	Other proposal
next trading day	1.6743	2.015

6. CONCLUSIONS

What does make prediction of the next possible close prices of stock market indices challenging task is non-linearity and high volatility of their prices changes during the trading process. Successful and accurate prediction of stock close prices would immensely help traders and investors build a high-return investment strategies and portfolios. Generally, stock market prediction can be categorized into three camps in terms of the features and factors used to build prediction models: Technical analysis-based proposals, fundamental analysis-based proposals and news and investors' moods based proposals. Technical analysts strongly believe that there are relationships between the historical stock price values and the next prices that an index may take in short and medium terms and they build and calculate indicators, charts to extract such hidden information.

On the other hand, fundamental analysts think that you would not invest in any company shares if you are not making fundamental analysis about the company itself besides other issues and according to them in order to build strong investment strategies and powerful portfolios you should strongly analyze the long-term factors which involve looking at revenue, expenses, assets, liabilities and all the other financial aspects of a company.

Also, some of economic analysts analyze economic and politic breaking news and decide their next actions in building their investment strategies. They believe that good news whether politic or economic will relax both national and foreign investors to invest more and more and this leads to increasing in stock shares demands and so their prices will increase. On other hand, bad news will make them feel afraid and pull back their investments and so decreasing the trading volume and this opens the way to lose the shares their prices and directions.

There are three most important indices for Turkish stock market: BIST 30, BIST 50 and BIST 100. BIST 30 shows better performance than the other two indices because it represents only the most powerful companies in Turkey in terms their capitals, trading volumes and stable managements compared to the other two indices which represent smaller companies suffer from such problems and this resides behind our choice for selecting BIST30 in our thesis.

We addressed in this thesis BIST 30 index prediction problem using deep learning technique where features are selected from common important technical indicators following feature engineering and our selection is proved by the most well known investing portal www.investing.com which is followed by the most traders and economic practitioners. Using historical data of BIST 30 index for long enough period from 01.01.2016 to 31.12.2018 from the same portal, we trained and tested our model for predicting for the next five trading days. According to our experiments, our model outperforms other techniques like ANN and SVR as well as comparable proposals in the literature (Patel et al., 2015, Sakarya et al., 2015).

Therefore, we conclude that deep learning as proved its performance in other time series forecasting such as energy demand forecasting it also proved itself as a promising solution for stock market forecasting subjects.

REFERENCES

Akita, R., Yoshihara, A., Matsubara, T. ve Uehara, K. (2016). *Deep learning for stock prediction using numerical and textual information.* The Institute of Electrical and Electronics Engineers, Computer and Information Science (ICIS), Okayama, Japan.

Bastı, E., Kuzey, C., & Delen, D. (2015). Analyzing initial public offerings' short-term performance using decision trees and SVMs. *Decision Support Systems, 73*, 15-27.

Bollinger, J. (2001). *Bollinger on bollinger bands.* New York: McGraw-Hill Education, 15.

Boyacioglu, M. A. ve Avci, D. (2010). An Adaptive Network-Based Fuzzy Inference System (ANFIS) for the prediction of stock market return: The case of the Istanbul Stock Exchange. *Expert Systems with Applications,* 37(12), 7908-7912.

Chen, Y. ve Hao, Y. (2017). A feature weighted support vector machine and K-nearest neighbor algorithm for stock market indices prediction. *Expert Systems with Applications,* 80, 340-355.

Connor, J. T., Atlas, L. E., ve Martin, D. (1991, July). *Recurrent neural networks and load forecasting.* At the paper Proceedings of the First International Forum on Applications of Neural Networks to Power Systems (pp. 22-25). The Institute of Electrical and Electronics Engineers.

Connor, J. T., Martin, R. D., ve Atlas, L. E. (1994). Recurrent neural networks and robust time series prediction. *IEEE Transactions on Neural Networks*, 5(2), 240-254.

Dechow, P. M., Hutton, A. P., Meulbroek, L. ve Sloan, R. G. (2001). Short-sellers, fundamental analysis, and stock returns. *Journal of Financial Economics,* 61(1), 77-106.

Dechow, P., Ge, W. ve Schrand, C. (2010). Understanding earnings quality: A review of the proxies, their determinants and their consequences. *Journal of Accounting and Economics,* 50(2-3), 344-40.

Granville, J. E. (1976). *Granville's new strategy of daily stock market timing for maximum profit.* New York: Prentice-Hall, Inc., 15.

Gui, B., Wei, X., Shen, Q. Qi, J. ve Guo, L. (2014). *Financial time series forecasting using support vector machine. The* Institute of Electrical and Electronics Engineers, CIS, 15-16.

Ince, H. & Trafalis, T. B. (2017). A Hybrid forecasting model for stock market prediction. *Economic Computation and Economic Cybernetics Studies and Research,* 51(3).

İnternet: Busseti, E., Osband, I. ve Wong, S. (2012). *Deep learning for time series modeling,* http://www.webcitation.org/query?url=http%3A%2F%2Fwww.semanticscholar.org.&date=2019-05-01, Son Erişim Tarihi: 17.03.2019.

İnternet: Ding, X. Zhang, Y. Liu, T. Duan, J. (2015). *Deep Learning for Event-Driven Stock Prediction.* At the paper AAAI Publications, Twenty-Fourth International Joint

Conference on Artificial Intelligence. http://www.webcitation.org/query?url=https%3A%2F%2Fwww.aaai.org%2Focs%2Findex.php%2FIJCAI%2FIJCAI15%2Fpaper%2Fview%2F11031%2F10986&date=2019-05-01, Son Erişim Tarihi: 17.03.2019.

İnternet: Vázquez, F. (2017). Deep Learning made easy with Deep Cognition. http://www.webcitation.org/query?url=https%3A%2F%2Fbecominghuman.ai%2Fdeep-learning-made-easy-with-deep-cognition-403fbe445351.+&date=2019-05-01, Son Erişim Tarihi: 17.03.2019.

İnternet: Website 1, http://www.webcitation.org/query?url=http%3A%2F%2Fwww.fidelity.com.&date=2019-05-01, Son Erişim Tarihi: 17.03.2019

İnternet: Website 2, Machine Learning For Beginners From Zero Level, http://www.webcitation.org/query?url=https%3A%2F%2Fblog.usejournal.com%2Fmachine-learning-for-beginners-from-zero-level-8be5b89bf77c.&date=2019-05-01, Son Erişim Tarihi: 17.03.2019.

İnternet: Website 3, Understanding of Convolutional Neural Network (CNN)—Deep Learning, http://www.webcitation.org/query?url=https%3A%2F%2Fmedium.com%2F%40RaghavPrabhu%2Funderstanding-of-convolutional-neural-network-cnn-deep-learning-99760835f148.+&date=2019-05-018, Son Erişim Tarihi: 17.03.2019.

İnternet: Website 4, Deep learning architectures, http://www.webcitation.org/query?url=https%3A%2F%2Fdeveloper.ibm.com%2Farticles%2Fcc-machine-learning-deep-learning-architectures.+&date=2019-05-01, Son Erişim Tarihi: 17.03.2019.

İnternet: Website 5, Applied Deep Learning - Part 3: Autoencoders. http://www.webcitation.org/query?url=https%3A%2F%2Ftowardsdatascience.com%2Fapplied-deep-learning-part-3-autoencoders-1c083af4d798.&date=2019-05-01, Son Erişim Tarihi: 17.03.2019.

İnternet: Yoshihara, A. Fujikawa, K. Seki, K. Uehara, K. (2014). Predicting Stock Market Trends by Recurrent Deep Neural Networks, PRICAI 2014: Trends in Artificial Intelligence, 759-769. http://www.webcitation.org/query?url=https%3A%2F%2Flink.springer.com%2Fchapter%2F10.1007%2F978-3-319-13560-1_60&date=2019-05-01, Son Erişim Tarihi: 17.03.2019.

Kim, K. J., ve Han, I. (2000). Genetic algorithms approach to feature discretization in artificial neural networks for the prediction of stock price index. *Expert systems with Applications*, *19*(2), 125-132.

Leigh, W., Purvis, R. ve Ragusa, J. M. (2002). Forecasting the NYSE Composite Index with Technical Analysis, Pattern Recognizer, Neural Network, and Genetic Algorithm: A Case Study in Romantic Decision Support. *Decision Support Systems,* 32, 361-377.

Lewellen, J. (2010). Accounting anomalies and fundamental analysis: An alternative view. *Journal of Accounting and Economics,* 50(2-3), 455-466.

Ma, X., Tao, Z., Wang, Y., Yu, H., ve Wang, Y. (2015). Long short-term memory neural network for traffic speed prediction using remote microwave sensor data. *Transportation Research Part C: Emerging Technologies*, 54, 187-197.

Ma, X., Yu, H., Wang, Y., ve Wang, Y. (2015). Large-scale transportation network congestion evolution prediction using deep learning theory. *PloS one*, *10*(3), e0119044.

Moghaddam, A. H., Moghaddam, M. H. ve Esfandyari, M. (2016). Stock market index prediction using artificial neural network. *Journal of Economics, Finance and Administrative Science,* 21(41), 89-93.

Nassirtoussi, A. K., Aghabozorgi, S., Wah, T. Y. ve Ngo, D. C. L. (2015). Text mining of news-headlines for FOREX market prediction: A Multi-layer Dimension Reduction Algorithm with semantics and sentiment. *Expert Systems with Applications,* 42(1), 306-324.

Ni, Z., Wang, D. ve Xue, W. (2015). Investor sentiment and its nonlinear effect on stock returns—New evidence from the Chinese stock market based on panel quantile regression model. *Economic Modelling,* 50, 266-274.

Oliveir, N., Cortez, P. ve Areal, N. (2017). The impact of microblogging data for stock market prediction: Using Twitter to predict returns, volatility, trading volume and survey sentiment indices. *Expert Systems with Applications,* 73, 125-144.

Patel, J., Shah, S., Thakkar, P. ve Kotecha, K. (2015). Predicting stock market index using fusion of machine learning techniques. *Expert Systems with Applications*, 42, 2162–2172.

Qian, B. & Rasheed, K. (2007). Stock market prediction with multiple classifiers. *Springer, Applied Intelligence*, 26(1), 25–33.

Qiu, X. Ren, Y. Suganthan, P. N. ve Amaratungab, C. A.J. (2017) Empirical Mode Decomposition based ensemble deep learning for load demand time series forecasting. *Applied Soft Computing*, 54, 246-255.

Qiu, X., Zhang, L., Ren, Y., Suganthan, P. N., ve Amaratunga, G. (2014, December). Ensemble deep learning for regression and time series forecasting. At the paper 2014 IEEE Symposium on Computational Intelligence in Ensemble Learning (CIEL), Orlando, FL, USA.

Sakarya, S., Yavuz, M., Karaoglan, A. D., ve Özdemir, N. (2015). Stock market index prediction with neural network during financial crises: a review on Bist-100. *Financial Risk and Management Reviews*, 1(2), 53-67.

Sands, T. M., Tayal, D., Morris, M. E., ve Monteiro, S. T. (2015, May). *Robust stock value prediction using support vector machines with particle swarm optimization.* At the paper *2015* The Institute of Electrical and Electronics Engineers Congress on Evolutionary Computation, Sendai, Japan

Shynkevich, Y., McGinnity, T.M., Coleman, S. ve Belatreche, A. (2015). *Stock price prediction based on stock-specific and sub-industry-specific news articles.* International Journal of Computer Science & Information Technology , 8(3), 12-17.

Teixeira, L. A. ve De Oliveira, A. L. I. (2010). A method for automatic stock trading combining technical analysis and nearest neighbor classification. *Expert Systems with Applications,* 37(10), 6885-6890.

Tsai, C. F., ve Hsiao, Y. C. (2010). Combining multiple feature selection methods for stock prediction: Union, intersection, and multi-intersection approaches. *Decision Support Systems*, 50(1), 258-269.

Welles Jr, J. (1978). *New concepts in technical trading systems.* Greensboro, NC: Hunter Publishing Company, 12.

Williams, L. (1973). *How ı made one million dollars last year trading commodities.* Conceptual Management, Montery, CA.

Zhang, Y. ve Wu, L. (2009). Stock market prediction of S&P 500 via combination of improved BCO approach and BP neural network. *Expert Systems with Applications,* 36(5), 8849-8854.

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