Received: 17 July 2023 | Revised: 17 August 2023 | Accepted: 21 August 2023 | Published online: 22 August 2023

RESEARCH ARTICLE

Archives of Advanced Engineering Science
2025, Vol. 3(3) 151–162
DOI: 10.47852/bonviewAAES32021366

BON VIEW PUBLISHING

Predicting Stock Market Index and Credit Default Swap Spreads Using Artificial Intelligence and Determining Nonlinear Relations

Ayben Koy[1] and **Andaç Batur Çolak**[2,*]

[1]*Faculty of Business, Finance and Banking Department, Istanbul Ticaret University, Türkiye*

[2]*Information Technologies Application and Research Center, Istanbul Ticaret University, Türkiye*

Abstract: In this study, a simulation model has been established to forecast the stock price index of Borsa Istanbul (BIST100) and 5-year maturity credit default swap (CDSs) spreads with an artificial intelligence approach. In the study where short-term and long-term relationships between variables were examined using nonlinear econometric models such as Kapetanios, Shin, and Snell and exponential smooth transition autoregressive vector error correction model, Türkiye's 1211 data sets obtained were used in the period 08.21.2015–08.17.2020. With this data set, a multilayer perceptron artificial neural network (ANN) model has been established. Levenberg–Marquardt algorithm was used as the training algorithm in the feedforward backpropagation network model with 25 neurons in the hidden layer. Six input variables, which are considered to be common parameters affecting the target values, were defined in the input layer, and BIST100 and CDSs were predicted at the output layer. The performance analysis of the network model was completed using various performance parameters, and in addition, a comprehensive performance analysis was performed by comparing the simulation results gotten from the neural network with the target values. The model was able to predict BIST100 with an average deviation of 0.04% and CDSs with an average error of −0.163%. These error rates indicate that the developed ANN has been designed to predict BIST100 and CDSs with ideal accuracy.

Keywords: BIST100, credit default swap (CDS), artificial intelligence, nonlinear relations

1. Introduction

Stock index and credit default swap (CDSs) spreads are among the basic data that investors consider in the decision-making process in international financial markets. Although the efficient market hypothesis (EMH) [1, 2], which is among the basic theories of finance science, states that there is no higher than normal return in the market based on data such as historical prices and transaction volumes of securities, the sector professionals and academicians continue to work on estimating asset prices with various models. In particular, predicting stock/stock index prices and beating the market have always been the main goals for the investors. Investors predict the future prices of stocks and the direction of the price using technical analysis and fundamental analysis methods. Investors holding assets of different markets in their portfolios closely follow CDSs, which are indicators of the default risk of that country/stock and also indicators for the investment climate. CDSs are the most traded and liquid market products among credit derivatives [3] as an instrument that takes credit risk off the balance sheet [4]. While CDSs reflect credit risk, providing insights into the probability of default for a given entity, stock market indices serve as broader indicators of market sentiment, economic conditions, and investor confidence. The intertwining of credit and equity markets underscores the importance of considering these indicators jointly.

Both stock markets and CDS markets, where the prices are constantly changing, are under the impact of many factors simultaneously. The default risk of a country and the performance of its stock market index should depend on the same economic fundamentals. However, while macroeconomic realizations become known in longer periods, both stock exchanges and CDS markets are the markets where the expectations are quickly reflected by investors' trading decisions. The stocks traded on an exchange are affected by various factors in the country level and global level in addition to business-specific factors. The majority of these factors also directly or indirectly affect the country's risk and CDSs. However, while most of these factors change monthly, quarterly, and annually, expectations for these factors change financial markets more rapidly and frequently.

Accurate predictions of financial indicators play a crucial role in making informed investment decisions, managing risk, and formulating effective economic policies. Traditionally, researchers have focused on analyzing individual financial instruments, such as CDSs and stock market indices, independently. However, the interdependence and correlation between these two important indicators have become increasingly evident, necessitating a more integrated approach to their

*Corresponding author: Andaç Batur Çolak, Information Technologies Application and Research Center, Istanbul Ticaret University, Türkiye. Email: abcolak@ticaret.edu.tr

analysis and prediction. There are many studies in the literature where CDSs and stock markets are discussed together [5–8]. Especially, the lead–lag/causality relationship of these two markets and the volatility transition between the two markets take a significant place among the studies where researchers examine the two markets together [9–13]. However, studies that explain or try to predict both markets with common dynamics are limited. There appears to be a gap in research that attempts to model and predict both of these indicators using common underlying dynamics. Many studies have focused on predicting each indicator independently, utilizing various methodologies such as artificial neural networks (ANNs), hybrid models, and nonparametric machine learning (ML) techniques. However, there seems to be limited research that explores the joint prediction of both indicators while accounting for their interconnectedness and shared underlying factors. The key challenge here was to identify and select relevant variables that capture both the market sentiment and credit risk aspects, as these indicators are intertwined.

The practice of ANN models of this study, which predicts the stock market and the CDS market with daily changing common variables, is also important in terms of developments in the financial sector. Especially, the use of artificial intelligence (AI) applications in portfolio management is becoming widespread in the financial sector. Different financial indicators are important when investing in emerging markets. These indicators can be affected by many factors such as the production structure of the relevant economy, foreign trade structure, and market-specific investor behavior. There exist a wide literature on predicting stocks and stock indices with ANN models; however, there are limited studies on CDSs. Due to the inadequate number of studies on Türkiye, this section presents the studies using ANN and examples of hybrid methodologies to predict the stock markets on Türkiye, and some of the studies on emerging stock markets, but a few studies on CDSs. Moreover, the studies on CDSs are mostly in developed markets and they are not on a predicting model.

The evidence from academic studies proves that ANN models generally outperform other models. In one of the initial studies by means of ANN for Borsa Istanbul (BIST100), the day of the week effect is studied by Egeli et al. [14]. According to the findings of this study, predictions-based ANN prototypes outperform models based on moving averages (MAs). In another study comparing autoregressive integrated moving average (ARIMA) models and ANN models, Adebiyi et al. [15] predict Dell Inc stock price with the data for 23 years. Although the results of the study showed that both ANN and ARIMA make successful predictions, ANN models perform better. Stock prices on the Brazilian Stock Exchange (BM&FBOVESPA) are predicted using ANN in a separate study by de Oliveira et al. [16]. They employ a massive data set with 11 essential analysis variables including Brent oil price, consumer confidence index, and vehicle sales, and 15 technical analysis variables like closing price, volume, and MAs. Telli and Coşkun [17] create numerous models using daily data for BIST100 between July 29 and November 15, 2015, taking into account factors such as parities (USDTRY, Dollar Index), stock indices of different nations, and an economic calendar associated with Türkiye. One of the most important findings is that the economic calendar can be used as a useful explanatory variable in predicting BIST100. Advances in analysis methods have revealed hybrid models that combine analysis methods in different branches such as time series and AI. In an early study using ANN for predicting emerging markets indices, Kim and Han [18] propose a hybrid model of ANN and genetic algorithms (GAs) to predict the Korean Stock Price Index. Bildirici and Ersin's [19] research is one example of a study that combines time series analysis with other methods to create a hybrid model. The paper analyzes the volatility of BIST100 using techniques that combine generalized autoregressive conditional heteroscedasticity (GARCH) models with ANN models for a daily data set over the time period of 23.10.1987–22.02.2008, providing evidence that ANN models increase predictions. For COVID19 period, Ozgur and Sarikovanlik [20] investigate the performance of single and hybrid ML algorithms in predicting daily stock market returns for the BIST100 and NASDAQ indices. The study compares the accuracy of traditional ARMA-GARCH models with three different ML algorithms (random forest, XGBoost, and ANNs) and develops new hybrid ML models. The results suggest that the developed novel hybrid prototypes accomplish better than the other models, particularly the traditional (ARMA-) GARCH models.

Although ANN is not used, different hybrid models other than the time series have also been used to predict stock market indices. The adaptive network-based fuzzy inference system (ANFIS) is used by Boyacioglu and Avci [21] to provide predictions for the BIST100. The index's monthly returns are predicted using six macroeconomic factors and three indices, with a 98.3% accuracy record. Similarly, Wei et al. [22] predicted the TAIEX (Taiwan Stock Exchange Capitalization Weighted Stock Index) during a six-year period using a correlation matrix, subtractive clustering, and ANFIS. The results of their analysis demonstrate that their proposed model is superior to alternative fuzzy time series methods. To forecast BIST100 using daily data from June 8, 2005, to November 27, 2013, Göçken et al. [23] employ hybrid ANN simulations built on a heuristic optimization methodology (harmony search (HS) or GA). The HS-ANN model outperformed the competition in a trial that included the use of technical indicators such closing price, MAs, and momentum price.

Due to the lack of research on CDSs prediction in Türkiye and the world, studies that address the factors affecting CDSs have also been included in the literature. CDSs, which are important indicators for country/firm risk, are generally examined in terms of being a leading indicator, or a predicting indicator in academic studies in line with their high liquidity markets. On the other hand, the research on calculating CDSs and on the indicators of CDSs has also expanded in literature. Moreover, a significant portion of the studies, especially studies using company-specific or industry-specific data, are applied to US data. Son et al. [24] are one of the limited studies on predicting CDSs. The four state-of-the-art nonparametric ML models including ANN, Bayesian neural networks, support vector regression, and Gaussian process regression, and two parametric models for CDSs with different maturities are used in the study. Their findings show that ANN model performs best for all cases for different maturities and different rating groups. Any other time series variable except daily CDSs is not used in this study. Hanias et al. [25] predict the CDSs for a group of emerging countries Greek, Türkiye, Russia, Brazil, and China. A nonlinear analysis with a combination on neural network with two hidden layers is employed to the daily data for 2-year period. Using quantile regression, Koutmos [26] explains the changes in bank CDSs with firm-specific and market-specific variables. In the study which also compares the models with the Fama and French 5 factor model [27], the explanatory variables are found displaying heterogeneity across the conditional distribution of CDSs changes. Guesmi et al. [28] are another study that uses Fama and French [29] factors. Their results indicate that the changes in both directions in industry stock price, business condition volatility, interest rates, and the SMB and HML Fama and French [27] factors have asymmetric impacts on industry CDS index spreads. While da Fonseca et al. [30] explain the CDSs with the changes in oil markets, Shahzad et al. [31] use macroeconomic variables such as industry stock indices, Chicago Board Options Exchange Volatility Index (VIX), and crude oil price, in a newer study, Naumer and Yurtoglu [32] investigate the relation with environmental, social, and governance (ESG)-based news and CDSs. In the corporate social responsibility aspect, the evidence of their study suggests that ESG- and non-ESG-related news have got an important role in explaining CDSs.

Using accounting and market-based characteristics, Pereira et al. [33] compare CDSs issued by companies in the USA, UK, and EU. Their research shows that market-based characteristics are more relevant predictors of CDSs, particularly during and after the financial crisis. On April 8, 2009, the North American CDS contracts saw the implementation of CDS Big Bang. In a study conducted by Wang et al. [34] it was observed that the liquidity of the market decreased. This decline was attributed to higher funding requirements or increased upfront costs associated with trading CDSs. The effect of these funding requirements was particularly noticeable for CDSs linked to smaller or riskier reference entities. The study relied on daily bid and ask quotes for CDS contracts involving North American companies. Ballestra et al. [35] model 65 companies' CDSs for different maturities for 12 years. In the models, they do not use any other macroeconomic or firm-based variable except CDSs, bond yields, and the risk-free rate. In the study using asymmetric causality tests and vector autoregressive moving average, Procasky [36] investigates the predictive power of CDSs or stock markets on replying to the new information. They find a significant heterogeneity between the investment grade and high yield market informational flow.

Mao et al. [37] propose a modified Long short-term memory (LSTM) model called the Merton-LSTM model that integrates the Merton determinants model to predict CDS indices. To understand the intrinsic link between the Merton determinants and CDS spreads, the Merton-LSTM model takes advantage of the nonlinear learning capabilities of LSTM while also expanding the model's capacity. Root-mean-squared error and the Diebold–Mariano test are used to evaluate the Merton-LSTM model and other ML models for their ability to predict the North America High Yield index (CDX.NA.HY) and North America Investment Grade index (CDX.NA.IG). The results demonstrate that the Merton-LSTM model provides the most accurate forecasts, even when the time period to predict is extended to 28 days. By taking into account CDS-related factors like historical time series data, market sentiment news, news semantic vectors, and a corporation's financial leverage data, Lin et al. [38] proposed a new CDS prediction model based on a generative adversarial network (GAN) called FN-Regression-GAN. The results demonstrate that FN-Regression-GAN outperforms the alternative models, indicating its superior predictive capabilities in the CDS domain.

This study based on Türkiye markets as a sample for emerging markets. The BIST100 index of BIST100 and Türkiye's 5-year maturity CDSs are predicted by an AI approach. The selected six factors (date, volume, SP500, WTI, GOLD, and USD variables) are defined as input variables, and BIST100 and CDSs are predicted same time in the output. On the other hand, nonlinear models are extensively used in financial studies to analyze relationships between variables. If there is a long-run relationship between the variables, these variables can be used for forecasting and economic analysis. For this purpose, we have used Kapetanios, Shin, and Snell (KSS) cointegration and exponential smooth transition autoregressive (ESTAR) error correction models (ECMs) in our study. This study, which estimates two important indicators belonging to the same economy with ANN, contributes to the literature since its counterparts in finance are mostly studies applying time series methods. This comparison will enhance our ability to anticipate market trends, systemic risks, and financial crises, enabling proactive risk management and policy formulation.

This paper is organized as follows: Section 2 reviews the data and methodology described, Section 3 with empirical results, and the study is concluded in Section 4.

2. Methodology

In this section, comprehensive information regarding the data employed in the study and the methodologies utilized is presented. The study incorporates both the KSS nonlinear cointegration as a nonlinear econometrics model and the presentation of the ANN model.

2.1. Data collection

The use of AI applications in trading decisions in financial markets is becoming widespread. In markets where information is promptly imitated in the price, systems trading according to changes in daily and intraday data replace portfolio managers, or systems support the portfolio managers. In line with this information, it is also among the goals of the study to provide information to market professionals with daily observations. All variables used in the study are shown in Table 1. Among all variables, stock price and volume are the two most relevant factors in determining the future direction of prices according to the technical analysis. Many studies analyze the affiliation among the emerging stock markets and developed markets as the US stock market, oil markets, and commodity markets. Literature shows that the demand and supply shocks driving the global crude oil and commodity markets have got long-run effect on the stock markets [39, 40]; moreover, there is evidence on the short-run effects [41]. The selected variables of these markets consist of

Table 1
Variables used in the study

Variables		Source
BIST100 Closing Price in USD	BIST100	Thomson Reuters Eikon
5 years' CDS spread for Türkiye	CDS	Thomson Reuters Eikon
BIST100 Volume in USD	Volume	Thomson Reuters Eikon
SP500 Closing Price in USD	SP500	Thomson Reuters Eikon
WTI – NYMEX Light Sweet Crude Oil Futures	WTI	Thomson Reuters Eikon
Gold /TRY cross rate	Gold	Thomson Reuters Eikon
USD/TRY	USD	Thomson Reuters Eikon

data that are mostly followed by professionals and frequently included in academic studies. While gold is a safe haven where investors' interest increases in the face of increased risk in the markets [42], on the other hand, the US stock market price changes are important indicators that provide information for all world stock markets and can affect all world stock prices in the short term. Five years' daily data for the period 08.21.2015–08.17.2020 have been used and each variable is composed of 1211 observations.

2.2. KSS nonlinear cointegration

KSS [43] nonlinear cointegration is a statistical method that extends the traditional linear cointegration framework to allow for nonlinear relationships between variables. In the linear cointegration framework, a set of time series are said to be cointegrated if there exists a linear arrangement of them that is stationary. This implies that there is a long-run relationship between the variables, which can be used for forecasting and economic analysis. However, in many cases, the relationship between variables may be nonlinear. For example, in financial markets, the relationship between asset prices may exhibit nonlinearities due to market frictions, transaction costs, and other factors. The KSS method extends the linear cointegration framework by allowing for a smooth transition between linear and nonlinear relationships between variables. Specifically, the KSS model assumes that the cointegrating relationship between variables can be represented as a smooth function of a latent variable. The latent variable captures the degree of nonlinearity in the relationship between variables. The KSS method has been employed in several arenas, including finance, economics, and environmental studies, where nonlinear relationships between variables are common. KSS cointegration test investigates the cointegration relationship with smooth transition autoregressive adjustment. The KSS cointegration model is based on an ECM:

$$\Delta y_t = \Phi u_{t-1} + \gamma u_{t-1}[1 - \exp(-\theta u_{t-1}^2)] + \omega' \Delta x_t + \sum_{i=1}^{p-1} \varphi_i' \Delta z_{t-1} + \varepsilon_t \quad (1)$$

is zero, the formula is

$$\Delta y_t = \delta u_{t-1}^3 + \omega' \Delta x_t + \sum_{i=1}^{p-1} \varphi_i' \Delta z_{t-1} + \varepsilon_t \quad (2)$$

In this model, the null hypothesis test no cointegration ($\delta = 0$) and the alternative one test cointegration with ESTAR adjustment is $\delta > 0$.

2.3. ANN architecture

Many different tools are used to perform the prediction process, which can be defined as reaching results using data obtained in various ways [44–48]. Conventional tools give good results in predicting linear functions. However, traditional methods are insufficient in predicting the data that changes irregularly with time, nonlinear and there is no regular relationship between them, and the predictions of these models are not accepted [49]. ANNs, which were developed in the mid-twentieth century, inspired by the biological structure of the human brain, are one of the AI algorithms that are commonly used to predict nonlinear complex functions [50]. One of the most used and high performance models among ANN algorithms is the multilayer perceptron (MLP) network [51–55]. The MLP network consists of an input layer, one or more hidden layers, and an output layer. These layers are interconnected through neurons, which act as computational elements. Neurons are characterized by parameters such as weight (w), bias (b), and a transfer function (f). Training is the process of establishing the relationship between the input and target variables in the MLP network. During this process, an algorithm is employed to adjust the weight values based on the discrepancy between the predicted values and the actual values. The feedforward backpropagation (FFBP) algorithm is a commonly used method for training MLP networks. The information flows forward from the input layer, while the calculated errors are propagated backward to the input layer to iteratively update the weights and biases. This iterative process continues until the error between the target data and the predicted data is minimized, signifying the completion of the network's training [52].

In this study, an ANN was developed to predict BIST100 and CDSs. In the MLP network developed with FFBP, date, volume, SP500, WTI, GOLD, and USD variables are defined in the input layer as input parameters. The model utilizes the Levenberg–Marquardt algorithm as its training function, with a hidden layer consisting of 25 neurons. The preferred transfer functions employed in the hidden and output layers are the Tangent sigmoid (Tan-Sig) and linear (Purelin) functions, respectively. Below are the definitions of these transfer functions:

Tangent sigmoid (Tan-Sig) transfer function is chosen for the hidden layer, and its mathematical representation is as follows:

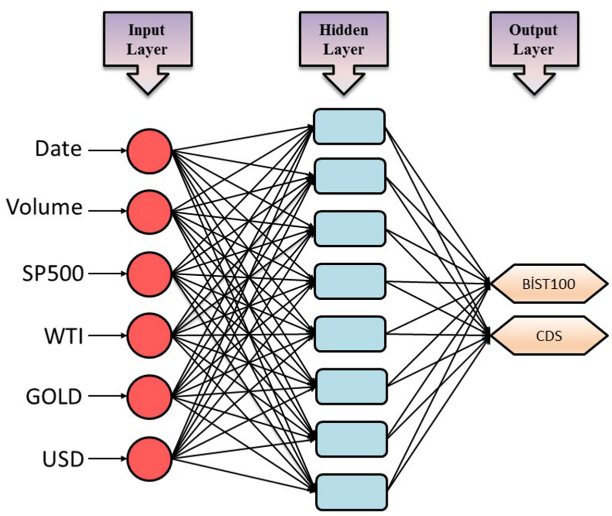
$$f(x) = \frac{1}{1 + \exp(-x)} \quad (3)$$

Linear (Purelin) transfer function: This function is used in the output layer, and it is defined simply as:

$$purelin(x) = x \quad (4)$$

The configuration topology of the developed ANN is given in Figure 1.

Figure 1
The configuration topology of the developed ANN



The performance of ANNs is directly influenced by various factors, one of which is the optimization of training data [56]. Therefore, in the development of the ANN model, special attention has been given to optimizing the data, ensuring the most favorable outcomes. Of the 1211 data used in the development of ANN, 848 (70%) were used for the training stage, 242 (20%) for the validation stage, and 121 (10%) for the test stage. Mean square error (MSE) and coefficient of determination (R) values given in Equations (3) and (4) were preferred to evaluate the performance analysis of ANN [57].

$$\mathrm{MSE} = \frac{1}{\mathrm{N}}\sum_{i=1}^{\mathrm{N}}\left(\mathrm{X}_{\mathrm{real(i)}} - \mathrm{X}_{\mathrm{ANN(i)}}\right)^2 \tag{5}$$

$$R = \sqrt{1 - \frac{\sum_{i=1}^{N}\left(\mathrm{X}_{\mathrm{real(i)}} - \mathrm{X}_{\mathrm{ANN(i)}}\right)^2}{\sum_{i=1}^{N}\left(\mathrm{X}_{\mathrm{real(i)}}\right)^2}} \tag{6}$$

Another parameter used in the analysis of the predictive performance of ANN is margin of deviation (MoD) value. Equation (5) was used to calculate the MoD value used in analyzing the error ratio between the predicted value obtained from ANN and the realized data [58].

$$\mathrm{MoD}\ (\%) = \left[\frac{\mathrm{X}_{\mathrm{real}} - \mathrm{X}_{\mathrm{ANN}}}{\mathrm{X}_{\mathrm{real}}}\right] \times\ 100 \tag{7}$$

3. Results and Discussion

This section provides an exhaustive exposition of the study's outcomes. Primarily, the relationships between the variables were examined with nonlinear econometric models. Subsequently, analysis of the results derived from the ANN models is conducted.

In this study, two variables belonging to the same economy, the BIST100 stock index and the Türkiye 5-year CDS premiums, were estimated. Before presenting the model results, descriptive statistics of the variables used are presented in Table 2. Positive Kurtosis values (1.69: 12.61) indicate that the series has got leptokurtic distributions that are peaked and possess fat tails. Negative skewness values of Oil and SP500 describe that distributions of the series are skewed to the left with fatter tails on the left side. Positive skewness of the other variables show that the tail of the distribution curve fort the related variables are longer on the right side. Jarque–Bera test results also support that the series do not show normal distribution.

The results of the KSS cointegration test, which tests the presence of a long-term nonlinear relationship between variables, are presented in Table 3. When examining the relationship between the BIST100 index and CDS with other variables, it was found that CDS moves together with other variables with high significance. There is a nonlinear cointegration relationship at the significance level of 0.01, especially between CDS and volume, S&P 500, gold, oil, and exchange rates. This indicates that these variables are interrelated in their price movements and behave according to each other's prices. Understanding and analyzing such a relationship are important for risk management, making investment decisions and predictions in financial markets. Only 7 out of 18 models established between BIST100 indexes have got significant results. It is interesting that a significant model could not be found between gold and the stock index.

The ESTAR ECM results are summarized in Table 4. Table 4, which only provides significance levels, shows that some of the models established between BIST100 index and other variables are significant, while in most of the models established with CDS, the error correction mechanism works. The ECM is a model used in time series analysis to eliminate the imbalance between short-term and long-term relationships and to test short-term and long-term causality among cointegrated variables. If the ECM is significant, it means that the variables in the model are cointegrated, and their long-term equilibrium relationship is statistically significant. The significance of ECM also indicates that there is a short-term dynamic relationship between the variables in the model, and this relationship can be used to make predictions or inform decisions about future changes in the variables.

Since CDSs show country risk, a negative relationship is expected between CDSs and stock market indexes. If the investment risk of an emerging economy increases, it is expected that the portfolio investments in the financial assets of that country and the value of the financial assets will decrease simultaneously. In Figures 2 and 3, the time dependence change of BIST100 and 5-year CDSs is given. During the observation period, the USD value of the bist100 index was taken into account due to the significant depreciation of the Turkish lira. With the USD value of the Bist100, it is clearly seen the figures that the negative relationship with the CDSs variable, which foreign investors attach importance to, continues throughout the observation period. In the 3D graph in Figure 3, while CDS increases in the areas where the color turns yellow, the stock market continues to lose value in USD. As the color turns red, the loss of value increases as the risk increases. In the blue areas that generally point pre-2018, although the CDSs are high, the losses in the stock market are not as high as the other dates in the observation period. The depreciation of the Turkish lira especially after the exchange rate attack in August 2018, the COVID19 pandemic, and the foreign investor had been leaving the BIST100

Table 2
Descriptive statistics

					Jarque–Bera test	
Variables	Mean	Std. Dev.	Skewness	Kurtosis	Value	Probability
BIST100	225.60	52.53	0.00	1.69	86.05	0.00
BISTVOL	1,240,000,000.00	822,000,000.00	2.61	12.61	6,032.27	0.00
CDS	303.85	107.54	1.00	3.46	210.53	0.00
GOLD	6106.80	2565.43	1.03	3.42	223.26	0.00
OIL	51.21	11.53	−0.75	5.99	563.09	0.00
SP500	2572.60	386.90	−0.01	2.00	50.06	0.00
USDTRY	4.47	1.34	0.36	1.70	112.20	0.00

Table 3
KSS (2006) cointegration test

KSS (2006) cointegration test	Raw	Demeaned	Detrend
BIST100 – Volume	−1.638460 (12)	−3.702043 (12)***	−2.132768 (12)
BIST100 – CDS	−2.740759 (12)**	−2.898364 (12)**	−2.844924 (12)**
BIST100 – SP500	−1.313768 (12)	−3.117397 (12)**	−2.264318 (12)
BIST100 – GOLD	−0.052390 (12)	−2.304583 (12)	−2.312183 (12)
BIST100 – OIL	−9.608108 (12)***	−2.259901 (12)	−2.183091 (12)
BIST100 – USDTRY	−1.643656 (12)	−2.441286 (12)	−6.284729 (12)***
CDS – BIST100	−3.016400 (12)**	−2.918290 (12)**	−2.714041 (12)*
CDS – Volume	−3.860488 (12)***	−4.814514 (12)***	−4.876277 (12)***
CDS – SP500	−4.568751 (12)***	−4.591359 (12)***	−3.620128 (12)***
CDS – GOLD	−3.37731 (12)***	−5.102972 (12)***	−4.688887 (12)***
CDS – OIL	−6.925549 (12)***	−4.480586 (12)***	−3.210969 (12)**
CDS – USDTRY	−3.920979 (12)***	−4.205798 (12)***	−4.573296 (12)***

Table 4
ESTAR ECM

	ESTAR ECM			
	I(u^3)	DX1	DX2	DY1
BIST100 – Volume	0.0451 *	0.4266	0.7585	0.0871
BIST100 – CDS	0.0180 *	0.0000 ***	0.6250	0.5100
BIST100 – SP500	0.1644	0.0000 ***	0.0149 *	0.1419
BIST100 – GOLD	0.0511	0.0000 ***	0.1230	0.0620
BIST100 – OIL	0.0373 *	0.0078 **	0.1039	0.0957
BIST100 – USDTRY	0.02425 *	0.0000 ***	0.0026 **	0.0628
CDS – BIST100	0.0000 ***	0.0000 ***	0.0018 **	0.0328 *
CDS – Volume	0.0000 ***	0.0334 *	0.6342	0.0000 ***
CDS – SP500	0.0093 **	0.0000 ***	0.0008 ***	0.0000 ***
CDS – GOLD	0.0000 ***	0.0000 ***	0.0001 ***	0.0002 ***
CDS – OIL	0.0000 ***	0.1834	0.0684	0.0000 ***
CDS – USDTRY	0.0000 ***	0.0000 ***	0.0005 ***	0.0066 **

Figure 2
Time-dependent change of BIST100 and CDSs

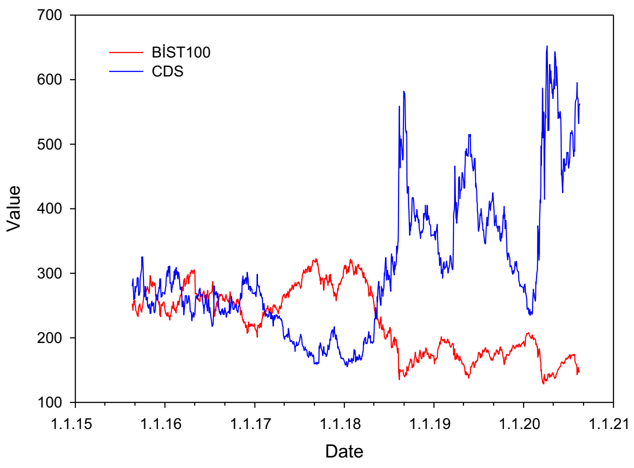


Figure 3
Time-dependent change of BIST100 and CDSs in 3D graphic

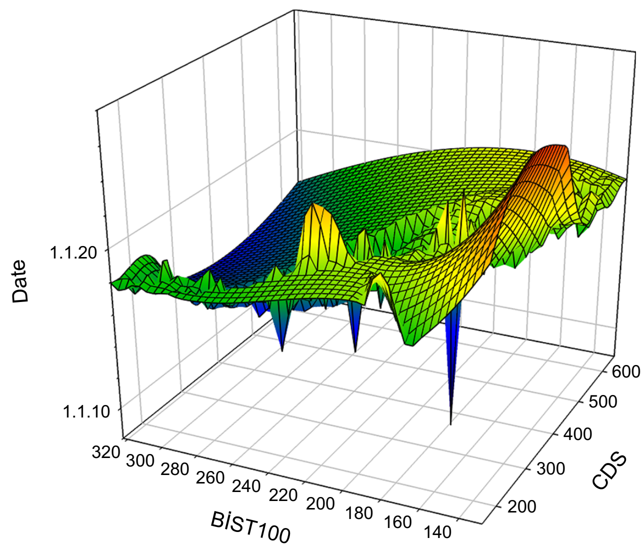


Figure 4
Training performance of the ANN

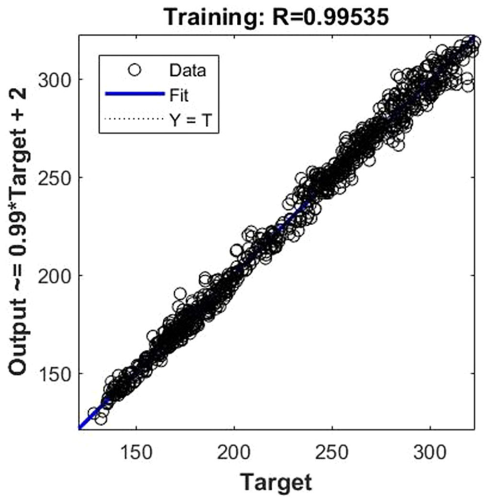
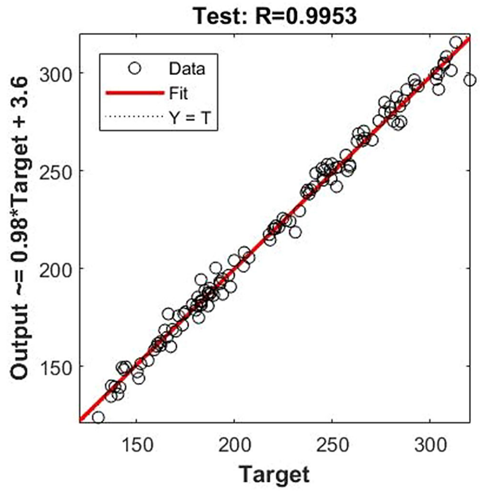


Figure 6
Test performance of the ANN



in the 2020 period can be counted among the reasons for the strengthening of the negative relationship.

Evaluating the performance of the data set used in the development of ANNs separately is a crucial aspect in analyzing the prediction performances of ANNs. Consequently, each data set utilized in the ANN development has undergone separate performance analysis. Figure 4 displays the training performance of the ANN using 848 data points. The graph portrays the realized data (target) on the x-axis and the ANN outputs on the y-axis. Observing the positioning of the data points on the graph, it is apparent that they cluster around the blue fitting line and the dotted zero error line. The *R*-value obtained for the training phase data set is 0.99535, indicating that the training phase of the developed ANN is optimally completed. Performance chart of the validation stage of ANN is given in Figure 5. The *R* value obtained for the validation stage, which was carried out with a total of 242 data sets, is 0.99322. It can be seen in the graph where the validation data points are located on the zero error line drawn in green. When both cases are evaluated, it is concluded that the validation stage of ANN is completed with ideal accuracy. Figure 6 shows the performance chart of the test phase, which was carried out with a total of 121 data sets. When the graph is examined, it is seen that the data points are located close to the zero error and fitting lines. However, the R value obtained for the test phase is also 0.9953. It is clearly understood from the graph and the obtained R value that the test phase of ANN is also ideally completed. Performance graph of all data used in ANN developed with 1211 data set is given in Figure 7. Due to the high number of data, it should be considered that the data points are in bulk. Upon analyzing the graph, it becomes evident that the data points are positioned precisely along the zero error and fitting line. Nevertheless, it is important to emphasize that the *R* value attained for all the data is 0.99492. This particular observation strongly indicates that the ANN developed has been trained to near perfection.

In Figures 8 and 9, the comparison between the AI prediction data and the actual data of BIST100 and CDSs, respectively, is given. While the time period of 5 years is located on the x-axis of the graphs, on the y-axis there are BIST100 and CDSs. It is seen by examining the graphics that the AI outputs expressed with a red dot are located

Figure 5
Validation performance of the ANN

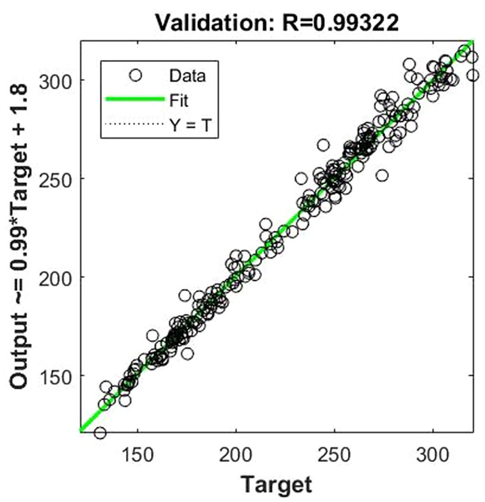


Figure 7
Overall performance of the ANN

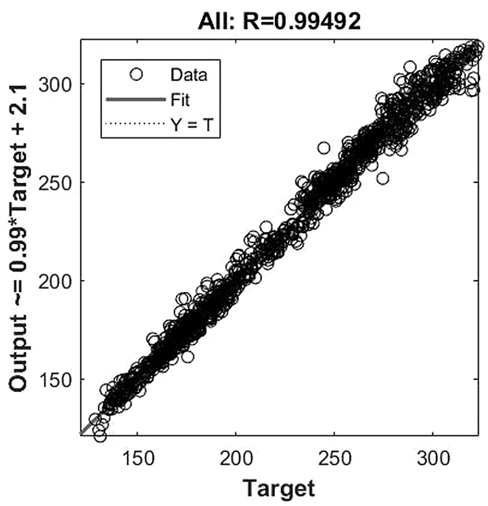


Figure 8
Comparison of realized BIST100 values with AI predictions

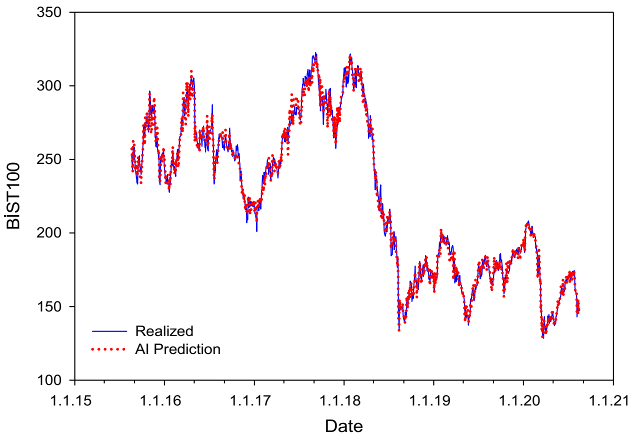


Figure 9
Comparison of realized CDSs with AI predictions

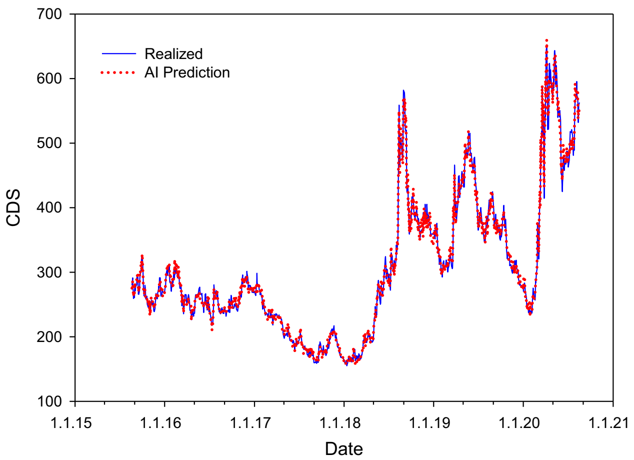


Figure 10
Comparison of BIST100 values and artificial intelligence outputs according to the number of test data

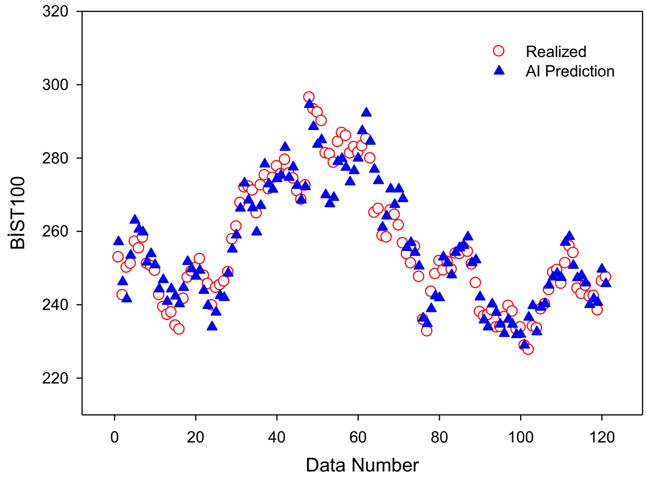
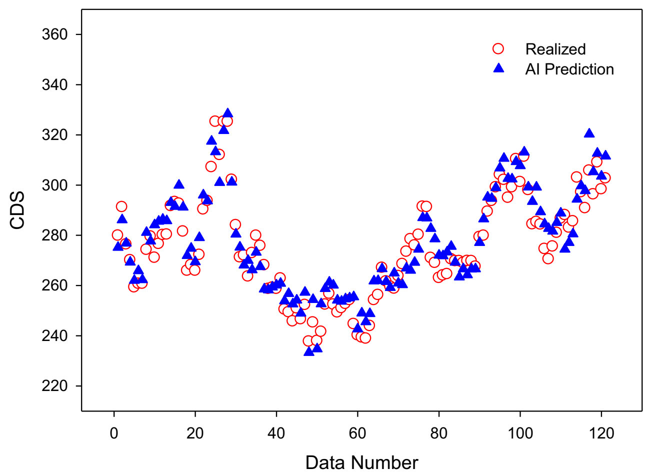


Figure 11
Comparison of CDSs and artificial intelligence outputs according to the number of test data



on the realized values drawn with the blue line. This good agreement between the realized values and the predicted values obtained from the AI simulation indicates that the developed simulation model is designed to predict the BIST100 and CDS data with very low error rates and an acceptable deviation. In the realm of finance, the EMH, a cornerstone theory, posits that security prices cannot be predicted based on data such as past prices and trading volumes of securities. It asserts that existing information is already reflected in prices and that abnormal returns beyond expectations are unattainable. However, simulation outcomes provide evidence that contradicts this theory.

A comparison of BIST100 and CDSs and AI outputs according to the number of test data is given in Figures 10 and 11. When the graphs are examined, it is seen that the AI outputs expressed in blue are located very close to the realized data points expressed in red. As can be seen from this comparison made for 121 data used for the test data set, the outputs obtained from the developed simulation and the real performed BIST100 and CDSs are in good agreement. This situation proves that the developed ANN has been designed in an ideal way. It is important to examine the MoD value in analyzing the predictive performance of ANNs. MoD value expresses the deviation margin between the output obtained from ANN and the realized values. In other words, it is the error rate between target values and outputs. In Figures 12 and 13, MoD values calculated using Equation (5) are shown. As can be seen from the figures, the MoD between the outputs obtained from the developed simulation model and the realized BIST100 and CDSs is acceptable. It is seen that it can predict with an error margin between −4.98% and 4.96%. However, attention should also be paid to the proximity of the data points to the zero error line. This situation is considered as another proof that the developed model has been designed to predict BIST100 and CDSs with acceptable accuracy. Performance parameters of ANN and data sets allocated for each section are given in Table 5.

To gain deeper insights into the relationship between the predicted values by the ANN and the actual values, the realized

Figure 12
MoD for BIST100 value

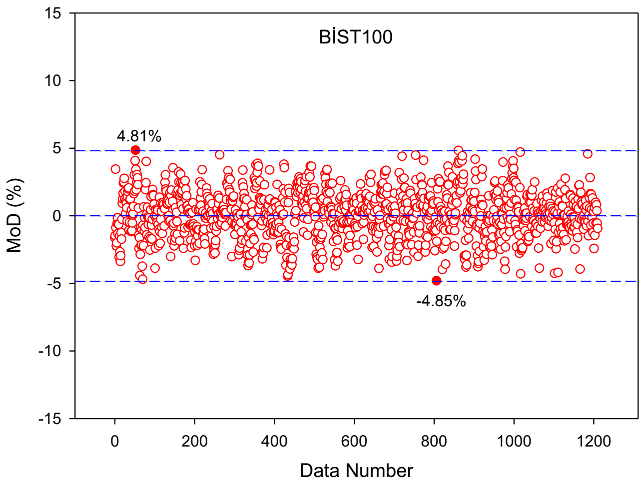


Figure 13
MoD for CDS value

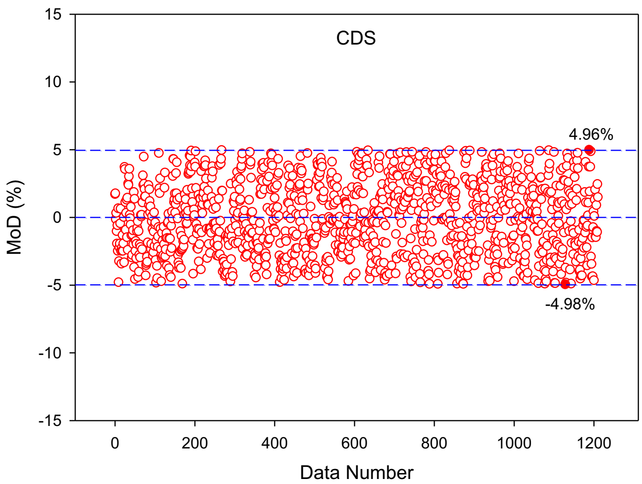


Table 5
Performance data of the ANN

Data set	MSE	R	Number of data
Training	2.58E-04	0.99535	848
Validation	3.64E-04	0.99322	242
Test	2.53E-04	0.99530	121
All	2.92E-04	0.99492	1211

Figure 14
Comparison of actual data and ANN predictions for BIST100

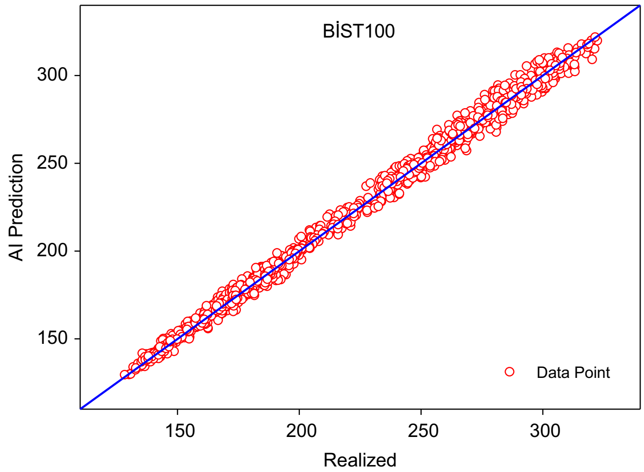
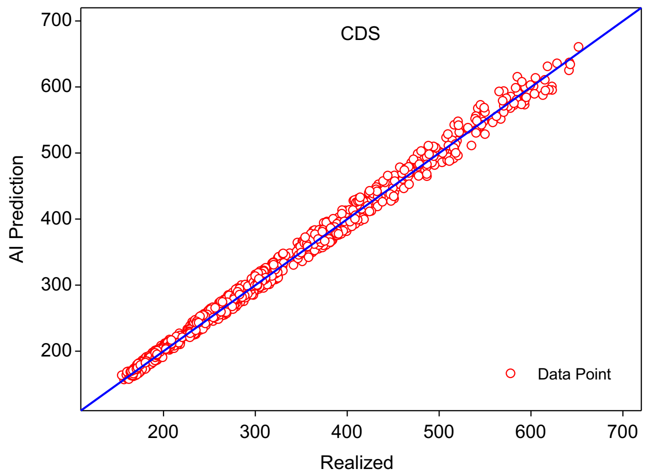


Figure 15
Comparison of actual data and ANN predictions for CDS



values and the ANN outputs are presented in Figures 14 and 15 in a different graph. While there are BIST100 and CDSs realized on the x-axis of the graphs, on the y-axes there are the values predicted by ANN. Upon examining the graphs, it becomes evident that the data points cluster around the equality line, indicating a close alignment between the predicted values by the ANN and the realized values. This situation shows that the values predicted by ANN are very close to the realized values; in other words, there is a very good fit between target and prediction data.

4. Conclusion

On the growing role of AI in trading decisions in the financial markets, the importance of models that can make predictions with high-frequency daily data has also increased. In this study, a simulation model was developed in order to predict BIST100 and CDSs with the AI approach and the outputs obtained from the simulation model were analyzed by comparing with the realized values. In the study, 5 years of data are used that have taken place in Türkiye. The ANN model, which was developed with a total of 1211 data sets, was developed to include 25 neurons in the hidden layer. Of the data used in the FFBP MLP network, 70% was used for training, 20% for validation, and 10% for testing. The data obtained from ANN, which was optimized as a result of experiments with different models, were compared with the realized data and the predictive performance of the ANN was analyzed. The developed simulation model was able to predict the BIST100 values with the margin of error between −4.85% and 4.81%, and the CDSs with the margin of error between −4.98% and 4.96%. The MSE value obtained for ANN is 2.92E-04 and the *R* value is 0.99492. All these data confirm that the AI-based simulation model has been developed in such a way that it can predict BIST100 and CDSs with low and acceptable error rates. It is considered that AI-based models can be used in future studies to predict different financial data and also can be used by professionals. The results also provide evidence abnormal returns can be obtained from financial markets by estimating the stock market index and CDS spreads with other daily changing parameters. SP500 index, which is the main index for the US stock markets, BIST100 volume, exchange rate, oil price, and gold price are among the indicators that can be used to predict the markets by financial professionals and academicians.

This study has several valuable implications and contributions for both the financial industry and decision makers in the field. The developed model's predictions are closely aligned with the realized values. This accuracy is crucial for investors and decision makers who rely on precise predictions to make informed trading decisions. Moreover, the results hold significant value for risk management and investment strategies. Decision makers can use these predictions to anticipate market trends, systemic risks, and potential financial crises. This predictive capability enables proactive risk management and the formulation of effective investment strategies to optimize returns and manage exposure to market fluctuations. The study also provides evidence that by accurately estimating the stock market index (BIST100) and CDS spreads with daily changing parameters, abnormal returns can be generated from financial markets. This insight is valuable for investors who seek to capitalize on market inefficiencies and exploit opportunities for abnormal returns. We suggest that the developed AI-based model could potentially contribute to generating alpha in investment portfolios.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data are available on request from the corresponding author upon reasonable request.

Author Contribution Statement

Ayben Koy: Conceptualization, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft. **Andaç Batur Çolak:** Methodology, Software, Validation, Investigation, Writing – original draft.

References

[1] Fama, E. (2017). Efficient capital markets: A review of theory and empirical work. In J. Cochrane & T. Moskowitz (Eds.), *The Fama portfolio: Selected papers of Eugene F. Fama* (pp. 76–121), University of Chicago Press.

[2] Fama, E. F. (1991). Efficient capital markets: II. *The Journal of Finance*, *46*(5), 1575–1617.

[3] Blanco, R., Brennan, S., & Marsh, I. W. (2005). An empirical analysis of the dynamic relation between investment-grade bonds and credit default swaps. *The Journal of Finance*, *60*(5), 2255–2281.

[4] Hull, J. C. (2000). *Options, futures and other derivatives*. USA: Prentice Hall.

[5] Chan, K. C., Fung, H. G., & Zhang, G. (2009). On the relationship between Asian credit default swap and equity markets. *Journal of Asia Business Studies*, *4*(1), 3–12.

[6] Chau, F., Han, C., & Shi, S. (2018). Dynamics and determinants of credit risk discovery: Evidence from CDS and stock markets. *International Review of Financial Analysis*, *55*, 156–169.

[7] Koy, A. (2015). The relationship between credit default swap spreads, equity indices and sector equity indices: An empirical study on Istanbul stock exchange. In *Proceedings of 17th International Academic Conferences*.

[8] Realdon, M. (2008). Credit default swap rates and stock prices. *Applied Financial Economics Letters*, *4*(4), 241–248.

[9] Coudert, V., & Gex, M. (2010). Disrupted links between credit default swaps, bonds and equities during the GM and Ford crisis in 2005. *Applied Financial Economics*, *20*(23), 1769–1792.

[10] Scheicher, M. (2009). The correlation of a firm's credit spread with its stock price: Evidence from credit default swaps. In G. N. Gregoriou (Ed.), *Stock market volatility* (pp. 405–418). CRC Press.

[11] Hammoudeh, S., & Sari, R. (2011). Financial CDS, stock market and interest rates: Which drives which? *The North American Journal of Economics and Finance*, *22*(3), 257–276.

[12] Lim, K., Kim, S., & Kim, S. Y. (2017). Information transfer across intra/inter-structure of CDS and stock markets. *Physica A: Statistical Mechanics and Its Applications*, *486*, 118–126.

[13] Srivastava, S., Lin, H., Premachandra, I. M., & Roberts, H. (2016). Global risk spillover and the predictability of sovereign CDS spread: International evidence. *International Review of Economics & Finance*, *41*, 371–390.

[14] Egeli, B., Ozturan, M., & Badur, B. (2003). Stock market prediction using artificial neural networks. *Decision Support Systems, 22*, 171–185.

[15] Adebiyi, A. A., Adewumi, A. O., & Ayo, C. K. (2014). Comparison of ARIMA and artificial neural networks models for stock price prediction. *Journal of Applied Mathematics*, *2014*(1), 614342.

[16] de Oliveira, F. A., Nobre, C. N., & Zarate, L. E. (2013). Applying artificial neural networks to prediction of stock price and improvement of the directional prediction index–Case study of PETR4, Petrobras, Brazil. *Expert Systems with Applications*, *40*(18), 7596–7606.

[17] Telli, Ş., & Coşkun, M. (2016). Forecasting the BIST 100 Index using artificial neural networks with consideration of the economic calendar. *International Review of Economics and Management*, *4*(3), 26–46.

[18] 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.

[19] Bildirici, M., & Ersin, Ö. Ö. (2009). Improving forecasts of GARCH family models with the artificial neural networks: An application to the daily returns in Istanbul Stock Exchange. *Expert Systems with Applications*, *36*(4), 7355–7362.

[20] Ozgur, C., & Sarikovanlik, V. (2022). Forecasting BIST100 and NASDAQ indices with single and hybrid machine learning algorithms. *Economic Computation and Economic Cybernetics Studies and Research*, *56*(3), 235–250.

[21] Boyacioglu, M. A., & 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.

[22] Wei, L. Y., Chen, T. L., & Ho, T. H. (2011). A hybrid model based on adaptive-network-based fuzzy inference system to forecast Taiwan stock market. *Expert Systems with Applications*, *38*(11), 13625–13631.

[23] Göçken, M., Özçalıcı, M., Boru, A., & Dosdoğru, A. T. (2016). Integrating metaheuristics and artificial neural networks for improved stock price prediction. *Expert Systems with Applications*, *44*, 320–331.

[24] Son, Y., Byun, H., & Lee, J. (2016). Nonparametric machine learning models for predicting the credit default swaps: An empirical study. *Expert Systems with Applications*, *58*, 210–220.

[25] Hanias, M. P., Magafas, L., & Ozun, A. (2011). Predicting the CDS return index. *Journal of Engineering Science and Technology Review*, *4*(3), 297–300.

[26] Koutmos, D. (2019). Asset pricing factors and bank CDS spreads. *Journal of International Financial Markets, Institutions and Money*, *58*, 19–41.

[27] Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1–22.

[28] Guesmi, K., Dhaoui, A., Goutte, S., & Abid, I. (2018). On the determinants of industry-CDS index spreads: Evidence from a nonlinear setting. *Journal of International Financial Markets, Institutions and Money*, *56*, 233–254.

[29] Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *The Journal of Finance*, *51*(1), 55–84.

[30] da Fonseca, J., Ignatieva, K., & Ziveyi, J. (2016). Explaining credit default swap spreads by means of realized jumps and volatilities in the energy market. *Energy Economics*, *56*, 215–228.

[31] Shahzad, S. J. H., Nor, S. M., Ferrer, R., & Hammoudeh, S. (2017). Asymmetric determinants of CDS spreads: US industry-level evidence through the NARDL approach. *Economic Modelling*, *60*, 211–230.

[32] Naumer, H. J., & Yurtoglu, B. (2022). It is not only what you say, but how you say it: ESG, corporate news, and the impact on CDS spreads. *Global Finance Journal*, *52*, 100571.

[33] Pereira, J., Sorwar, G., & Nurullah, M. (2018). What drives corporate CDS spreads? A comparison across US, UK and EU firms. *Journal of International Financial Markets, Institutions and Money*, *56*, 188–200.

[34] Wang, X., Wu, Y., Yan, H., & Zhong, Z. (2021). Funding liquidity shocks in a quasi-experiment: Evidence from the CDS big bang. *Journal of Financial Economics*, *139*(2), 545–560.

[35] Ballestra, L. V., Pacelli, G., & Radi, D. (2020). Modeling CDS spreads: A comparison of some hybrid approaches. *Journal of Empirical Finance*, *57*, 107–124.

[36] Procasky, W. J. (2021). Price discovery in CDS and equity markets: Default risk-based heterogeneity in the systematic investment grade and high yield sectors. *Journal of Financial Markets*, *54*, 100581.

[37] Mao, W., Zhu, H., Wu, H., Lu, Y., & Wang, H. (2023). Forecasting and trading credit default swap indices using a deep learning model integrating Merton and LSTMs. *Expert Systems with Applications*, *213*, 119012.

[38] Lin, S. Y., Liu, D. R., & Huang, H. P. (2022). Credit default swap prediction based on generative adversarial networks. *Data Technologies and Applications*, *56*(5), 720–740.

[39] Kilian, L., & Park, C. (2009). The impact of oil price shocks on the U.S. stock market. *International Economic Review*, *50*(4), 1267–1287.

[40] Sakellaris, P. (1997). Irreversible capital and the stock market response to shocks in profitability. *International Economic Review*, *38*(2), 351–379.

[41] Arouri, M. E. H., Lahiani, A., & Bellalah, M. (2010). Oil price shocks and stock market returns in oil-exporting countries: The case of GCC countries. *International Journal of Economics and Finance*, *2*(5), 132–139.

[42] Triki, M. B., & Maatoug, A. B. (2021). The GOLD market as a safe haven against the stock market uncertainty: Evidence from geopolitical risk. *Resources Policy*, *70*, 101872.

[43] Kapetanios, G., Shin, Y., & Snell, A. (2006). Testing for cointegration in nonlinear smooth transition error correction models. *Econometric Theory*, *22*(2), 279–303.

[44] Gao, W., Guirao, J. L. G., Basavanagoud, B., & Wu, J. (2018). Partial multi-dividing ontology learning algorithm. *Information Sciences*, *467*, 35–58.

[45] Gao, W., Wang, W., Dimitrov, D., & Wang, Y. (2018). Nano properties analysis via fourth multiplicative ABC indicator calculating. *Arabian Journal of Chemistry*, *11*(6), 793–801.

[46] Gao, W., Wu, H., Siddiqui, M. K., & Baig, A. Q. (2018). Study of biological networks using graph theory. *Saudi Journal of Biological Sciences*, *25*(6), 1212–1219.

[47] Dimitrov, D., & Abdo, H. (2019). Tight independent set neighborhood union condition for fractional critical deleted graphs and ID deleted graphs. *Discrete and Continuous Dynamical Systems – Series S*, *12*(4&5), 711–721.

[48] Gao, W., Guirao, J. L. G., Abdel-Aty, M., & Xi, W. (2019). An independent set degree condition for fractional critical deleted graphs. *Discrete and Continuous Dynamical Systems – Series S*, *12*(4&5), 877–886.

[49] Bahiraei, M., Heshmatian, S., & Moayedi, H. (2019). Artificial intelligence in the field of nanofluids: A review on applications and potential future directions. *Powder Technology*, *353*, 276–301.

[50] Ariana, M. A., Vaferi, B., & Karimi, G. (2015). Prediction of thermal conductivity of alumina water-based nanofluids by artificial neural networks. *Powder Technology*, *278*, 1–10.

[51] Canakci, A., Ozsahin, S., & Varol, T. (2012). Modeling the influence of a process control agent on the properties of metal matrix composite powders using artificial neural networks. *Powder Technology*, *228*, 26–35.

[52] Canakci, A., Varol, T., & Ozsahin, S. (2013). Analysis of the effect of a new process control agent technique on the mechanical milling process using a neural network model: Measurement and modeling. *Measurement*, *46*(6), 1818–1827.

[53] Feng, Q., Zhang, J., Zhang, X., & Wen, S. (2015). Proximate analysis based prediction of gross calorific value of coals: A

comparison of support vector machine, alternating conditional expectation and artificial neural network. *Fuel Processing Technology*, *129*, 120–129.

[54] Vaferi, B., Eslamloueyan, R., & Ayatollahi, S. (2011). Automatic recognition of oil reservoir models from well testing data by using multi-layer perceptron networks. *Journal of Petroleum Science and Engineering*, *77*(3-4), 254–262.

[55] Vaferi, B., Samimi, F., Pakgohar, E., & Mowla, D. (2014). Artificial neural network approach for prediction of thermal behavior of nanofluids flowing through circular tubes, *Powder Technology*, *267*, 1–10.

[56] Çolak, A. B. (2021). An experimental study on the comparative analysis of the effect of the number of data on the error rates of artificial neural networks. *International Journal of Energy Research*, *45*(1), 478–500.

[57] Çolak, A. B., Yıldız, O., Bayrak, M., & Tezekici, B. S. (2020). Experimental study for predicting the specific heat of water based Cu-Al2O3 hybrid nanofluid using artificial neural network and proposing new correlation. *International Journal of Energy Research*, *44*(9), 7198–7215.

[58] Çolak, A. B. (2021). Experimental study for thermal conductivity of water-based zirconium oxide nanofluid: Developing optimal artificial neural network and proposing new correlation. *International Journal of Energy Research*, *45*(2), 2912–2930.

How to Cite: Koy, A., & Batur Çolak, A. (2025). Predicting Stock Market Index and Credit Default Swap Spreads Using Artificial Intelligence and Determining Nonlinear Relations. *Archives of Advanced Engineering Science*, *3*(3), 151–162. https://doi.org/10.47852/bonviewAAES32021366

Appendix

Nomenclature

AI	Artificial Intelligence
ANFIS	Adaptive Network-Based Fuzzy Inference System
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
BNN	Bayesian Neural Networks
CDS	Credit Default Swap
CSR	Corporate Social Responsibility
EMH	Efficient Market Hypothesis
ESG	Environmental, Social, and Governance
GA	Genetic Algorithms
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GP	Gaussian Process
HS	Harmony Search
KOSPI	Korean Stock Price Index
MA	Moving Averages
ML	Machine Learning
MLP	Multilayer Perceptron
MoD	Margin of Deviation
SVR	Support Vector Regression
TAIEX	Taiwan Stock Exchange Capitalization Weighted Stock Index
VAR	Vector Autoregressive
VARMA	Vector Autoregressive Moving Average
VIX	Volatility Index