Middle East Technical University
Informatics Institute

RESEARCH PROPOSAL

COMPARISON OF STOCK MARKET PREDICTION ARCHITECTURES BASED ON GENERATIVE ADVERSARIAL NETWORK FOR A SHALLOW STOCK MARKET: BORSA ISTANBUL

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January 2021

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ARAŞTIRMA ÖNERİSİ

SIĞ BİR HİSSE SENEDİ PİYASASI İÇİN ÜRETİCİ ÇEKİŞMELİ AĞA DAYALI HİSSE SENEDİ PİYASASI TAHMİN MİMARİLERİNİN KARŞILAŞTIRILMASI: BORSA İSTANBUL

Danışman Adı:
(ODTÜ)

Öğrenci Adı: Şükrü Alataş

Ocak 2021

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LIST OF SYMBOLS / ABBREVIATIONS

AE	Autoencoders
ANN	Artificial neural networks
AR	Average Return
ARIMA	Autoregressive integrated moving average
ARMA	Auto-regression and moving average
BIST	Borsa Istanbul
CNN	Convolutional Neural Network
DAN2	Dynamic Architecture for Artificial Neural Networks
DBN	Deep Belief Networks
DNN	Deep neural network
GAN	Generative Adversarial Network
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
KNN	K-nearest neighbors
LR	Logistic regression
LSTM	Long-Short Time Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MLP	Multi-layer perceptron
NASDAQ	National Association of Securities Dealers Automated Quotations
NB	Naive Bayes
NYSE	New York Stock Exchange
RF	Random forest
RMSE	Root Mean Square Error
RMSRE	Root Mean Square Relative Error
RNN	Recurrent Neural Networks
SAE	Stacked-Autoencoders
SVM	Support vector machine

I. Introduction

Stock market forecasting is a fundamental process for professional market players, like traders or investors. Even if the player does not have a professional prospect for the stock market, the prediction capability directly determines its success in the market. The decisions to buy or sell a stock could be bonded for many different aspects of the global or local economy, the market, and the stock itself. These aspects are separated into two are technical analysis and fundamental analysis (Gunduz et al., 2017). The fundamental analysis deals with the more fundamental prospects about the economy in general (like inflation, unemployment) and the company's performance in the sector of its business. These aspects could be used to understand the current situation and the future trends about the stock and infer some stock's performance predictions. The technical analysis, on the opposite, uses historical data of the stock (like price, volume, etc.) to predict the stock's future performance.

However, predicting stock prices is not an easy task due to the complexity and chaotic dynamics of the markets and the many unstable stochastic variables involved (Marszałek & Burczyński, 2014).

There are several forecasting technical analysis methods that are mostly using numerical data, such as historical stock prices. (Gunduz et al., 2017; Hagenau et al., 2013; K. J. Kim & Han, 2000; Marček, 2004). These methods model the relationship between the historical behavior and future movement of the price and using historical market samples to predict the future trend or value of the price (K. J. Kim & Han, 2000).

These previous studies were mostly conducted on the stock markets like the New York Stock Exchange (NYSE), Shanghai Stock Exchange, which have the world's largest stock exchanges. This high volume of trading keeps the stock prices and the volatility of the market low. Because every player cannot change the price of a stock on his own, the market's atomicity rule could be instantiated with the help of a high volume. Atomicity also turns these markets more predictable due to the features of a stock or the whole stock market depend on a crowded group of players' decisions.

On the contrary, the stock markets that have not this much trading volume, we can call them shallow stock markets, suffer from the lack of atomicity. These stock markets depend on more prominent players' decisions and foreign traders. This makes these markets more volatile and fragile to the real prospects like inflation, unemployment rate, etc. As a result of this, it is hard to predict these markets' direction with technical analysis techniques.

Borsa Istanbul has a total market capitalization of $211.66 billion when the New York Stock Exchange has $22.38 trillion, nearly 100 times more. According to the World Bank's statistics in 2018, the turnover ratio, which is an indicator to reflect the proportion of stocks that have changed in one year, was 247.8% for Borsa Istanbul when it was 108.5% NYSE. This indicates the Borsa Istanbul volatility is nearly 2.5 times more in the 100 times lower market volume against NYSE.

These indicators prove that it is harder to predict future stock performance with the technical analysis in a market like Borsa Istanbul. But, there are also promising new tools that have arisen for technical analysis. We will take a look into these solutions in chapter 2. We will briefly mention traditional and machine-learning-based technical analysis techniques first. Afterward, we will take a closer look at the arisen deep neural network (DNN) based tools. Then, we will introduce a new DNN architecture named "Generative Adversarial Network" or GAN.

This new architecture brings a fresh perspective to DNN tools as well as DNN-based stock market prediction methods. Although there are very few attempts using GAN-based architectures for the prediction of stock markets in the literature, they had very promising results on the well-known US and China-based stock markets. However, as mentioned before, they need to be tested on a stock market like Borsa Istanbul to prove their contribution to the literature.

Our assumption about this study's first possible contribution is to test these GAN-based architectures' performance in a very different stock market with different dynamics like Borsa Istanbul. The second contribution is to compare the former approaches on the market along with these new GAN-based architectures on this type of stock market.

Our first research question is: Can GAN-based architectures achieve better performance for predicting a stock market with a lower market cap and higher volatility?

And the second research question is: What is the best technical analysis approach for predicting a stock market with a lower market cap and higher volatility?

And finally, in chapter 3, we will provide our proposed methodology for answering these research questions.

II. Related Work

This section has brief information about the previous attempts of traditional statistical approaches first, then the machine learning and deep neural network-based approaches.

A. Traditional and Emerging Approaches

Traditional statistical methods such as linear regression, "auto-regression and moving average" (ARMA), and "Generalized Autoregressive Conditional Heteroscedasticity" (GARCH) are commonly used for the prediction of stock markets. Their interpretability is the critical factor for their commonness (Long et al., 2019). Machine learning methods are also used for prediction for stock markets along with these traditional statistical methods. Naive Bayes (NB), logistic regression (LR), random forest (RF), and k-nearest neighbors (KNN) are the most commonly used machine learning models in this domain (Patel et al., 2015; Sen & Chaudhuri, 2017). Support vector machine (SVM) and artificial neural networks (ANNs) are also machine learning algorithms that are used to predict the stock market (Atsalakis & Valavanis, 2009; Pan et al., 2017; Xiong et al., 2015). Besides these algorithms' unique capability of the nonlinear fitting over a time-series, over-fitting is one of the biggest obstacles of these methods in practical applications (Long et al., 2019). Along with the several ANN-based models, the results showed that multi-layer perceptron (MLP) outperforms the other ANN-based approaches (Guresen et al., 2011).

Apart from these methods, Deep Neural Networks (DNN), which are based on ANNs, have greater flexibility and a broad range of applicability for many tasks, including computer vision, speech recognition, natural language processing, translation, etc. (Lecun et al., 2015). DNNs have proven they can learn complex relationships from data with several different applications in various fields. It is possible to learn the relationship between input and output data and their other features with the help of DNNs o use them in stock market prediction (Gunduz et al., 2017; Peng & Jiang, 2016; C. Zhu et al., 2014).

In DNNs, Deep Belief Networks (DBN), Autoencoders (AE), Stacked-Autoencoders (SAE), Convolutional Neural Network (CNN), Recurrent Neural Networks (RNN), and Long-Short Time Memory (LSTM) are the most common methods for predicting stock markets. Many different studies were conducted with these DNNs to predict the stock market (K. Chen et al., 2015; Peng & Jiang, 2016; Türkmen & Cemgil, 2015; C. Zhu et al., 2014).

B. Generative Adversarial Network

General Adversarial Network (GAN) is a type of DNN composed of two rival DNN that play a game to achieve the best possible result (Goodfellow et al., 2014). There are two fundamental DNN in GAN's architecture; one of them is the Generator, which is responsible for generating new output. And the second part is named Discriminator, which is responsible for the make a decision about the output which is generated from the Generator. If the discriminator decides the generated output is fake, the generator gets this feedback and tries to generate a new output to deceive the Discriminator. After a while, the Generator generates outputs that look very close to real. And the Discriminator accepts that output as real.

The architecture was first proposed with image generation purpose in 2014 by Goodfellow et al. and take many contributions from on. There are many studies about GAN which are mainly focused on image generation for different domains.

There are many studies about GAN which are mainly focused on image generation for different domains. For example, GAN-based architectures can generate images from texts (Reed et al., 2016; Xu et al., 2018; H. Zhang et al., 2017), transform images from one domain to another (Bousmalis et al., 2017; Choi et al., 2018; T. Kim et al., 2017; Yi et al., 2017), transfer one image's style to another (X. Chen et al., 2016; Karras et al., 2019; J. Y. Zhu et al., 2016), creates images that belong to not existed persons (Karras et al., 2019) or not existed clothing (Kang et al., 2017; S. Zhu et al., 2017).

Fundamentally, since a GAN based architecture contains at least two DNN, lots of different DNN based work could transform to the GAN in theory. For example, DNN based stock exchange prediction models. There are not so many studies that propose a GAN-based solution to stock market prediction in the literature. But, they offered promising results.

The very beginning of the study in the literature is proposed by Zhou et al. in 2018 contains a GAN-based architecture to predict stock prices from the China Stock Exchange. The study compares some of the traditional and machine-learning-based approaches with the proposed architecture, named "GAN-FD," to predict the China Stock Market. Fundamentally, The GAN-FD contains LSTM based generator and a CNN-based discriminator. They compete to optimize the whole architecture to predict the best possible price of the stock. They used different window sizes for training and testing sets to see the validity of the architecture. Also, they offered to use the RMSRE (Root Mean Square Relative Error) metric instead of the RMSE (Root Mean Square Error). The study is evaluated with the 42 companies from CSI 300 index stock data from January 1, 2016, to December 31, 2016, which includes 244 trading days and nearly 60.000 data points.

They compared the proposed architecture performance from different perspectives. They created different versions of the proposed architecture named GAN-F, GAN-D, which are GAN-based alternative architectures for prediction. And also, they created an LSTM based DNN named LSTM-FD. They used ARIMA, GARCH, SVM, ANN, and those proposed GAN-based architectures to compare their performance. As a result, the proposed architecture predicted the minimum RMSRE in 246 scenarios out of 378 scenarios (42 stocks and 9 groups of windows sizes) (X. Zhou et al., 2018).

One of the other studies in the literature is proposed by Zhang et al. in 2019 contains another GAN-based architecture that is similar in some points to the first architecture to predict stock prices. This new architecture offers an LSTM-based generator similar to the first study. However, it contains an MLP (Multi-Layer Perceptron) based discriminator. The study also compares some of the traditional and machine-learning-based approaches with the proposed architecture. They evaluate the outputs with Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Average Return (AR) metrics. The study is conducted with the values of 20 years of stock data from different companies like IBM, Microsoft, and indexes like S&P 500, NYSE, and NASDAQ (National Association of Securities Dealers Automated Quotations) from the U.S. and PAICC from China. They used SVM, LSTM, ANN, and proposed GAN-based architectures to evaluate the performance. As a result, the proposed architecture predicted much more accurate stock prices in every metric. For example, it achieved a 3.04 MAE score when the closest rival (LSTM) is 4.12 (K. Zhang et al., 2019).

These studies show GAN-based approaches could achieve promising results for predicting stock prices. But, as told, all of these studies focus on bigger and deeper stock markets. Our proposed study will compare these studies outputs in a smaller and shallow stock market, which is "Borsa Istanbul," which is 100 times smaller and 2.5 times more volatile than NYSE.

III. Methodology

In this section, we provide our methodology when conducting the research. We will follow a quantitative experimental research methodology.

Briefly, we propose to conduct the research in the following steps. First, we will gather all the stocks' closing price data, as well as index data of Borsa Istanbul, from 01.01.2018 through 01.01.2020 timeframe, from a public data source. Then, we will select three groups of stocks from the Borsa Istanbul by selection criteria that will be detailed later. After conducting the selection procedure, we will use GAN-FD (Zhou 2018), GAN-MLP (Zhang 2019), SVN, LSTM, MLP, and ARIMA models with five input window size options (3, 7, 15, 30, and 60 days) for train the model, and six future dates (1, 3, 7, 15, 30, and 60 days) for prediction of the closing price. Then, we will compare the predicted and actual closing prices with MAE and RMSRE indicators. Finally, we will compare the result to find the answers to our research questions.

A. Gathering Data

The data of the more significant stock markets like NYSE or NASDAQ can be found on many public data sources. The accessibility of the resource is well for that markets' data. However, the stock markets like Borsa Istanbul is a challenge for researchers to gather and analyze the data. When taking a closer look into the literature, Yahoo Finance is a common public data source for many researchers in the financial area. The website stores and provides historical data for decades-long.

Borsa Istanbul data is also available on Yahoo Finance. The website can provide the historical data for all of the stocks on a daily basis (Open, High, Low, Close, Adjusted Close, and Volume).

B. Stock Selection

Stock selection is one of the main issues of this study. The selected stocks can differ the study's possible outcomes dramatically. To mitigate this issue, there is a need to define selection criteria.

In the literature, there are several different evaluation methods defined for financial assets. The risk and return relationship are one of the commonly used indicators to calculate the financial asset. Besides, evaluating the performance of an asset-based on an average return is not meaningful without the risk of that asset. So, this benchmark aims to compare the performance of the assets with the risk of those assets held.

Sharpe Ratio and Treynor Ratio are the well-known indicators for this area. The Sharpe ratio was proposed by William F. Sharpe aims to measure the return of an asset with standard deviation (or the volatility) of that asset (Sharpe, 1994). The Treynor ratio measures the return with the beta (β) value, which indicates the volatility of an asset. The Sharpe Ratio and the Treynor ratio is very similar to each other. However, the Sharpe ratio evaluates the risks of an asset itself alone when the Treynor ratio evaluates the risk-adjusted to the market. In order to select the stocks, we will use the Sharpe Ratio because it evaluates the stocks' risk and return alone, which is more important for selecting the stocks.

Sharpe Ratio was first proposed in 1966. After being popular, its basic formula has been modified over time (Scholz, 2007). The final refined formula of the Sharpe Ratio is shown in Figure 1, which consists of the asset return (R_a), risk-free return (R_b), and the standard deviation of the asset excess return (σ_b).

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p}$$

Figure 1 Sharpe Ratio

The resulting number from this Sharpe Ratio reflects the relationship between risks and return, as mentioned before. To be more clear, for example, a Sharpe Ratio of 0.5, which is considered as a bad investment because of its risk-return ratio, shows that every 1.0% of return is a corresponding 2.0% of the risk. Another example a Sharpe Ratio of 2.0, which is considered as a good investment because the investor gets two more times higher returns to its risks, shows that every 2.0% of return has a corresponding risk of 1.0%. The higher Sharpe ratio corresponds to the higher comfort level of the investors.

Although the ratio is a commonly used and well-known indicator for the stock market, there is a common disagreement about the risk-free return value of the formula. One of the common usages is that use the interest rate of a risk-free bond issued by a government or use the general interest rate of an economy. The other approach uses a common index of the stock market as a risk-free return. We will use the BIST 100 index because we want to analyze the stocks solely within the stock market, not the general situation of the economy. There is an example calculation of the Sharpe ratio for four days of trading values in Table 1.

Table 1 Sharpe Ratio Example

	Sample Stock Return	BIST 100 Return	Excess Return
Day 1	-0.50%	-0.40%	-0.10%
Day 2	1.10%	0.15%	0.95%
Day 3	0.50%	0.60%	-0.10%
Day 4	0.80%	0.90%	-0.10%

The standard deviation of excess returns is 0.006062178, and the average excess return is 0.0025. Finally, the Sharpe Ratio can be calculated as 0.412393049. The generally accepted thresholds of the ratio consider as the ratio which is less than 1 is a bad investment, between 1 and 2 is a good investment, and more than 2 is a great investment.

We will select the stocks from the Borsa Istanbul into three sections according to their Sharpe ratio. The first sections will consist of the stocks with the Sharpe ratio lower than 0.5. The second section will consist of the stocks with the Sharpe ratio between 0.75 and 1.25. The last section will consist of the stocks with the Sharpe ratio between 1.75 and 2.25. This selection will provide our stocks different stocks in the market by different volatility and return patterns.

C. Models and Prediction

As mentioned before, In this study, we will compare the GAN-based prediction approaches with the other Machine-Learning based approaches and the traditional statistical approaches. We will predict the six future dates of the adjusted closing price with GAN-FD (X. Zhou et al., 2018), GAN-MLP (K. Zhang et al., 2019), SVM, LSTM, ANN, and ARIMA models with five input window size options. Then we will compare the predicted price with the real one, which will be detailed in the next section. While GAN-based methods are detailed in the second chapter, brief information about the remaining models is given in this section.

The autoregressive integrated moving average (ARIMA) model is based on the autoregressive moving average (ARMA) model. ARIMA is the generalized version of ARMA. They can both be used prediction of time series like stock market prediction while ARIMA is more robust on non-stationary time series, which are affected by seasonality as we see in the stock market, especially short-term prediction (Ariyo et al., 2014). In the literature, there are studies proposed to use ARIMA with financial predictions like energy market prediction (Javier et al., 2003), oil palm price predictions (Nochai & Nochai, 2006), or stock market predictions (Ariyo et al., 2014; Sterba & Hilovska, 2010).

In machine learning, support vector machines (SVMs) are among the most robust estimation methods supervised learning models with associated learning algorithms that analyze data for classification and regression analysis (Cortes & Vapnik, 1995). SVMs achieve performance with a high generalization because they were proved to be resistant to the over-fitting problem. So that, SVM keeps its balance be optimal, especially for regression analysis, unlike other machine-learning-based approaches or neural networks, which requires nonlinear optimization to avoid over-fitting (Hu et al., 2013). There are studies, which had promising results, are proposing to use SVM for the prediction of stock markets (Hu et al., 2013; Huang et al., 2005; Tay & Cao, 2001).

Artificial neural networks (ANNs) are also called "neural networks (NNs)," inspired by the animal brains' biological neural networks (Y.-Y. Chen et al., 2019). An ANN is consists of lots of connected nodes (artificial neurons) like a biological brain. These nodes' connections work like the synapses in a biological brain. The artificial neuron computes real numbers as a result of some calculations and transmits these real numbers to its connected neurons regarding the weight of this connection. Since ANN is a concept, there are different ANN-based models proposed to use for stock market predictions, such as The Multilayer Perceptron (MLP) and Dynamic Architecture for Artificial Neural Networks (DAN2) (Ghiassi & Saidane, 2005). And also, there are hybrid models that consist of ANN with traditional approaches. While the Generalized Autoregressive Conditional Heteroscedasticity (Bollerslev, 1986) is a statistical method to predict financial time series. GARCH based ANN (GARCH-ANN) was developed to use an advanced ANN model with the traditional GARCH method (Hyup Roh, 2007).

MLP is one of the most widely known ANN models capable of approximating arbitrary functions (Principe et al., 2000). Like GARCH-ANN, a hybrid model named "GARCH-MLP" that consists of MLP with the traditional GARCH model is also proposed for predicting the stock market (Hyup Roh, 2007). A widely cited study was conducted to compare these ANN-based approaches for stock market prediction by Guresen et al. in 2011. In this study, daily stock exchange rates of NASDAQ from October 7, 2008, to June 26, 2009, were used, and GARCH, GARCH-ANN, MLP, GARCH-MLP, DAN2, and GARCH-DAN2 were compared. The results showed that MLP outperforms the other approaches (Guresen et al., 2011).

Recurrent Neural Networks (RNNs) are another type of ANN that consists of the nodes connected to form a directed graph. RNNs can use their internal state or memory to process variable-length sequences of inputs (Abiodun et al., 2018). Long short-term memory (LSTM) is an RNN-based architecture that is widely adopted in deep learning (Hochreiter & Schmidhuber, 1997). Like all other RNNs, LSTM has several feedback connections to remember or forget the previous states of the network. LSTM is proposed to use for text classifications (C. Zhou et al., 2015), language modeling (Sundermeyer et al., 2012), and predictions like systems load (Gensler et al., 2017; Marino et al., 2016; Shao et al., 2016), or stock price prediction (K. Chen et al., 2015; Long et al., 2019).

As mentioned before, the selected models (ARIMA, SVM, MLP, LSTM, GAN-MLP, and GAN-FD) will be trained with the adjusted closing prices' of the selected stock with five input window sizes options (3, 7, 15, 30, and 60 days). On every round, an input size option is selected first; then, the models will be trained with the data of selected stocks regarding this input window size through the selected time frame. After the training, the prediction phase is started. Every model is tried to predict six different future dates (1, 3, 7, 15, 30, and 60 days) through the selected time frame consequently for each stock. Every model for each stock output a 5x6 matrix regarding the time frame, input window, and prediction. After the calculation is finished, the evaluation part is started.

D. Data Analysis and Evaluation

The data analysis part will be conducted with the two metrics: Mean Absolute Error (MAE) and Root Mean Squared Relative Error (RMSRE). Each predicted data point will be compared with the real values regarding these two metrics. And, we will continue to the evaluation part. Finally, we will answer the research questions with the help of evidence regarding the evaluation.

In statistics, mean absolute error (MAE) is a measure of errors between paired observations. MAE has been widely used in similar research to understand the correctness of the selected method (Rather et al., 2015; Tay & Cao, 2001; K. Zhang et al., 2019). MAE is calculated with the formula shown in Figure 2.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right|$$

Figure 2 MAE Formula

The other metrics that measure average error, such as Root Mean Squared Error (RMSE), are used with/against the MAE in the research. The fundamental difference of the measurement of average error-based methods that they are based on the sum of squared errors, which are functions of the average error. So that, the distribution of error magnitudes and they could not show the average error alone (Willmott & Matsuura, 2005).

Although the analysis conducted by Willmott & Matsuura indicated that MAE is the most natural measure of average error magnitude, we took a closer look into the literature to find an alternative of MAE to compare the results and confirm the evaluations.

Root Mean Squared Relative Error (RMSRE), which is based on RMSE, is another indicator that can be used to evaluate the correctness of the predictions. The lower RMSRE indicates that the prediction is more aligned with the real data. RMSRE is not popular as MAE, or Root Mean Squared Error (RMSE) metric, but RMSRE facilitates the uniform comparison of the results of the stocks more regarding the RMSE counterpart (X. Zhou et al., 2018). RMSRE is calculated with the "related error," which lowers the effect of the magnitude as shown with the formula in Figure 3.

$$\mathrm{RMSRE} = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} \Delta X_{\mathrm{rel},i}^{2}}$$

Figure 3 RMSRE Formula

After the calculations, we will take the mean values of MAE and RMSRE for each stock section regarding the Sharpe ratio. As a result, we will get 5x6 matrixes for each prediction model and for each stock section regarding the time frame. Then, we will conduct an evaluation of the analysis results, and we will try to answer the research questions.

E. Assumptions, Limitations, and Delimitations

The GAN-based models, which will be used in this research, will be developed from the ground-up. All the available information about these models was given in the related papers may not be enough to build the architectures to use in the research. The missing parts will be completed with the literature research. So that, the resulting models may not fully equal with the proposed in the papers.

On the other hand, the resulting model may not be produced the exact same figures as the papers. This may be related to the nature of the neural networks or the small differences between the model proposed and the model developed. These differences will not be measured in the research. And, it will be assumed that these differences are as low as making no difference in this research.

The stock price information will be gathered from the Yahoo Finance website, which is a very popular data source for similar researchers. The values will be assumed as equal to the actual stock price. They will not be checked or investigated further.

Some of the stock price information will not be available in the coverage for the time frame. These stocks will not be included in the research. Similarly, not all stocks trading in Borsa Istanbul will be considered in the research. The stocks will be found randomly and selected with the given criteria, as mentioned in this chapter before. As a result, some of the stocks will not be included in the research. We will make an effort to use all available stocks in this research but, to keep the research simple and understandable and to take an equal count of stocks to each section, some of the stocks will be ignored and not included in the research.

References

Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Mohamed, N. A. E., & Arshad, H. (2018). State-of-the-art in artificial neural network applications: A survey. In *Heliyon* (Vol. 4, Issue 11, p. e00938). Elsevier Ltd. https://doi.org/10.1016/j.heliyon.2018.e00938

Ariyo, A. A., Adewumi, A. O., & Ayo, C. K. (2014). Stock Price Prediction Using the ARIMA Model. *2014 UKSim-AMSS 16th International Conference on Computer Modelling and Simulation*, 106–112. https://doi.org/10.1109/UKSim.2014.67

Atsalakis, G. S., & Valavanis, K. P. (2009). Surveying stock market forecasting techniques - Part II: Soft computing methods. *Expert Systems with Applications*, *36*(3 PART 2), 5932–5941. https://doi.org/10.1016/j.eswa.2008.07.006

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307–327.

Bousmalis, K., Silberman, N., Dohan, D., Erhan, D., & Krishnan, D. (2017). Unsupervised pixel-level domain adaptation with generative adversarial networks. *Proceedings of 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017*, *2017-Janua*, 95–104. https://doi.org/10.1109/CVPR.2017.18

Chen, K., Zhou, Y., & Dai, F. (2015). A LSTM-based method for stock returns prediction: A case study of China stock market. *Proceedings - 2015 IEEE International Conference on Big Data, IEEE Big Data 2015*, 2823–2824. https://doi.org/10.1109/BigData.2015.7364089

Chen, X., Duan, Y., Houthooft, R., Schulman, J., Sutskever, I., & Abbeel, P. (2016). InfoGAN: Interpretable Representation Learning by Information Maximizing Generative Adversarial Nets. *Proceedings of the 30th International Conference on Neural Information Processing Systems*, 2180–2188.

Chen, Y.-Y., Lin, Y.-H., Kung, C.-C., Chung, M.-H., & Yen, I.-H. (2019). Design and Implementation of Cloud Analytics-Assisted Smart Power Meters Considering Advanced Artificial Intelligence as Edge Analytics in Demand-Side Management for Smart Homes. In *Sensors* (Vol. 19, Issue 9). https://doi.org/10.3390/s19092047

Choi, Y., Choi, M., Kim, M., Ha, J.-W., Kim, S., & Choo, J. (2018). StarGAN: Unified Generative Adversarial Networks for Multi-domain Image-to-Image Translation. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 8789–8797. https://doi.org/10.1109/CVPR.2018.00916

Cortes, C., & Vapnik, V. (1995). Support-Vector Networks. *Machine Learning*, *20*(3), 273–297. https://doi.org/10.1023/A:1022627411411

Gensler, A., Henze, J., Sick, B., & Raabe, N. (2017). Deep Learning for solar power forecasting - An approach using AutoEncoder and LSTM Neural Networks. *2016 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2016 - Conference Proceedings*, 2858–2865. https://doi.org/10.1109/SMC.2016.7844673

Ghiassi, M., & Saidane, H. (2005). A dynamic architecture for artificial neural networks. *Neurocomputing*, *63*(SPEC. ISS.), 397–413. https://doi.org/10.1016/j.neucom.2004.03.014

Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). Generative adversarial nets. *Proceedings of Advances in Neural Information Processing Systems*, *3*(January), 2672–2680.

Gunduz, H., Yaslan, Y., & Cataltepe, Z. (2017). Intraday prediction of Borsa Istanbul using convolutional neural networks and feature correlations. *Knowledge-Based Systems*, *137*, 138–148. https://doi.org/10.1016/j.knosys.2017.09.023

Guresen, E., Kayakutlu, G., & Daim, T. U. (2011). Using artificial neural network models in stock market index prediction. *Expert Systems with Applications*, *38*(8), 10389–10397. https://doi.org/10.1016/j.eswa.2011.02.068

Hagenau, M., Liebmann, M., & Neumann, D. (2013). Automated news reading: Stock price prediction based on financial news using context-capturing features. *Decision Support Systems*, *55*(3), 685–697. https://doi.org/10.1016/j.dss.2013.02.006

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Computation*, *9*(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

Hu, Z., Zhu, J., & Tse, K. (2013). Stocks market prediction using Support Vector Machine. *2013 6th International Conference on Information Management, Innovation Management and Industrial Engineering*, *2*, 115–118. https://doi.org/10.1109/ICIII.2013.6703096

Huang, W., Nakamori, Y., & Wang, S. Y. (2005). Forecasting stock market movement direction with support vector machine. *Computers and Operations Research*, *32*(10), 2513–2522. https://doi.org/10.1016/j.cor.2004.03.016

Hyup Roh, T. (2007). Forecasting the volatility of stock price index. *Expert Systems with Applications*, *33*(4), 916–922. https://doi.org/10.1016/j.eswa.2006.08.001

Javier, C., Rosario, E., Francisco, J. N., & Antonio, J. C. (2003). ARIMA models to predict next electricity price. *IEEE Transactions on Power Systems*, *18*(3), 1014–1020.

Kang, W.-C., Fang, C., Wang, Z., & McAuley, J. (2017). Visually-aware fashion recommendation and design with generative image models. *Proceedings of IEEE International Conference on Data Mining, ICDM*, *2017-Novem*, 207–216. https://doi.org/10.1109/ICDM.2017.30

Karras, T., Laine, S., & Aila, T. (2019). A style-based generator architecture for generative adversarial networks. *Proceedings of the IEEE Computer Society*

Conference on Computer Vision and Pattern Recognition, *2019-June*, 4396–4405. https://doi.org/10.1109/CVPR.2019.00453

Kim, K. J., & 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. https://doi.org/10.1016/S0957-4174(00)00027-0

Kim, T., Cha, M., Kim, H., Lee, J. K., & Kim, J. (2017). Learning to discover cross-domain relations with generative adversarial networks. *Proceedings of 34th International Conference on Machine Learning, ICML 2017*, *4*, 2941–2949.

Lecun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. In *Nature* (Vol. 521, Issue 7553, pp. 436–444). Nature Publishing Group. https://doi.org/10.1038/nature14539

Long, W., Lu, Z., & Cui, L. (2019). Deep learning-based feature engineering for stock price movement prediction. *Knowledge-Based Systems*, *164*, 163–173. https://doi.org/10.1016/j.knosys.2018.10.034

Marček, D. (2004). Stock price forecasting: Statistical, classical and fuzzy neural network approach. *Lecture Notes in Artificial Intelligence (Subseries of Lecture Notes in Computer Science)*, *3131*, 41–48. https://doi.org/10.1007/978-3-540-27774-3_5

Marino, D. L., Amarasinghe, K., & Manic, M. (2016). Building energy load forecasting using Deep Neural Networks. *IECON Proceedings (Industrial Electronics Conference)*, 7046–7051. https://doi.org/10.1109/IECON.2016.7793413

Marszałek, A., & Burczyński, T. (2014). Modeling and forecasting financial time series with ordered fuzzy candlesticks. *Information Sciences*, *273*, 144–155.

Nochai, R., & Nochai, T. (2006). ARIMA model for forecasting oil palm price.

Proceedings of the 2nd IMT-GT Regional Conference on Mathematics, Statistics and Applications, 13–15.

Pan, Y., Xiao, Z., Wang, X., & Yang, D. (2017). A multiple support vector machine approach to stock index forecasting with mixed frequency sampling. *Knowledge-Based Systems*, *122*, 90–102. https://doi.org/10.1016/j.knosys.2017.01.033

Patel, J., Shah, S., Thakkar, P., & Kotecha, K. (2015). Predicting stock and stock price index movement using Trend Deterministic Data Preparation and machine learning techniques. *Expert Systems with Applications*, *42*(1), 259–268. https://doi.org/10.1016/j.eswa.2014.07.040

Peng, Y., & Jiang, H. (2016). Leverage financial news to predict stock price movements using word embeddings and deep neural networks. *2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL HLT 2016 - Proceedings of the Conference*, 374–379. https://doi.org/10.18653/v1/n16-1041

Principe, J. C., Euliano, N. R., & Lefebvre, W. C. (2000). *Neural and adaptive systems: fundamentals through simulations* (Vol. 672). Wiley New York.

Rather, A. M., Agarwal, A., & Sastry, V. N. (2015). Recurrent neural network and a hybrid model for prediction of stock returns. *Expert Systems with Applications*, *42*(6), 3234–3241. https://doi.org/10.1016/j.eswa.2014.12.003

Reed, S., Akata, Z., Yan, X., Logeswaran, L., Schiele, B., & Lee, H. (2016). Generative adversarial text to image synthesis. *Proceedings of 33rd International Conference on Machine Learning, ICML 2016*, *3*, 1681–1690.

Scholz, H. (2007). Refinements to the Sharpe ratio: Comparing alternatives for bear markets. *Journal of Asset Management*, *7*(5), 347–357. https://doi.org/10.1057/palgrave.jam.2250040

Sen, J., & Chaudhuri, T. (2017). A robust predictive model for stock price forecasting.

Proceedings of the 5th International Conference on Business Analytics and Intelligence (ICBAI 2017), Indian Institute of Management, Bangalore, INDIA.

Shao, D., Zhang, T., Mannar, K., & Han, Y. (2016). Time series forecasting on engineering systems using recurrent neural networks. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *10086 LNAI*, 459–471. https://doi.org/10.1007/978-3-319-49586-6_31

Sharpe, W. F. (1994). The Sharpe Ratio. *The Journal of Portfolio Management*, *21*(1), 49 LP – 58. https://doi.org/10.3905/jpm.1994.409501

Sterba, J., & Hilovska, K. (2010). The implementation of hybrid ARIMA neural network prediction model for aggregate water consumption prediction. *Aplimat—Journal of Applied Mathematics*, *3*(3), 123–131.

Sundermeyer, M., Schlüter, R., & Ney, H. (2012). *LSTM Neural Networks for Language Modeling*.

Tay, F. E. H., & Cao, L. (2001). Application of support vector machines in financial time series forecasting. *Omega*, *29*(4), 309–317. https://doi.org/10.1016/S0305-0483(01)00026-3

Türkmen, A. C., & Cemgil, A. T. (2015). Finansal Piyasalarda Gösterge Sinyali Tahmini Için Derin Öǧrenme Uygulamasi. *2015 23rd Signal Processing and Communications Applications Conference, SIU 2015 - Proceedings*, 2521–2524. https://doi.org/10.1109/SIU.2015.7130397

Willmott, C. J., & Matsuura, K. (2005). Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Climate Research*, *30*(1), 79–82.

Xiong, T., Li, C., Bao, Y., Hu, Z., & Zhang, L. (2015). A combination method for interval forecasting of agricultural commodity futures prices. *Knowledge-Based*

Systems, *77*, 92–102. https://doi.org/10.1016/j.knosys.2015.01.002

Xu, T., Zhang, P., Huang, Q., Zhang, H., Gan, Z., Huang, X., & He, X. (2018). AttnGAN: Fine-Grained Text to Image Generation with Attentional Generative Adversarial Networks. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 1316–1324. https://doi.org/10.1109/CVPR.2018.00143

Yi, Z., Zhang, H., Tan, P., & Gong, M. (2017). DualGAN: Unsupervised Dual Learning for Image-to-Image Translation. *Proceedings of the IEEE International Conference on Computer Vision*, *2017-Octob*, 2868–2876. https://doi.org/10.1109/ICCV.2017.310

Zhang, H., Xu, T., Li, H., Zhang, S., Wang, X., Huang, X., & Metaxas, D. (2017). StackGAN: Text to Photo-Realistic Image Synthesis with Stacked Generative Adversarial Networks. *Proceedings of the IEEE International Conference on Computer Vision*, *2017-Octob*, 5908–5916. https://doi.org/10.1109/ICCV.2017.629

Zhang, K., Zhong, G., Dong, J., Wang, S., & Wang, Y. (2019). Stock Market Prediction Based on Generative Adversarial Network. *Procedia Computer Science*, *147*, 400–406. https://doi.org/10.1016/j.procs.2019.01.256

Zhou, C., Sun, C., Liu, Z., & Lau, F. (2015). A C-LSTM neural network for text classification. *ArXiv Preprint ArXiv:1511.08630*.

Zhou, X., Pan, Z., Hu, G., Tang, S., & Zhao, C. (2018). *Stock Market Prediction on High-Frequency Data Using Generative Adversarial Nets*. https://doi.org/10.1155/2018/4907423

Zhu, C., Yin, J., & Li, Q. (2014). A stock decision support system based on DBNs. *Journal of Computational Information Systems*. https://doi.org/10.12733/jcis9653

Zhu, J. Y., Krähenbühl, P., Shechtman, E., & Efros, A. A. (2016). Generative visual manipulation on the natural image manifold. *Proceedings of Computer Vision - ECCV 2016*, *9909 LNCS*, 597–613. https://doi.org/10.1007/978-3-319-46454-1_36

Zhu, S., Fidler, S., Urtasun, R., Lin, D., & Loy, C. C. (2017). Be Your Own Prada: Fashion Synthesis with Structural Coherence. *Proceedings of the IEEE International Conference on Computer Vision*, *2017-Octob*, 1689–1697. https://doi.org/10.1109/ICCV.2017.186