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Araştırma Makalesi

The Effectiveness of Artificial Intelligence in Financial Analysis: Evidence from Istanbul Stock Exchange 100 (ISE 100).

Finansal Analizde Yapay Zekânın Etkinliği: İstanbul Menkul Kıymetler Borsası 100 (İMKB 100) Üzerine Kanıtlar

Fikriye ÜSTÜNER	Erhan ÇANKAL
Lecturer, Ankara Hacı Bayram Veli University	Assoc. Prof., Ankara Yıldırım Beyazıt University
Polatlı Social Sciences Vocational School	Faculty of Business Administration
fikriye.ustuner@hbv.edu.tr	ecankal@ybu.edu.tr
https://orcid.org/0000-0002-6010-0260	https://orcid.org/0000-0001-5115-055X

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Abstract

The study aims to analyze the effects of macroeconomic indicators on the Istanbul Stock Exchange (ISE 100) index using deep learning techniques based on artificial neural networks, a technology within the realm of artificial intelligence. To forecast ISE 100 index the monthly closing prices for seven macro-economic indicators (Money Supply (M2), Producer Price Index (PPI), Industrial Production Index (IPI), Exchange Rate (USD/TRY), Bond Interest Rates, Brent Oil Prices, and Gold Prices) are used in January 2001 to January 2022. The ISE 100 index has been forecasted within the framework of both deep learning models, including Long Short-Term Memory (LSTM), and Logit and Probit models, and the forecast performances of these methods have been compared. Analysis results reveal that the effects of selected macroeconomic variables on the ISE 100 index intensify during crisis periods, including the COVID-19 pandemic and the global financial crisis of 2008. In addition, the changes in the real sector have a significant impact on the capital sector, and the deep learning model is more successful in predicting financial crises. The results of the analysis show that the LSTM deep learning architectures, developed to analyze the effects of macroeconomic indicators on the ISE 100 index, have a very low error level and give more effective and satisfactory results than Logit-Probit regression models. These results offer guidance information to emerging markets and policymakers.

Keywords: *Artificial Intelligence, Deep Learning Architecture (LSTM), Macroeconomic Indicators and ISE 100, Financial Forecasting, Logit-Probit.*

JEL Classification : *C45, C58, E47, F62*

Öz

Bu çalışmanın amacı, yapay zekâ alanında bir teknoloji olan yapay sinir ağlarına dayalı derin öğrenme tekniklerini kullanarak makroekonomik göstergelerin Borsa İstanbul (BIST 100) endeksi üzerindeki etkilerini analiz etmektir. BIST 100 endeksini tahmin etmek için yedi makroekonomik göstergenin (Para Arzı (M2), Üretici Fiyat Endeksi (ÜFE), Sanayi Üretim Endeksi (SÜE), Döviz Kuru (USD/TL), Tahvil Faiz Oranları, Brent Petrol Fiyatları ve Altın Fiyatları) Ocak 2001-Ocak 2022 dönemindeki aylık kapanış fiyatları kullanılmıştır. BIST 100 endeksi, Uzun Kısa-Dönem Hafiza (LSTM) dahil olmak üzere hem derin öğrenme modelleri hem de Logit ve Probit modelleri çerçevesinde tahmin edilmiş ve bu yöntemlerin tahmin performansları karşılaştırılmıştır. Analiz sonuçları, seçilen makroekonomik değişkenlerin, BIST 100endeksi üzerindeki etkilerinin COVID-19 pandemisi ve

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2008 küresel finansal krizi de dahil olmak üzere kriz dönemlerinde yoğunlaştığını ortaya koymaktadır. Ayrıca, reel sektördeki değişimlerin sermaye sektörü üzerinde önemli bir etkiye sahip olduğu ve derin öğrenme modelinin finansal krizleri öngörmede daha başarılı olduğu görülmüştür. Analiz sonuçları, makroekonomik göstergelerin BIST 100 endeksi üzerindeki etkilerini analiz etmek için geliştirilen LSTM derin öğrenme mimarilerinin çok düşük hata seviyesine sahip olduğunu ve Logit-Probit regresyon modellerine göre daha etkin ve tatmin edici sonuçlar verdiğini göstermektedir. Bu sonuçlar gelişmekte olan piyasalara ve politika yapıcılara yol gösterici bilgiler sunmaktadır.

Anahtar Kelimeler: *Yapay Zekâ, Derin Öğrenme Mimarisi (LTSM), Makroekeonomik Göstergeler ve BIST 100, Finansal Öngörü, Logit-Probit.*

JEL Sınıflandırması: *C45, C58, E47, F62*

1. Introduction

The increasing volatility in the global financial markets, due to systemic shocks such as the 2008 global economic crisis and the COVID-19 pandemic, has shown how important it is to forecast the possible chaos and uncertainties in financial markets and the fluctuations that may occur in micro and macroeconomic factors affecting price movements to prevent and reduce the effects of financial breaks and uncertainties in the markets. This situation has revealed the fact that economic decision-makers can gain significant advantages and opportunities if they can accurately forecast the future value of capital market instruments and asset prices. This has also led to an increase in demand for reliable forecasting models that can accurately predict the nonlinearity and high-frequency variations inherent in financial time series.

Although used for many years, traditional econometric model techniques have been unable to satisfactorily explain the complex relationship between stock market activity and macroeconomic variables. Due to the linear or curvilinear relationship between the variables, making estimations based on linear relationships implies that traditional models may not guarantee the accuracy of their estimations (Donaldson & Kamstra, 1999, p. 228). For this reason, model estimation is achieved by combining models derived from various econometric and computer technologies, thereby strengthening the model by minimizing specification errors, measurement errors, and deviations.

The fact that accurate estimations that reduce financial uncertainty and costs will bring successful results and thus play an essential role in reducing the problems and expenses that may arise for both investors and governments, and that the benefit functions can be maximized, has increased interest in forecasting modeling and led to the emergence of new forecasting techniques. Artificial Intelligence (AI) technologies, which are one of these new prediction techniques that are very compatible with the structure of financial data based on computer technologies, have been widely used in recent years (Henrique et al., 2019). Notably, deep learning architectures, such as Long Short-Term Memory (LSTM) networks, have introduced new paradigms in forecasting modeling.

This study aims to test the predictive efficiency of these methods using the Logit and Probit models, traditional econometric techniques, and a deep learning neural network model from AI technologies to determine whether selected macroeconomic variables can explain changes in the value of the ISE 100 Index. Thus, it will be revealed from the methods used which modeling technique can best predict the shift in dynamics of the economic and financial systems.

This study aims to comparatively assess the predictive performance of classical models and LSTM in modeling the ISE 100 index.

2. Literature Review

In the finance literature, the number of studies examining the effect of macroeconomic variables on asset prices is increasing. However, most studies aim to estimate the effects of macroeconomic variables on stock returns. Because stocks are the most risky investment instruments in the capital market, they can respond very quickly to economic developments. For these reason, examples of studies on stock market indexes and stock forecasts are given (Boyer & Zheng, 2009; Chakravarty, 2005; A.-S. Chen, Leung, & Daouk, 2003; N.-F. Chen, Roll, & Ross, 1986; Coşkun, Kiraci, & Muhammed, 2016; Cowles, 1933; Fama, 1990; Fama & French, 1996; Gonenc & Karan, 2003; Ali, & Jamil, 2015; Gürsoy, 2019; Ilahi, Kocabiyik & Fattah, 2020; Lintner, 1965; Liu & Shrestha, 2008; Markowitz, 1952; Mossin, 1966;

Mukherjee & Naka, 1995; Roll & Ross, 1980; Sayilgan & Süslü, 2011; Schwert, 1990; Sharpe, 1964; Treynor, 1965; Wongbangpo & Sharma, 2002 Kaymaz & Yilmaz, 2022). These studies primarily focus on estimating macroeconomic variables and stock market performance. They identified key variables influencing the asset pricing.

Since economic and financial variables are time series formed by ordering observation values according to time, the use of econometric methods in monetary and financial modeling has increased gradually due to recent developments in the field of time series analysis. In addition, AI technologies, which have found a wide range of applications as a powerful statistical modeling technique, have become an alternative to econometric methods and a predictive method with comparable performance. This method, which can yield highly successful results in the classification and prediction of time series, is also widely used in the fields of statistics, economics, and finance (Kaastra & Boyd, 1996, p. 216).

Numerous studies in the literature examine the modeling and estimation of financial variables using AI methods. These studies examine the economic performance and forecasting of markets, the prediction of financial crises, the forecasting of exchange rates, and the forecasting of stock prices. The following studies and their findings are examples of studies conducted with AI methods in the literature.

Wu and Lu (1993) used ANNs and Box-Jenkins' ARIMA model to estimate the Standard & Poor's 500 index for the period 1971–1990. They concluded that the ANNs outperformed the time series (Wu & Lu, 1993, pp. 257–264).

Hsieh (1993) showed that it gives very successful results in financial management by using artificial neural networks, which try to simulate the physical process on which intuition is based, or the adaptive biological learning process, and have the ability to produce solutions even for uncertain and incomplete data for the given problem (C. Hsieh, 1993, p. 12).

Yao, Poh and Jasic (1996) estimated the exchange rates between the US dollar and the five main currencies of the period, using the exchange rates for 2,910 days for the period from 18 May 1984 to 7 February 1995. They used the Japanese Yen, German Mark, British Pound, Swiss Franc, and Australian Dollar as the five basic currencies of the period. They estimated the exchange rates using ARIMA and ANN models and found that the ANN model gave more effective results in calculating exchange rates (Yao, Poh, & Jasic, 1996, pp. 754–759).

In recent studies, it has been observed that AI technologies are used in conjunction with traditional statistical methods, enabling better results by leveraging the strengths and advantageous aspects of both approaches. One of the studies that yielded these successful results is the 1999 study by Hu and Tsoukalas, which estimated the volatility of European Monetary System exchange rates by combining the GARCH, EGARCH, and IGARCH models with the moving average variance (MAV) model and an artificial neural network model. In this study, it was concluded that ANNs outperformed the least squares and simple averaging methods (Hu & Tsoukalas, 1999).

Donaldson and Kamstra (1999) estimated the price volatility of the S&P 500 stock index using ANNs with the GARCH and moving average variance (MAV) models. They demonstrated that, compared to the traditional weighted least squares method, they could account for interaction effects in time series estimations and that ANNs were more effective in non-linear time series (Donaldson & Kamstra, 1999, pp. 227–236).

Dahlquist, Engström, and Söderlind (2000) measured the performance of 210 funds between 1993 and 1997, using the alpha coefficient obtained by linear regression of fund returns and various benchmarks. They concluded that the funds generally did not perform well (Dahlquist, Engstrom, & Soderlind, 2000, pp. 409–423).

Zhang (2001) tested the applicability of ANNs to linear time series problems. Zhang compared eight different ARIMA models with nonlinear multilayer ANN models for predicting IBM stock closing prices. As a result, the study revealed that ANNs are successful in solving both linear and nonlinear problems (Zhang, 2001, pp. 1183–1202)

Bollen and Buse (2001) investigated, in their study of 230 funds from 1985 to 1995, whether there is a difference in timing ability when using daily returns and monthly returns. Regression analyses developed by Treynor and Mazuy (1966) and Henriksson and Merton (1981) were used as a method. According to the technique developed by Treynor and Mazuy, 11.9% of the funds were utilized in the case of monthly returns, and 34.2% of the funds demonstrated timing ability in the case of daily returns. Similar results were obtained with the method developed by Henriksson and Merton (Bollen & Busse, 2001, pp. 1075–1094).

Chen, Leung, and Daouk (2003) have tested the direction of the Taiwan Stock Exchange Index, one of the fastest growing financial stock markets from developing Asian countries, with probabilistic neural networks and the Kalman Filter, which is one of the parametric statistical methods, using the generalized moment method and the random walk model, and the probabilistic neural. It has been observed that the network model makes predictions with superior performance compared to other traditional methods, and higher returns are obtained from investment strategies made according to this method (A.-S. Chen et al., 2003, pp. 901–923).

Kim, Oh, Sohn, and Hwang (2004) examined the effects of the 1997 financial crisis in South Korea on the country's economic structure. They developed an early warning system with multi-layer ANN models. They divided the year 1997 into three main periods: the stable period from January 3 to September 18, the unstable period from September 19 to October 21, and the crisis period from October 22 to December 27. They used the KOSPI stock index as an input variable in the model, considering that index volatility provides information about the market's direction. They calculated the index's end-of-day closing value, daily return, 10-day moving average, variance, and variance ratio. In the study covering the period 1994-2001, they found that the volatility of the KOSPI index was a harbinger of the crisis and realized that ANN models were impressively successful in early detection of the 1997 economic crisis, in classifying the market movements, and in following the fundamental trend of the economy (T. Y. Kim, Oh, Sohn, & Hwang, 2004, pp. 583–590).

Yu, Tresp, and Schwaighofer (2005) combined parametric linear models with non-parametric Gaussian processes, concluding that nonlinear estimations yield better results than traditional estimations (Yu, Tresp, & Schwaighofer, 2005, pp. 1012–1019).

Dutta, Jha, Kumar, and Mohan (2006) used the multi-layer ANN method in modeling the Mumbai Stock Exchange index. They concluded that the ANN model successfully predicted the index values (Dutta, Jha, Laha, & Mohan, 2006, pp. 283–295).

Panda and Narasimhan (2007) estimated the future value of exchange rates with a linear autoregressive model, a random walk model, and an ANN model using weekly data of Indian Rupee/US Dollar (INR/USD) exchange rates for the period January 1994–June 2003. They found that the ANN model gave more effective results for the firm and investors in estimating the exchange rate (Panda & Narasimhan, 2007, pp. 227–236).

Tseng, Cheng, Wang, and Peng (2008) estimated the volatility of Taiwan Stock Index (TXO) prices with a new hybrid asymmetric volatility approach, the multi-layer ANN option pricing model. They used EGARCH and Grey-GARCH models as comparison criteria. They concluded that the ANN model predicts market volatility more effectively (Tseng, Cheng, Wang, & Peng, 2008, pp. 3192–3200).

Liang, Zhang, Xiao, and Chen (2009) estimated option prices using Hong Kong stock market data for the period 2006–2007 using ANN, finite difference, and Monte Carlo methods. Forecasting was done first using traditional option pricing methods, and then ANN and support vector regression (SVR) were used to reduce forecast errors. Thus, future option prices were estimated using both parametric and non-parametric methods, and the authors concluded that the ANN method demonstrated superior forecasting performance (Liang, Zhang, Xiao, & Chen, 2009, pp. 3055–3065).

According to Tsai and Wang (2009), two methods are used in the literature to estimate stock prices. These are fundamental analysis, which uses information from the company's financial statements, and technical analysis, which uses figures and graphs based on historical data. However, since fundamental and technical analysis alone are insufficient to make the right decision, they employed two analysis methods based on computer technologies that have better forecasting performance. With a hybrid model combining ANNs and decision tree management (DT), they achieved forecasts with an accuracy of 77%, which is higher than the individual models (Tsai & Wang, 2009), following the fundamental trend of the economy (T. Y. Kim et al., 2004, pp. 583–590).

At the beginning of October 2008, the global stock market was estimated to be approximately \$36.6 trillion in the United States. Considering that the total global derivatives market is 11 times the size of the entire global economy, with a nominal value of approximately \$791 trillion, it also highlights why stock market forecasting is so important and why it is the subject of numerous academic studies. Dase and Pawar (2010) compiled studies from the literature that utilize the artificial neural network method to make stock market index predictions, yielding successful results in large datasets. In these studies, it has been demonstrated that the artificial neural network method exhibits high predictive performance in forecasting stock indices and determining the optimal strategy for buying, holding, or selling stocks (Dase & Pawar, 2010, pp. 10–14).

In Vadlamudi's (2017) study, in which studies in the literature on stock market estimation were examined, it was shown that AI methods made more effective predictions than traditional methods when techniques such as linear regression, AI networks, and genetic algorithms were compared (Vadlamudi, 2017, pp. 123–128).

Chen, Zhang, Yeo, Lau, and Lee (2017) employed the parametric statistical methods of linear regression (LR) and Support Vector Regression (SVR) to predict the volatility of stocks on the Chinese Stock Exchange. This market is highly regarded in both the business world and the academic community. They estimated and analyzed the results using Repetitive Artificial Intelligence (RNN) and Gated Recurrent Units (GRU), which are AI methods. The results showed that the AI methods were more successful and demonstrated higher estimation performance (W. Chen, Zhang, Yeo, Lau, & Lee, 2017, pp. 1–6).

Chong, Han, and Park (2017) employed three data representation methods using a dataset comprising high-frequency daily stock returns. Principal component analysis, an autoencoder, a constrained Boltzmann machine, and a three-layer deep neural network (DNN) model were applied to predict future stock returns in the Korean stock market. They observed that DNNs performed better than the linear autoregressive model in the training set, but the advantage was mainly lost in the test set (Chong, Han, & Park, 2017, pp. 187–205).

According to Lin, Chien, and Cheng (2018), behavioral finance suggests that investors' behaviors, such as greed and fear, during transactions in financial markets also influence market trends. Consequently, traditional economic analysis and technical analysis can be used to forecast short-term market trends from this highly complex data, but it is argued that their method are inadequate. By utilizing neural networks in their work, they have demonstrated that financial trading markets exhibit a distinct trading logic, integrating physical momentum behavior into financial engineering technology analysis and market profile theory. They showed that buying and selling behavior in financial markets can be explained by the physical trends of the quantitative and technical analysis, as outlined in the market profile theory (C.-C. Lin, Chen, & Chen, 2018, pp. 756–764).

Nunes, Gerding, McGroarty, and Niranjan (2019) demonstrated that the multilayer AI model yielded better results, marking the first comprehensive study to utilize both a multivariate linear regression model and a multilayer artificial neural network model to predict the European yield curve. This result also paved the way for the development of more accurate forecasting systems for fixed-income markets (Nunes, Gerding, McGroarty, & Niranjan, 2019, pp. 362–375).

Cao and Wang (2020) used principal component analysis and ANNs for an accurate and effective stock prediction model. They demonstrated that the artificial neural network model they developed provides an effective stock selection strategy (Cao & Wang, 2020, pp. 7851–7860).

Jing, Wu, and Hefei (2021) created a hybrid model by combining the stock prices traded on the Shanghai Stock Exchange with investor sentiment analysis and DL analysis, which is an AI method. They concluded that the hybrid model they created by using the Long-Short-Term Memory Neural Network approach to classify the hidden emotions of the investors and to analyze the technical indicators in the stock market using the Convolutional Neural Network model outperformed the basic classifiers in classifying investor sentiment and outperformed the prediction of stock prices (Jing, Wu, & Wang, 2021, p. 115019).

Cheng, Yang, Xiamg, and Lui (2022), noting that the financial market capitalization of listed companies in the US reached $30 trillion in 2019, which is more than 1.5 times the US Gross Domestic Product, emphasized how important it is for both investors and financial institutions to predict the price movements of stocks in this vast but volatile market. In their analysis using Multimodal Graph Neural Networks (MAGNN), they explained the construction process of the leading lag effect and heterogeneous graphs, which is a new approach for financial time series analysis that plays a significant role in hedging market risks and optimizing investment decisions. They concluded that this method shows superior performance in market forecasting. They have demonstrated that this method offers investors a profitable and interpretable option, enabling them to make informed investment decisions (D. Cheng et al., 2022, pp. 108–2018).

Many studies have been conducted using various econometric analysis methods to predict financial crises, detect chaos and uncertainties, and determine the mobility of capital markets. The effectiveness of these methods has been compared. In this sense, in addition to the econometric methods mentioned above, studies using Logit and Probit models, although few, have also made their presence felt in the literature. These studies are listed below.

Frankel and Rose (1996) employed a probit model to identify leading indicators of currency crises for over 100 developing countries, using annual data from 1971 to 1992. They concluded that high domestic credit growth, high foreign interest rates, and persistently low foreign direct investment-to-debt ratios indicate a high probability of a collapse (Frankel & Rose, 1996, pp. 351–366).

Kaminsky and Reinhart (1999) examined the sources and extent of 76 currency crises and 26 banking crises using monthly data on 16 macroeconomic variables, whose findings they considered indicative. They concluded that financial liberalization leads to a banking crisis, banking sector problems trigger a currency crisis, and the currency crisis caused by the banking crisis weakens the already weak banking sector. This process, which triggers each other by deepening the banking crisis, becomes a vicious circle. They also concluded that when currency and banking crises occur together, the impact is more profound than when they occur separately (Kaminsky & Reinhart, 1999, pp. 473–500).

Kim (2003) forecasted the stock price index, a financial time series, with a logistic model and ANNs and concluded that ANNs are a promising method in stock market forecasting (K. Kim, 2003, pp. 307–319).

Uğurlu and Aksoy (2006) used the separation model and the logit model to identify the indicators of corporate financial crises in emerging markets during periods of economic depression. They emphasized that the separation model, which was the primary method for predicting financial failure until the 1980s, has now been replaced by logistic regression and that ANNs have yielded better results in predicting financial failure in recent years (Uğurlu & Aksoy, 2006, pp. 277–295).

Kaya and Yılmaz (2007) performed a logit analysis using 31 explanatory variables for the period 1990–2002, employing the logit and signal methods, which are widely used in estimating currency crises, on the monthly data from the 2003–2005 period in Turkey. Except for two of these variables, the findings of the signal analysis conducted with 29 variables were combined to form a typical cluster. They then used five macroeconomic variables, which they defined as "traditional indicators" for this period, incorporating the findings of this standard cluster, to form a financial pressure index. They tested the performances of the models they established and concluded that both methods gave successful results, but the leading indicators differed in terms of periods and economies (Kaya & Yilmaz, 2007).

Davis and Karim (2008) employed the polynomial logit model and an early warning system to predict leading indicators, enabling the early detection of crises in the banking sector. They found that the polynomial logit model performed better in predicting a global banking crisis, whereas the early warning system for country-specific banking crises performed better (Davis & Karim, 2008, pp. 89–120).

Lin, Khan, Chang, and Wang (2008), along with Kaminsky and Reinhart (1999), examined four models to predict exchange rate crises using data from 20 countries between 1970 and 1998. They measured the model performance of the early warning systems they created using four modeling techniques: the logistic regression model, a traditional method; the KLR model; ANNs; and fuzzy logic. They concluded that the most successful models are fuzzy logic, ANNs, and logistics models, respectively (C.-S. Lin, Khan, Chang, & Wang, 2008, pp. 1098–1121).

Öğüt, Doğanay, and Aktaş (2009) used data mining techniques, ANNs, Support Vector Machine, and multivariate statistical techniques (discriminant analysis and logistic regression methods) to detect manipulations in the prices of stocks on the Istanbul Stock Exchange. They concluded that multivariate techniques performed better (Öğüt, Mete Doğanay, & Aktaş, 2009, pp. 11944–11949).

Kovacova and Klistik (2017) concluded that the probit model performed better in their study, which used logit and probit regression models, in which Slovak companies create their bankruptcy forecasts (Kovacova & Kliestik, 2017, pp. 775–791).

Kantar and Akkaya (2018) estimated the effects of financial liberalization in Turkey using the financial pressure index and logit and probit models, which they created with 19 macroeconomic variables for the period from January 2005 to January 2017. They aimed to identify the leading indicators of the financial crisis. They concluded that the increase in deposit rates, the rise in domestic debt stock, and the decline in gross reserves all contribute to an increase in the probability of a crisis (Kantar & Akkaya, 2018, pp. 575–590).

According to Akkaya and Kantar (2019), the importance of predicting banking crises, which has become a more pressing issue following the 2008 global crisis, has increased due to the significant economic effects they have. For this reason, in their study, they examined the fragility structure of the Turkish banking sector using annual data and using logit and probit models (limited dependent variable models) for the period 1996-2017. While the exchange rate and deposit interest variables, which have high explanatory power in all three models, are statistically significant in the logit model, they have concluded that the loan amount, deposit amount, and deposit interest variables are statistically significant in the probit model (Akkaya & Kantar, 2019, pp. 131–145).

Some studies, taking the Turkish capital markets into account, also reveal that artificial neural network modeling produces more successful results than other models. Yıldız (2001) studied industrial, commercial, and service enterprises in Turkey between 1983 and 1997, which are subject to the Capital Markets Board and/or listed on the Istanbul Stock Exchange (ISE). He concluded that the ANN model is more successful than the separation analysis in predicting financial failure (Yildiz, 2001, pp. 47–62).

Diler (2003) estimated the direction of the ISE National-100 Index the following day using the error back-propagation method with ANN modeling and concluded that the method could predict the next-day value of the ISE National-100 Index with 60.81% accuracy (Diler, 2003, pp. 65–82).

Benli (2005) developed financial failure prediction models based on logistic regression and an artificial neural network model by using data from 17 privately owned commercial banks transferred to the Savings Deposit Insurance Fund and 21 privately owned commercial banks in the 1997–2001 period. It has been determined that the artificial neural network model's power to predict financial failure (82.4%) is superior to that of the logistic regression model (76.5%). Therefore, it has been established that the artificial neural network model can serve as a valuable tool for predicting financial failure among all information users (Benli, 2005, pp. 31–46).

Altay and Satman (2005) tried to estimate the returns of the ISE 30 and ISE all indexes using multilayer ANN and linear regression methods. It has been concluded that while ANN models do not give better results than linear regression for monthly and daily returns, they are pretty successful in estimating the direction of index returns (Altay & Satman, 2005, pp. 18–33).

Karaçor and Alptekin (2006), sought answers to the following questions in their study. Could the November and February crises have been prevented with the help of leading indicators? Have the leading indicators worked for the Turkish economy? If it did, could we predict possible crises? Can we avoid the crisis? Can we manage the crisis? By using macroeconomic indicators such as exports, international reserves, the real exchange rate, the real deposit interest rate, and the production index, which are accepted as leading indicators of the crisis, and concluded that the leading indicators predict the crisis process with little error (Karaçor & Alptekin, 2006, pp. 237–256).

Avcı (2007) estimated the daily and session returns of the ISE-100 index using a multi-layered ANN model and determined that the forecast performance is strong, making it a suitable financial performance measure. This study demonstrates that effective and robust predictions can be achieved using the ANN modeling technique (Avci, 2015, pp. 128–142).

Altan (2008) estimated the exchange rate with an ANN and a vector autoregressive (VAR) model using monthly data on the exchange rate (TL/USD) for the period January 1987–September 2007. It has been concluded that the predictions made with an ANN architecture that learns by multi-layer feed-forward and back-propagation yield very effective results (Altan, 2008, pp. 141–160).

Aladağ, Eğrioğlu, and Kadılar (2009) modeled their study with ANNs, which are increasingly important in time series analysis and are used in many fields. They analyzed Canadian Lynx data with the hybrid model they created by combining ARIMA and Elman's reversible artificial neural network model. They concluded that this proposed model has the best prediction accuracy performance (Aladag, Egrioglu, & Kadilar, 2009, pp. 1467–1470).

Karacameydan F., Akel V. (2012). To forecast the net asset values of 38 Turkish mutual funds (19 A-type and 19 B-type), six macroeconomic variables are utilized for the period from January 2001 to December 2008. Net asset values of mutual funds have been forecasted within the frame of both ANN and regression models, and forecasting performances of the methods have been compared. Analysis results reveal that the ANN method is capable of forecasting net asset values of mutual funds at a very low error level and seems to outperform the regression method (Akel & Karacameydan, 2012).

In their study, Yolcu, Eğrioğlu and Aladağ (2013) concluded that time series with linear and non-linear structures are better predicted by ANNs and hybrid artificial neural network models, which are more effective methods than traditional methods (Yolcu, Egrioglu, & Aladag, 2013, pp. 1340–1347).

Avcı (2015) predicted the Istanbul Stock Exchange 30 Index using multilayer ANNs models and observed that the buy-and-hold strategy had a significant advantage in most of the examined periods (Avci, 2015, pp. 443–461).

Adayeri (2024) discusses the way artificial intelligence is transforming financial analysis. The study emphasizes the benefits AI offers in fields like risk management, sentiment analysis, algorithmic processing, fraud detection, and forecasting. Although AI is known to improve decision-making processes in terms of accuracy, speed, and efficiency, it also comes with disadvantages including data quality, ethics, regulation, and cybersecurity. Fintech/regtech applications, blockchain integration, and machine learning are expected to create innovative opportunities in the financial sector in the future.

3. Data and Methodology

This study aims to predict the long-term relationship between the ISE 100 index value and the selected macroeconomic variables for the period from January 2001 to January 2022, using Logit and Probit analysis, as well as the deep neural networks method. The study also compares the estimation performances of the results obtained from both methods. Thus, the effectiveness of AI technologies, which emerged from developments in traditional econometric methods and computer technologies and have continued to develop rapidly in recent years, will also be measured in time series analysis. For the models used in the research, the most commonly used variables in studies on the market index in the literature were selected (W. Chen et al., 2017; D. Cheng et al., 2022; Donaldson & Kamstra, 1999; Kara, Acar Boyacioglu, & Baykan, 2011; Staub, Karaman, Kaya, Karapınar, & Güven, 2015) and the meaningful variables obtained from the created meaningful models were given as input to the models created by ANNs and DL methods. The effectiveness of the modeling methods was tested.

The study consists of 253 monthly observation values covering the time interval between 2001:01 and 2022:01. In order to estimate the value of the ISE 100 index selected as the input (dependent) variable, or, in other words, to investigate the effects on the stock market in Turkey, seven macroeconomic variables were determined. These are the Dollar Rate (TL/$), Money Supply, Producer Price Index, Industrial Production Index, Gold Price (TL/Gr), Active Bond Interest Rate, and Brent Oil Price. In addition, since the effects of the global economic crisis experienced in the world in 2008 were more limited in Turkey than in developed countries, these periods were not excluded from the data set in order not to spoil the integrity of the data set and to see the effects of the crisis in Turkey in the 2001 period.

Seven macroeconomic variables were used as independent (input) variables in the models. ISE 100 index values were used as the dependent (output) variable to represent the stock markets. This index serves as the primary benchmark for the ISE market. In addition, since monthly series were used in the study, the Gross Domestic Product series could not be obtained, so the industrial production index was used to represent this variable. All variables were subjected to statistical analysis, and the EViews 12, STATA 15, and MATLAB R2021b programs were used in the analysis.

The data sets used in the analysis were compiled as monthly series from the Central Bank of the Republic of Turkey Electronic Data Distribution System (EVDS), the Turkish Statistical Institute (TUIK) statistics, the monthly statistical bulletins of the Capital Markets Board, the statistics of the Ministry of Treasury and Finance, and the Eurostat databases.

Based on this information and the logit and probit regression model, which was created with the probability of the index value P_i, the i'th period being greater or less than the geometric mean, will be as in equation (3.1) and equation (3.2):

$$\ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1\text{ERUSD} + \beta_2\text{PPI} + \beta_3\text{IPI} + \beta_4\text{M2} + \beta_5\text{GP} + \beta_6\text{TYBY} + \beta_7\text{BRT} + u_t \quad (3.1)$$

$$P_i = 1 - \phi(-x, \beta) = \phi(\beta_0 + \beta_1\text{ERUSD} + \beta_2\text{PPI} + \beta_3\text{IPI} + \beta_4\text{M2} + \beta_5\text{GP} + \beta_6\text{TYBY} + \beta_7\text{BRT}) \quad (3.2)$$

In the DL model, ISE 100 was used as the dependent (output) variable, and seven macroeconomic variables were used as independent (input) variables. In the DL model, which is based on the artificial neural network architecture, the dataset is divided into two parts: 70% for training and 30% for testing. In financial analyses in the literature, AI applications often distinguish between data sets based on different ratios; however, this distinction is typically determined by trial and error, similar to other model parameters (Chong et al., 2017; Jing et al., 2021; C.-C. Lin et al., 2018). In this case, the 2001:01–2015:08 period consists of the first 177 observations as the training set and the last 76 observations as the test set from 2015:09 to 2022:01.

To solve the problems in their studies, researchers employ modeling and analysis, aiming to create the most effective and explanatory parameter sets that represent the problem. In the studies carried out as a result of the development of the DL approach, the issues of how to best design a multi-layer artificial neural network structure, how many layers it will consist of, how many neurons it will contain, what the dropout value will be, and which optimization algorithm or activation function to choose have been seen as how important issues are for the solution. However, since there is no definitive proposition for selecting these parameters, they were obtained through trial and error, tailored to the specific problem and data set (Jing et al., 2021; Kaastra & Boyd, 1996, pp. 220–224).

4. Empirical Results and Discussion

In this section, the models used during the study are introduced. In order to measure the change in the value of the Istanbul Stock Exchange Index by the change in the selected macroeconomic variables, Logit and Probit models from qualitative response regression models and a DL model from AI technologies will be estimated. Thus, the effectiveness of these modeling techniques will be tested.

Economic models are established by taking into account the equilibrium relations envisaged in economic theory. The existence of significant econometric relations between the variables in the established model also depends on the stationarity of the series. In a stationary process, the series fluctuates around a fixed long-term average, and the effect of any shock is not permanent. On the other hand, a non-stationary series will not follow a long-term deterministic path and will permanently reflect the effects of shocks in the short term on the long-term values. Time series are not stationary because they usually show a volatile structure. Therefore, the variables to be used in the analysis must first be made stationary.

To determine the stationarity of a time series, inferences are made using graphical analysis. The original graphics of the series of variables are given, it is seen that all the dependent and independent variables used in the regression models are not stationary; in other words, the series contain unit roots. Trend or seasonal mobility was observed in each variable.

Although there are many different unit root test techniques, the most popular ones are the ADF (1981) and PP (1988) unit root tests, which are used to determine whether financial time series are stationary. The stationarity test of the series was conducted using three unit root test models: one with a constant term, one with a constant term and a trend, and one without a constant term but with a trend. The results of the stationarity analysis are presented in Table 1.

Table 1. Unit Root Test Results at Level

Variables	T-Statistics ADF	T-Statistics PP	Critical Value		
	Trend & Intercept	Trend & Intercept	1%	5%	10%
ISE100	-0.5926[0]	-0.6834	-3.9967	-3.4286	-3.1377
TYBY	-5.4044[15] *, **, ***	-6.4646 *, **, ***	-3.9967	-3.4286	-3.1377
ERUSD	4.7760[12]	4.3645	-3.9967	-3.4286	-3.1377
PPI	3.7943[6]	9.58833	-3.9967	-3.4286	-3.1377
IPI	-1.80939[12]	-10.6153*, **, ***	-3.9967	-3.4286	-3.1377
M2	7.86595[12]	10.3237	-3.9967	-3.4286	-3.1377
GP	7.2818 [10]	7.9621	-3.9967	-3.4286	-3.1377
BRT	-2.64021[0]	-2.02866	-3.9967	-3.4286	-3.1377
Note: All three models were tried in the level values and first order differences of the series and constant term and trend models were used in model selection as long as they were meaningful. The values in square brackets represent the appropriate lag length of the variables determined according to the SIC. The minimum lag length at which autocorrelation is removed was chosen. *, ** and *** indicate stationarity at 10%, 5% and 1% significance levels, respectively.					

If a time series becomes stationary when it is differentiated d times, the series is said to be d-integrated and is denoted as I(d). When the first differences of the series, except the interest of the active bond, are taken in the analysis, it is concluded that not all of them are integrated at the same level; the PPI series is integrated at I(2), and the other series are also integrated at the I(1) level. If the series is not stationary, future predictions cannot be made by making generalizations. While the series are not singularly stationary, their linear combinations can be stationary. For this reason, after the ADF test, the Engle-Granger test was performed on the series consisting of the residuals obtained from the regression, and the null hypothesis was rejected. Therefore, according to Engle-Granger, the series are cointegrated. Thus, the regression will reveal a genuine relationship.

Table 2. Unit Root Test Results at Ln

Variables	**T-Statistics ADF**	**T-Statistics PP**	**Critical Value**		
	Trend & Intercept	**Trend & Intercept**	**1%**	**5%**	**10%**
lISE100	-2.7080[0]	-2.5823	-3.9951	-3.4279	-3.1373
TYBY	-5.4044[15] *, **, ***	-6.4646 *, **, ***	-3.9951	-3.4279	-3.1373
lERUSD	-0.0178[2]	-0.3388	-3.9951	-3.4279	-3.1373
lPPI	0.1964[2]	-1.5855	-3.9951	-3.4279	-3.1373
lIPI	-2.7569[12]	-9.5753 *, **, ***	-3.9951	-3.4279	-3.1373
lM2	-2.1832[0]	-2.1813	-3.9951	-3.4279	-3.1373
lGP	-3.0737[1]	-2.4055	-3.9951	-3.4279	-3.1373
lBRT	-2.8523[0]	-2.3922	-3.9951	-3.4279	-3.1373

dlISE100	-17.4022[0] *, **, ***	-17.5399*, **, ***	-3.9951	-3.4279	-3.1373
dlERUSD	-12.1062[1] *, **, ***	-9.8556*, **, ***	-3.9951	-3.4279	-3.1373
dlPPI	-7.2550[1] *, **, ***	-5.6983 *, **, ***	-3.9951	-3.4279	-3.1373
dlIPI	-6.1426[11] *, **, ***	-87.3719 *, **, ***	-3.9951	-3.4279	-3.1373
dlM2	-16.4110[0] *, **, ***	-16.4004 *, **, ***	-3.9951	-3.4279	-3.1373
dlGP	-11.4887[1] *, **, ***	-11.3133 *, **, ***	-3.9951	-3.4279	-3.1373
dlBRT	-13.7588[0] *, **, ***	-13.8688 *, **, ***	-3.9951	-3.4279	-3.1373
Note: All three models were tried in the level values and first order differences of the series and constant term and trend models were used in model selection as long as they were meaningful. The values in square brackets represent the appropriate lag length of the variables, as determined by the SIC. d stands for first-order difference. The minimum lag length at which autocorrelation is removed was chosen. *, ** and *** indicate stationarity at 10%, 5% and 1% significance levels, respectively.					

Upon examining the test statistics in Table 2, it is evident that all ADF and PP coefficients for the first-order differences of both the dependent and independent variables are significant at the $\alpha = 0.05$ reliability level. It has been determined that all variables are stationary at the I(1) level and their series do not contain unit roots. All series are I(1) co-integrated, and the Phillips-Perron unit root test results also confirm the ADF test results. For this reason, the first-order differences of the variables are taken into account when estimating the models.

Table 3. Correlation Coefficients Between the Independent Variables

	TYBY	BRT	ERUSD	GP	IPI	M2	PPI
TYBY	1	-0.03312	0.24945	0.1678	-0.00835	0.13426	0.36378
BRT	-0.03312	1	-0.09913	-0.0337	0.00648	-0.04088	0.13353
ERUSD	0.24945	-0.09913	1	0.733	0.03381	0.21283	0.60858
GP	0.16779	-0.03367	0.73304	1	-0.06753	0.26173	0.48518
IPI	-0.00835	0.00648	0.03380	-0.06753	1	0.09101	0.00243
M2	0.13426	-0.04088	0.21283	0.2617	0.09102	1	0.09195
PPI	0.36378	0.13353	0.60858	0.4852	0.00244	0.09195	1

As seen in Table 3, the correlation coefficients between the independent variables remain below 0.73 and mostly demonstrate weak linear relationships.

4.1. Logit and Probit Models and Results

In the linear probability model, the conditional expected value of the dependent variable is the conditional probability of the event occurring, given the values of the independent variable. The linear probability model can be estimated by the classical least squares method. However, the error term is not normally distributed, exhibits heteroscedasticity, and the estimation values can fall outside the range of 0–1. Additionally, the error term generally has a low R-squared value. For this reason, Logit and Probit models have been developed as alternative models to address these problems (Bengio, Goodfellow, & Courville, 2015, p. 584; Gujarati & Porter, 2009, pp. 552–553). The primary difference between the two models is that the Logit curve has a thicker tail, approaching the axis (0 or 1) more slowly, compared to the Probit curve. The difference in the coefficients obtained from these models is due to the different functions used for probabilities (Gujarati & Porter, 2009, p. 571). The issue of selecting a model in the application is presented according to the user's preference.

The parameters of the Logit and Probit models are estimated using the maximum likelihood method. To use this method, it is assumed that the probability distribution of the error term follows a normal distribution. In this case, when the series are stationary, the standard distribution assumption regarding the error term is fulfilled before estimating the parameters of logit and probit regression models, which are qualitative dependent response models. A stationarity analysis is therefore required for the variables used in the model.

Because the parameters of the Logit and Probit models cannot be estimated using the classical least squares method, the maximum likelihood method is used. In this method, the standard normal distribution, which is used as the Z test statistic, is employed to assess the statistical significance of the coefficients. To test the co-significance of the coefficients in the Logit and Probit models, Wald, Score (also known as Lagrange Multiplier, LM), and Likelihood Ratio (LR) tests are employed. In the analysis, the standard normal distribution Z statistic was used to test for the statistical significance of the coefficients, and the LR statistic was used to test the general importance of the models.

R^2, the coefficient of determination, which is used as a measure of goodness of fit or how explanatory the model is in classical linear regression models, is not a good measure for Logit and Probit models. Because these measures are not based on variance, they are not an accurate measure of whether the model is well explained or not, as they are calculated based on the change in the values of similarity ratios. The correct classification rate obtained from the classification table was also used to evaluate the goodness of fit of the models created. The obtained probability values are classified according to the determined cutoff point, and it is predicted which of the 0 or 1 values each unit will take. A value of 0.50 is typically used as the cutoff point. If the probability value is greater than this value, the unit is assigned to group 0, and if it is less than this value, the unit is assigned to group 1.

In binary logit-probit models, the STATA program calculates the pseudo-R-squared value as a measure of goodness of fit, and the EViews 12 program calculates the McFadden R-squared. Pseudo-R^2 was used in this study.

The coefficients obtained from models created using Logit and Probit techniques cannot be interpreted directly, unlike those in a linear regression model. However, the sign of the examined coefficients indicates the direction of the relationship between the independent variables and the probability of the event occurring. A positive sign indicates a direct relationship, while a negative one indicates an inverse relationship.

In this study, both Logit and Probit model estimations were performed using the relevant macroeconomic variables. For this, a threshold value was calculated for our independent variable, the ISE 100 index. Thus, the transformation of the dependent variable into a binary variable with a qualitative response was achieved. The geometric mean of the ISE 100 variable was calculated and converted to a binomial distribution, assigning a value of 0 to values below the mean and 1 to values above it. The geometric mean is a measure of central tendency that takes into account geometric differences between data, rather than arithmetic differences. The geometric mean, which encompasses all observations in the dataset and conforms to algebraic operations, facilitates the processing of relative numbers.

While investigating whether the variables used in this study are suitable for the Logit model and the Probit model, the dependent variable for each independent variable was first added to the Logit and Probit models separately, allowing for the observation of the relationship between the dependent variable and the independent variables, the test results obtained in this context are given in Tables 4 and 5 below.

Table 4. Logit Model Compatibility Results

Variables	BinaryISE100				
	Coefficient	**Prob**	**Log-Likelihood**	**LR Statistic**	**Prob (LR St.)**
TYBY	0.763828	0.0000	-94.087715	147.70	0.0000
LnERUSD	24294.1	0.0000	-82.945841	169.99	0.0000
LnPPI	553424.8	0.0000	-40.502838	254.87	0.0000
LnIPI	4.48e+07	0.0000	-44.480443	246.92	0.0000
LnM2	1.33e+50	0.0000	-38.382249	259.11	0.0000
LnGP	136.1367	0.0000	-41.043973	253.79	0.0000
LnBRT	12.36735	0.0000	-134.60854	66.66	0.0000

Table 5. Probit Model Compatibility Results

Variable	BinaryISE100				
	Coefficient	**Prob**	**Log-Likelihood**	**LR Statistic**	**Prob (LR St.)**
TYBY	-0.160051	0.0000	-93.265235	149.35	0.0000
LnERUSD	5.747567	0.0000	-83.387448	169.10	0.0000
LnPPI	7.528884	0.0000	-39.850861	256.18	0.0000
LnIPI	9.398173	0.0000	-44.761852	246.36	0.0000
LnM2	66.07681	0.0000	-37.872111	260.13	0.0000
LnGP	2.776939	0.0000	-40.080625	255.72	0.0000
LnBRT	1.452791	0.0000	135.30463	65.27	0.0000

As shown in Table 4 and Table 5 above, which display the compatibility results, each variable is compatible with the dependent binary variable ISE 100 for both the Logit and Probit models. A 1% change in each variable causes the ISE 100 to take a higher or lower value than its geometric mean. In other words, each variable in the model is a significant predictor of the dependent variable and is statistically significant. It was also in line with our expectations economically. Therefore, our variables are suitable for both the Logit and Probit models. However, since the changes in interest rates and gold prices in the Probit model align with expectations, this model is considered more appropriate.

In this study, the Logit and Probit models were estimated using the maximum likelihood method, taking into account the obtained data and evaluations. The results are summarized in Table 6. It was observed that the variables used in the models were statistically significant at the 1%, 5%, and 10% significance levels, indicating they were essential variables affecting the dependent variable.

To test the overall significance of the Logit and Probit models, Hosmer-Lemeshow and Pearson goodness-of-fit tests, which are generally right-tailed, were performed. The Akaike Information Criterion (1973), which is an indicator of the goodness of fit of an estimated statistical model, and the Schwartz or Bayesian Information Criteria (1978), which enables model selection among a group of parametric models with different numbers of parameters, were also calculated. According to these tests, the model with the smallest AIC or BIC value is the best. Additionally, the correct classification rates were found to be 95.6% and 94.8%, respectively.

In the Logit and Probit models, since each of the coefficients obtained (log-odds) is a log-bet value, they cannot be interpreted directly as in linear regression models. However, the signs in the coefficients obtained indicate the direction of the relationship between the variables and the probability of the event occurring. If the coefficient obtained is negative, the relationship between the variables will be in the opposite direction; if it is positive, the relationship will be in the same direction.

Table 6. Results of The Logit Model & The Probit Model

	Logit Model		**Probit Model**	
Variables	**Odss Ratio**	**Prob**	**Coefficient**	**Prob**
c	8.1e-277	0.133***	-321.2098	0.066***
TYBY	0.540201	0.004*	-0.362669	0.002*
LnERUSD	13.79592	0.765***	2.213481	0.611***
LnPPI	9.424175	0.904***	1.408437	0.872***
LnIPI	2.43e+08	0.005*	10.29269	0.004*
LnM2	4.50e+85	0.231***	98.83031	0.145***
LnGP	0.000015	0.066***	-6.232234	0.056***
LnBRT	2.109222	0.872***	0.7311821	0.757***
Log-Likelihood	-22.420721		-22.222259	
LR Statistic	291.04		291.43	
Prob (LR St.)	0.0000		0.0000	
Pseudo R2	0.8665		0.8677	
Hosmer-Lemeshow chi2 (Prob>chi2)	3.52 (0.8974)		0.50 (0.9999)	
Pearson chi2 (Prob>chi2)	64.49 (1.0000)		53.70 (1.0000)	
AIC	60.84144		60.44452	
BIC	89.10856		88.71163	
Correct Classification Rate	95.65%		94.86%	
Note: *, **, ***; represent 10%, 5%, and 1% significance levels respectively				

As seen in Table 6, the coefficients obtained using the Logit and Probit models are statistically significant at 1% and 10% significance levels, respectively. When the coefficients of the variables were evaluated individually, the results were obtained as expected. While an inverse relationship was expected between the interest rate of the active bond and gold prices, it was observed that this expectation was met, and a positive relationship was found between other variables, again aligning with expectations. As the interest rate of the active bond increases, the return also increases, causing the investor's demand to shift from the stock market to this instrument. The investor will show the same reaction when gold prices increase and will choose gold as a haven. In other words, there is a negative relationship between the stock market, the two-year bond rate, and gold prices. It is observed that a 1% increase or decrease in other macroeconomic variables included in the model causes the dependent variable to take higher or lower values than the average, depending on the coefficients of the variables, which in turn increase or decrease the dependent variable at different rates.

These results are confirmed by four separate tests calculated for the models, which determine whether the model is statistically significant or not. Since the probability values of the Hosmer-Lemeshow and Pearson tests are higher than 0.05, our models are statistically significant. Again, the AIC and BIC criteria are also undervalued. Accurate classification rates were found to be 95.65% for the logit model and 94.86% for the probit model. In addition, considering the LR test statistic and the associated probability values, it is evident that all coefficients in both the Logit and Probit models are significant collectively. Additionally, the pseudo-R-squared values, which are the output of the STATA program and indicate the significance of the entire model, were found to be 0.865 for the Logit model and 0.866 for the Probit model. The correct classification rate results for the two models are shown in Table 7 and Table 8.

Table 7. Correct Classification Rate Table for The Logit Model

Classified	D	F	Total
Positive	151	5	156
Negative	6	91	97
Total	157	96	253
Correctly Classified (%)	96.79	93.81	95.65

Table 8. Correct Classification Rate Table for The Probit Model

Classified	D	F	Total
Positive	150	6	156
Negative	7	90	97
Total	157	96	253
Correctly Classified (%)	96.15	92.78	94.86

In the Probit model, unlike the Logit model, to meet our economic expectations, gold prices appear as a variable that adversely affects both the stock market index and the two-year bond interest rate. The variable is also statistically significant. Gold is a widely recognized investment tool and is often regarded as a haven for investors. Many investors are drawn to this area due to the sustained increase in gold prices over recent years. There is no doubt that speculative attacks in the stock market, interventions in the capital market, the lack of transparency and reliability of the capital market, as well as speculative news on this subject, hurt all investors. Since all of these factors make small investors nervous, they cause investors to turn to safer investment instruments, and the failure to transform savings into investments leads to a contraction in the economy. When this mechanism, which has a spiral structure, operates in the opposite direction, it harms social welfare.

Comparing the performance of the Logit and Probit models, the compatibility test values of both models are very close to each other. However, the main difference between the two models lies in the logistic distribution having a slightly thicker tail. However, there is practically no reason to prefer one over the other. One is preferred over the other because of its comparative mathematical simplicity. The correct classification rate varies from 95.65% for the Logit model to 94.86% for the Probit model, which is relatively low at 0.8 percentage points. However, the variables in the Probit model were estimated to meet economic expectations. The statistical tests of the variables included in the model are also an indication of this. Additionally, the pseudo-R-squared values of both models were over 86%.

4.2. Deep Learning Models and Analyses

In this study, the DL model, a method based on the working mechanism of AI technologies and one of the ANNs, was investigated to measure its ability to explain the Istanbul Stock Exchange index values using the selected macroeconomic variables. It has been shown in many empicial studies that AI applications, especially in estimating non-linear time series, give as good or better results than well-known traditional econometric methods, and because of this success, they are used as good estimation tools (Akel & Karacameydan, 2018; N. Chen & Zhang, 1998, p. 40; Jing et al., 2021).

The data used in this study consists of non-linear, seasonally unadjusted, and trend-containing time series in which seven macroeconomic variables and ISE 100 values are taken as independent variables. For this reason, the series is normalized in the range of [-1, 1] using the equation ($x_i = (x_i - \mu)/\sigma$).

Significant variables obtained from the meaningful models established as a result of the analyses made with Logit and Probit regression modeling methods; Dollar Rate, Industrial Production, Domestic Consumer Price Index, Active Bond Interest Rate, Gold Prices, Money Supply, and Brent Oil Price are used as input variables in the established deep learning neural network models.

With the DL method, based on the working of ANNs, various models can be produced using different criteria. The performances of the models created are depends on many parameters, such as the number of inputs, the number of input layers, the number of hidden layers, activation functions, the learning method used, the learning rate, the number of mini-batches, the number of epochs, weight values, memorization value, and even the speed of the processor used in the analysis. It is closely related to critical components, such as capacity. The most widely used ANN model in the literature is the multilayer perceptron, and the most commonly used DL model is LSTM (W. Chen et al., 2017; D. Cheng et al., 2022; Jing et al., 2021; Sarker, 2021).

DL, one of the applications of AI that provides the opportunity to design deep neural networks using pre-trained models, is a method applied to image, time series, and text data. Convolutional neural networks (ConvNets, CNN) and Long Short-Term Memory (LSTM) networks can be used to classify and regress data. An LSTM network is a type of recurrent neural network (RNN) that processes input data by looping through time steps and updating the network state. The network contains information remembered at all previous time steps, and using data from these previous time steps, it predicts the value a time series might take in the next period. This network learns to predict the value of the next period. In this method, there are two estimation methods: open-loop and closed-loop estimation.

A standard reversible neural network architecture (RNN) contains a single layer, while an LSTM network consists of four communicating layers. The basic core parts in an LSTM network structure are the sequence input layer and the LSTM layer. In the sequence input layer, the inputs are serial or time-series data within the network. The LSTM layer learns the long-term dependencies between serial data at successive time steps. Starting with the serial input layer, the network architecture consists of the LSTM layer, the entirely dependent layer, and the output layer.

In this study, an AI architecture will be created by using a DL algorithm, which is the last point reached by ML algorithms from AI technologies. Convolutional neural networks are used in various combinations to form the foundation of modern DL architectures. The DL architecture consists of layers for input, convolution, activation, pooling, memory, full coupling, and classification. In the convolution layer, filters (also known as kernels) are used to convolve the data in the input layer horizontally and vertically.

There are activation functions such as ReLu, Sigmoid, and Step (Step), which are the most commonly used in the literature, in the activation layer. The ReLu activation function is used in this study. In the pooling layer, the most frequently used functions in the literature are the maximum pooling, minimum pooling, and average pooling value functions. In the dropout layer, AI algorithms function to prevent the network from memorizing the data, allowing it to forget the data during training. For this reason, the dropout layer is used in network architecture.

Since the model we created is an LSTM model, the full connection (FullConnected, FC) layer and classification layers are also utilized in the model's structure. Thus, the data is transformed into a one-dimensional vector and passed to the classification layer. As in ANNs, the classification layer, which is the last layer in DL algorithms, evaluates the data from the previous complete link layer and generates the network's outputs. The Softmax classifier, a probabilistic calculation method, is typically used in this layer. Thus, values in the range 0–1 are generated for each possible class (Metlek & Çetiner, 2021, pp. 4–18).

For an LSTM model, there must be several input neurons that match the number of input data. In the created LSTM network, seven input neurons, 200 hidden units, 50 fully connected layers units, 50% dropout, and an output layer with the same number of units as the input data were created. In the training phase, after several attempts, Adam and SGD optimization functions were employed, with 100 cycles per iteration and a minibatch size of 20. The initial learning rate was set to 0.01, and the gradient threshold was 1. Each cycle, the data is shuffled. The goal here is to prevent the network from memorizing the general structure of the DL prediction models created using the specified parameters.

The parameters that comprise the AI architecture of DL models are listed in Table 9.

Table 9. Deep Learning Network Architecture Parameters

ANN type	**Deep Learning LSTM**
Number of input layer neurons	7
Number of output layer neurons	1
Number of fullyconnected layers	2
Number of hidden layer neurons	200
Optimization function	adam, sgdm
Activation function used in hidden layer	ReLU
Activation function used in the output layer	Softmax
Optimization algorithm	Gradient Descent
Scaling method used	Normalization
Initial learning rate	0.01
Fullyconnected layer	50
Droupout	50
Gradient threshold	1
Epoch	100
Minibatchsize	20

The data set is divided into 70% training and 30% test sets, which is the most widely used in the literature. The first 177 observation values (covering the period from 2001:01 to 2015:08) were designated as the training set, and the last 76 observation values (from 2015:09 to 2022:01) were defined as the test set. Another reason for determining the test set in this range is to assess whether the global crisis and its seasonal effects, which began in 2008 and persisted until the start of 2009, can be accurately captured by the model.

As an indicator of whether the established DL model is a good predictor, the corrected R^2 and performance criteria, whose calculation methods are outlined in section and are frequently used in performance measurements of MLPs, are employed. These metrics are performance metrics, such as R^2, MSE (Mean Squared Error), SSE (Sum of Squared Errors), and RMSE (Root Mean Squared Error). The most suitable network structure was determined by comparing the findings from the training and testing phases, taking into account these performance criteria.

Table 0. Simulation Results for *adam*

adam		**Train**		**Test**	
Train (%)	Test (%)	MSE	RMSE	MSE	RMSE
20	80	0.1267	0.3559	0.0851	0.2917
30	70	0.0466	0.2159	0.3496	0.5913
40	60	0.0317	0.1782	0.1555	0.3943
50	50	0.2027	0.4502	0.4081	0.6388
60	40	0.0588	0.2425	0.0749	0.2738
70	30	0.1245	0.3528	0.3409	0.5839
80	20	0.1379	0.3714	0.3697	0.6081

The effectiveness of each of the seven DL models developed was evaluated using the MSE and RMSE performance metrics. According to the results in Table 10, DL networks were created with an unnormalized data set using the man optimization algorithm. As expected, the performance values differed according to the data set partitioning. The training set achieved the smallest MSE value at 40%. However, the test set did not reach the global minimum, but the performance indicator values were high.

Table 11. Simulation Results for *sgdm*

sgdm		**Train**		**Test**	
Train (%)	Test (%)	MSE	RMSE	MSE	RMSE
20	80	0.0481	0.2195	0.0361	0.1901
30	70	0.0279	0.1672	0.0992	0.3150
40	60	0.3653	0.6044	0.5380	0.7334
50	50	0.0287	0.1695	0.0830	0.2881
60	40	0.0334	0.1829	0.1357	0.3684
70	30	0.1222	0.3496	0.1975	0.4441
80	20	0.0547	0.2339	0.1981	0.4451

As shown in Table 11, seven DL network models were created using the SGDM optimization algorithm with the unnormalized dataset. The training set achieved the smallest MSE value at 40%. However, the test set did not reach the global minimum, but the performance indicator values were high. According to these two tables, the performance values of DL network models remain high even when the optimization algorithm is changed, provided that the analysis is performed without normalizing the series.

Table 12 below provides a summary of the outcomes of the examination of DL models, which were developed by normalizing the research's dataset using the normal distribution and employing the *adam and sgdm* optimization algorithms.

Table 12. Deep Learning Results

		Train		**Test**	
Train (70%)	Test (30%)	MSE	RMSE	MSE	RMSE
adam		0.0440	0.2099	0.1396	0.3736
sgdm		0.0448	0.2117	0.1444	0.3800

As can be seen from the tables above, the system that gives the best results is a linear system, and the best results are achieved by normalization.

Figure 3. Training Progress with *adam*

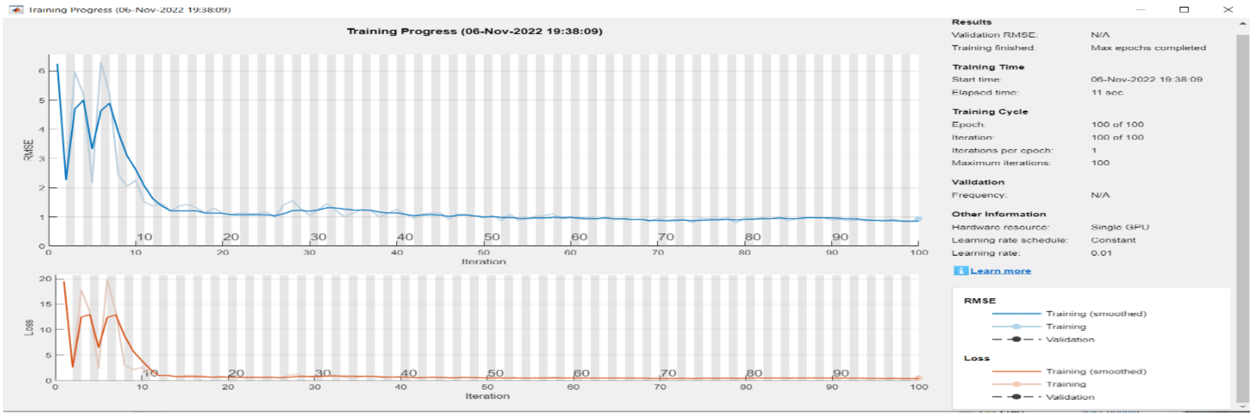
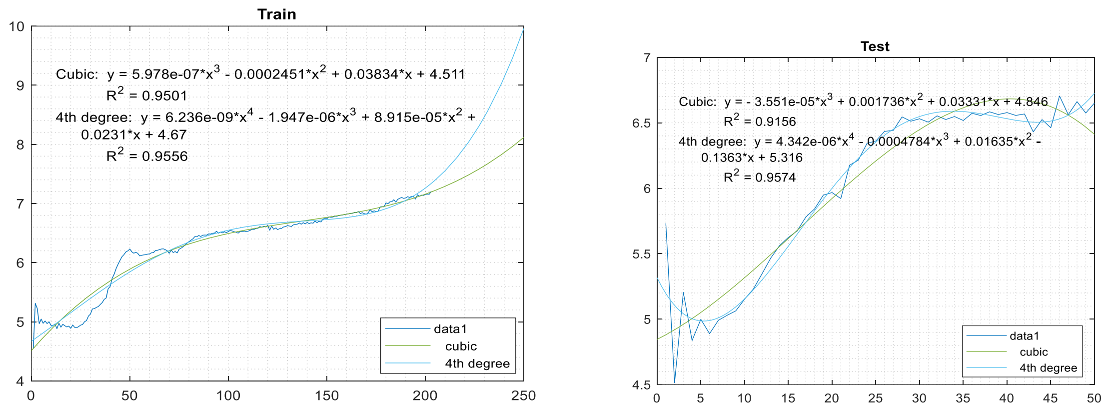


Figure 3 illustrates the effectiveness of learning when the optimization algorithm determines the Adam algorithm and the number of epochs to 100 during the training phase of the six-layer LSTM DL model obtained (while considering the other determined parameters). As the number of epochs increases, the error between the original series gradually decreases and progresses towards the global minimum.

The graphs in Figure 4 below show the training and test curve graphs obtained from the analysis using the adam optimization algorithm. It is observed that the complexity of the system increases as the degree of mathematical expressions in the chosen regression models for training and testing curves in the graphs increases, and thus, this becomes an advantage. Thus, an obscure system becomes identifiable with a simpler expression.

Figure 4. Train and Test Results with *adam*



It can be seen that the two fully connected layered LSTM models aid in the simplification of complex problems. It is also observed that the mathematical equation of the LSTM models is a fourth-order function, and the R-squared value is relatively high at 0.95. This indicates that the model is highly significant, and the explanatory power of the variables is relatively high. In other words, the network demonstrated a highly successful performance during both the training and testing phases. The model is a good forecasting model, and the margin of error in the estimates was 0.0440.

Figure 5. Training Progress with *sgdm*

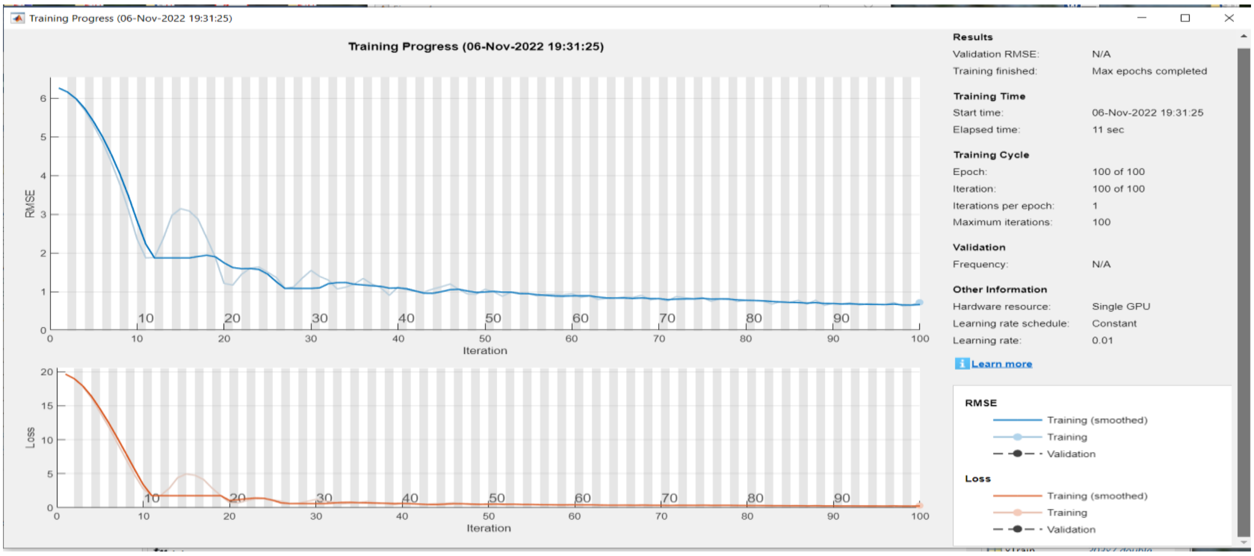
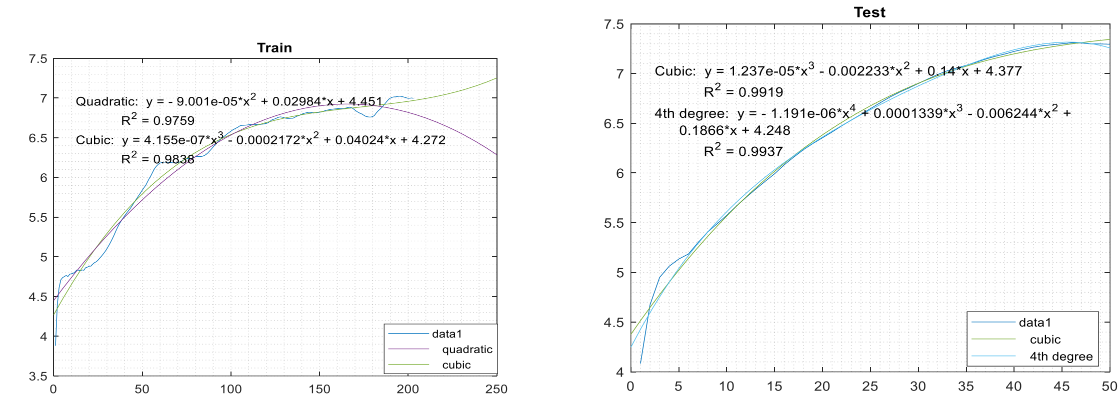


Figure 5 illustrates the effectiveness of learning when the optimization algorithm determines the *sgdm* algorithm and the number of epochs to 100 during the training phase of the six-layer LSTM DL model obtained (while considering the other determined parameters). As the number of epochs increases, the error between the original series gradually decreases and progresses towards the global minimum.

The graphs in Figure 6 below show the training and test curve graphs obtained from the analysis using the *sgdm* optimization algorithm. It is observed that the complexity of the system increases as the degree of mathematical expressions in the chosen regression models for training and testing curves in the graphs increases, and thus, this becomes an advantage. Thus, an obscure system becomes identifiable with a simpler expression.

Figure 6. Train and Test Results with *sgdm*



As shown in the tables and figures above, a deep neural network architecture with the best performance was developed through trials using various parameters. It is an optimization process based on the learning process in DL applications. In DL models, the SGD (stochastic gradient descent) optimization algorithm is used hypothetically. However, in this study, the financial time series was modeled both unnormalized and normalized, using both optimization algorithms. Model performances are compared. It has been seen that the optimization algorithm, which is slower than the global minimum and has a lower margin of error, is sgdm and predicts the models with the minimum error. According to the results obtained, it was observed that the selected macroeconomic variables were essential in explaining the changes in the ISE 100 index values and were statistically significant.

The correctness and sufficiency of the learning of an artificial neural network are tested with the test set. According to Figures 4 and 6, which present the results of the training and test phases, both phases have been completed. As can be seen from these graphs, which display the estimated values alongside the actual values, the estimation errors are pretty low and gradually approach zero. To evaluate the prediction success of the deep neural network models created after the training and testing phases, the findings in Table 13 were obtained by calculating R^2, mean square error, and root mean square error.

Table 13. Deep Learning Performance Results

	Train			***Test***		
	R^2	MSE	RMSE	R^2	MSE	RMSE
adam	0.9501	0.0440	0,2099	0,9156	0,1396	0,3736
sgmd	0,9759	0,0448	0,2117	0,9919	0,1444	0,3800

When the findings in Table 13 and the graphs showing the results of the training and testing phases are evaluated together, it becomes evident that the error margins of the networks in both phases are relatively low and approach zero. In other words, it is seen that multilayer LSTM deep neural network models perform quite successfully in the in-sample and out-of-sample periods. During the in-sample period, the R^2 value of the multilayer deep neural network model developed to estimate the ISE 100 index value was 97.59%, while the MSE value was at the lowest level at 0.0448.

Out-of-sample predictions are of greater importance in the comparison of prediction accuracies, as they consist of predictions made from new data that was not used in model training. Considering this situation, it is evident that the created multilayer deep neural network model predicts the ISE 100 index value most accurately, with an R^2 value of 99.19%. This model's MSE value was at its lowest with 0.1444. Generally, it is observed that there is a strong and positive relationship between the independent variables and the ISE100 value. It is observed that the relationship between the variables exceeds 50% in all variables, and the MSE is at a very low level.

Although the variables were not seasonally adjusted, and dummy variables were not used in the model creation, the deep neural network models performed quite successfully. The deep neural network models developed in general have a good understanding of the effects of the economic crisis in Turkey in 2001 and the global financial crisis that emerged in the USA in mid-2007, adversely affecting all world economies in 2008, on macroeconomic variables and the ISE 100 index.

Forecasting modeling is of great importance and widely used in the field of economics, as well as in many other fields. Forecasting modeling plays a vital role in determining the future behavior of governments, producers, consumers, and the financial sector, collectively referred to as microeconomic decision-makers. Making accurate forecasts is of great importance, especially when making informed decisions in the field of finance. Simply put, good foresight leads to good choices.

In many empirical studies in the literature, econometric models have been employed as predictive models. In recent years, AI and deep neural network models have been used in comparison with econometric models due to their superior prediction performance. This is because AI models can outperform classical models in predicting nonlinear, seasonal, and trending time series.

In this part of the study, the comparison of Logit, Probit, and DL methods has been made. The comparison was made based on the estimation performances of the techniques used. The performances of the Logit and Probit models with the best performance were examined, and the prediction results obtained from the regression analysis are presented comparatively in Tables 14 and Table 15.

Table 14. Logit Model Performance

Classified	D	F	Total
Positive	151	5	156
Negative	6	91	97
Total	157	96	253
Correctly Classified (%)	96.79	93.81	95.65
Sensitivity (%)			96.18
Specificity (%)			94.79
Error Rate (%)			4.35

Table 15. Probit Model Performance

Classified	D	F	Total
Positive	150	6	156
Negative	7	90	97
Total	157	96	253
Correctly Classified (%)	96.15	92.78	94.86
Sensitivity (%)			95.54
Specificity (%)			93.75
Error Rate (%)			5.14

In this part of the study, the comparison of Logit, Probit, and DL methods has been made. The comparison was made based on the estimation performances of the methods used. The performances of the Logit and Probit models with the best performance were examined, and the prediction results obtained from the regression analysis are presented comparatively in Tables 14 and Table 15.

Table 16. DL Model Performance

	Accuracy	Loss	Total (%)
Accuracy (%)	99.61	0	100
Loss (%)	0	0.39	100
Total (%)	99.61	0.39	100

The DL model learned the in-sample period series correctly at a rate of 98.81% with a loss of 1.19% during the training phase. In other words, the rate at which the model learned about the crises experienced in Turkey in 2000 and 2001, as well as the reflections of the 2008 global crisis, is 98.81%.

As shown in Table 16, the DL model accurately learned the in-sample period series and predicted 100% of the periods in the test dataset for the out-of-sample prediction. After 2015, the effects of the developments in the markets due to the political events in July 2016 in Turkey and the price increases resulting from the COVID-19 pandemic in 2020, as well as their reflections on market indicators, have been estimated at 100%. In other words, the model's validation rate is 100%.

Although the validation rates of the created models are high, the validation percentage of the DL model is 100%. The margin of error is zero. In other models, the margin of error ranges from 4.35% to 5.14%.

5. Conclusion

Following the rapid advancements in computer technology, the use of AI technologies has become widespread in the finance sector, as well as in many other fields. The reason for the increase in interest in AI is that artificial intelligence technologies' ability to comprehend problems, read data correctly, and solve them quickly is quite advanced. Due to these characteristics and its success in various fields, including health, defense, and engineering, it has begun to be applied in the field of finance since the 2008 financial crisis. Especially for policymakers and investors, it has begun to shift towards methods that aim to eliminate financial uncertainties.

The effectiveness of AI has been proven once again in this study, in which the DL method, one of the new generations of AI technologies, was tested alongside traditional statistical and econometric methods, such as logit and Probit regression modeling techniques. This study found that AI technologies outperform classical econometric methods in analyzing financial time series with dynamic and volatile structures. Changes in the seven selected macroeconomic variables will affect the future values of the ISE100 index in which direction and to what extent. Studies have shown that even new modulation techniques developed by AI technologies outperform each other in estimating their performance. The new formations that have emerged all over the world in recent years, the ongoing economic crises since 2008, the COVID-19 pandemic that began in 2020, and the military crisis between Russia and Ukraine in 2022 have underscored the need to evaluate the world as a whole, rather than as individual countries and borders.

These developments have demonstrated that a positive or negative situation in any part of the world has reached global proportions, affecting all countries. This situation has made all the components that countries face in maintaining or increasing the level of social welfare uncertain. These days, as discussions abound about whether AI applications will bring benefit or harm in the future, it is clear that change is inevitable. Countries should be open to new technological structures or methods to ensure their continuity and to predict and structure the future in every field.

Linear stochastic regression models can have an advantage over other models if they can effectively understand and explain the essential relationships between variables. However, linear models are insufficient when the relationship between the variables in the studied problem is not linear. At this point, AI models can make successful predictions when the appropriate network structure for nonlinear relationships is determined.

In this study, the value of the ISE 100 index for the period from January 2001 to January 2022 is estimated using the DL modeling technique, a non-linear estimation model, after the variables to be used as input are determined by applying the Logit and Probit methods. General information is provided about the size and development of stock markets in Turkey and around the world. Then, AI technologies, such as ANNs, and finally DL modeling, which is ML, were examined in detail. The DL model was designed, and the ISE100 value was modeled using the appropriate network architectures and seven macroeconomic variables. Estimated models were evaluated within themselves, and performance comparisons were made by performing Logit and Probit analyses. In Logit and Probit analysis, the ISE100 index was used as the dependent variable, with seven independent variables: the Dollar Rate (TL/$), the Money Supply, the Producer Price Index, the Industrial Production Index, Gold Prices (TL/Gr), the Active Bond Interest Rate, and the Brent Oil Price.

The estimated DL models showed a consistent structure and good predictive performance. In the prediction comparison made with Logit and Probit models, it was concluded that the DL technique performed better than the other methods. In addition, it is notable that the DL method is more successful than the Logit and Probit methods in predicting financial crises.

When the Logit and Probit model results are examined, it is evident that the models created are the best. Since the probability values of the Hosmer-Lemeshow and Pearson goodness-of-fit tests were higher than 0.05, the models were statistically significant, and the lowest AIC and BIC values, along with the highest Pseudo R-squared values, were found to be 0.865 for the Logit model and 0.866 for the Probit model. The accurate classification rates were found to be 95.65% and 94.86% for the Logit and Probit models, respectively. It has been concluded that the estimation results of the Logit and Probit models are very close to each other. According to the Logit and Probit analysis results, the coefficients obtained for each independent variable are significant, and the coefficient sizes and test statistics values are similar. It has been observed that the Probit model gives better results than the Logit model.

The fact that the predictions made with Logit and Probit analyses show significant deviations from the fundamental values and the better prediction performance of the network even though the seasonal effects are not reflected in the deep neural networks cause a generalization to be made that the nonlinear modeling for financial variables, that is, the deep neural network method, is more effective.

There are very few studies that use deep neural networks or DL models to predict financial markets and stock markets indexes around the world. The method of ANNs has been used in several studies to predict the direction of the Turkish stock market, but the DL model has not been used. In this study, the use of Logit and Probit analysis, as well as the DL model, to predict the direction of the ISE100 index, along with the large number and variety of macroeconomic variables included in the analysis, adds originality to the study.

Today, developments in the fields of communication technology and finance, the global economic crises that started in the US loan market and affected the national markets of all the countries of the world, and the socio-economic processes experienced after epidemics such as the COVID-19 pandemic have shown that international capital markets have gained a national capital market identity. It is observed that models created with AI techniques, which can make successful predictions and model non-linear relationships, thus explaining changes in the capital market, are an effective estimation tool for investors seeking to hedge risk and gain returns in such a broad market. Due to these features, artificial neural network techniques are becoming an increasingly important tool for problem-solving in the financial sector.

This study contributes to the discussion on AI in financial analysis by providing empirical evidence of the observable effects of AI applications on financial performance and strategic decision-making. Given its fundamental opportunities and limitations, it is expected that AI will be used in financial analysis more efficiently in the future.

Based on this study, the following can be suggested as future research topics for the ISE100 index: While expanding the basket of macroeconomic variables that affect the ISE100 value, the stock being studied can be limited. In other words, a similar analysis can be made for particular stocks in Turkey. The analysis of the value of the Turkish stock market over a more extended period, by comparing other econometric models with AI methods and/or using hybrid models, can be another subject of study.

It has been determined that artificial intelligence technologies offer highly successful optimizations compared to traditional methods in terms of how investors or decision-makers take a position in the capital markets, including which investment instruments they prefer and which instruments are included in the portfolio basket. Therefore, artificial intelligence technologies have emerged as a highly successful method in the field of finance. These models, which are created by learning from the data with the lowest error, will take their place in the literature as the best optimization and prediction models.

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Finansal Analizde Yapay Zekânın Etkinliği: İstanbul Menkul Kıymetler Borsası 100 (İMKB 100) Üzerine Kanıtlar

Fikriye ÜSTÜNER	Erhan ÇANKAL
Lecturer, Ankara Hacı Bayram Veli University	Assoc. Prof., Ankara Yıldırım Beyazıt University
Polatlı Social Sciences Vocational School	Faculty of Business Administration
fikriye.ustuner@hbv.edu.tr	ecankal@ybu.edu.tr
https://orcid.org/0000-0002-6010-0260	https://orcid.org/0000-0001-5115-055X

Genişletilmiş Türkçe Özet

Toplumsal refah ve ekonomik kalkınma, ülkelerin finansal piyasalarını oluşturan para piyasası ile sermaye piyasalarının gelişmişliği ile yakından ilgilidir. Sermaye piyasalarının gelişmişliğinin ölçüsünün ne olduğu konusunda ortak bir görüş olmamakla birlikte iyi bir finansal sistemin; sağlam bir kamu maliyesi ve kamu borç yönetimi, güvenilir ve istikrarlı mali düzenlemeleri, kimisi ulusal ve kimisi uluslararası ve/veya her iki kökenden gelen çeşitli bankaların varlığı, iç finansmanı dengeleyebilecek ve uluslararası finansal ilişkileri yönetebilecek bir merkez bankası ve iyi işleyen menkul kıymetler borsası olmak üzere beş bileşeni vardır. Bu bileşenlere sahip düzenli finansal bir sistem ülkelerin ekonomik büyüme ve gelişmesinde önemli rol oynamaktadır (Rousseau & Sylla, 2003, pp. 374–375).Tanımlanan bu bileşenlerden de anlaşılacağı üzere bir ülkenin finans piyasası ne kadar gelişmişse, toplumdaki risk düzeyi ve kırılganlık da o kadar düşük olacaktır. Ayrıca bu öngörülebilir yapı, özel sektörü de teşvik ederek ülkelerin kalkınmaları ve dolayısıyla toplumsal refahlarının yükselmesi süreçlerinde önemli işlev görecek ve tasarruflar yatırımlara dönüşerek ekonomik büyümenin artmasına yol açacaktır.

1980'li yıllardan başlayıp 1990'lı yıllara kadar olan dönemde dünyada yaşanan finansal krizler nedeniyle gelişmiş ve gelişmekte olan ülkeler, ekonomilerini korumak ve finansal dalgalanmaların etkilerini en aza indirebilmek için çeşitli reformlar yapmışlardır. Bu reformlar; faiz oranlarını serbest bırakmak, kredi tavanlarını kaldırmak, bankaların Merkez Bankası'nda bulundurmak zorunda oldukları mevduat munzam karşılık oranlarını düşürmek ya da tamamen kaldırmak, bankacılık sektörünün hem yabancı hem de yerleşiklere açılmak ve sermaye hareketlerini serbestleştirmek gibi finansal serbestleşme politikalarını içeren uygulamalar biçiminde olmuştur (Güloğlu & Altunoğlu, 2011, pp. 107–134). Bu dönemde yaşanan finansal krizlerin, özellikle gelişmekte olan ülkelerde, büyümenin sürdürülebilmesi için atılan finansal serbestleşme adımları ile ekonomik ve politik riskler nedeniyle ülkeyi terk eden sıcak para sonrası ya da uluslararası sermaye hareketleri, aşırı borçlanma, döviz kuru politikaları ve yüksek enflasyon oranları nedeniyle yaşandığı görülmüştür. Türkiye'de finansal serbestleşme hareketlerinden sonra 1994 ve 2001 yıllarında yaşanan finansal krizler ile 1997 yılındaki Asya krizi ve 1997-98 yıllarındaki Rusya krizi de spekülatif sermaye hareketlerinden kaynaklanan krizlerdir. Bu krizler yaşandığı ülke ekonomilerinde yol açtıkları maliyetleri göstermesi bakımından da önemli birer örnektirler.

Bu ekonomik krizlere ek olarak 2007 yılında Amerika'da ortaya çıkan ve daha sonra İngiltere'ye sıçrayan ve 2008 yılının ikinci çeyreğinden itibaren küresel bir krize dönüşen Mortgage krizi de krizlerin dünyadaki yansımalarını göstermesi nedeniyle önemli bir örnektir (Eğilmez, 2009, pp. 52–53). Bu ve

sözü edilen diğer finansal krizlerin, gelişmişlik düzeyine bakılmaksızın ülke piyasalarının birbirini büyük ölçüde etkilediğini, dünyada büyük finansal dalgalanmalara ve finansal yıkımlara yol açtığını ve büyük ekonomilerde yaşanan finansal şokların bankalar başta olmak üzere çeşitli finansal kurumların iflasına ve hatta ülkelerin iflasına bile yol açabileceğini göstermiştir.

Dünya finans piyasalarında yaşanan bu gelişmeler, piyasalarda oluşan finansal kırılmalar ve belirsizliklerin önlenmesinde ve/veya etkisinin azaltılmasında, finansal piyasalardaki olası kaos ve belirsizlikler ile fiyat hareketlerini etkileyen mikro ve makro ekonomik faktörlerde meydana gelebilecek dalgalanmaları tahmin etmenin ne kadar önemli olduğunu göstermiştir. Bu durum da ekonomik karar vericilerin, sermaye piyasası araçlarının ve varlık fiyatlarının gelecekteki değerini doğru tahmin edebilmeleri halinde önemli avantajlar ve fırsatlar elde edebileceklerini gerçeğini ortaya çıkarmıştır. Bu fırsatların sadece finansal fırsatlar olmadığı ülkelerin bekası için de ne kadar önemli olduğu günümüzde tecrübe edilmektedir.

Gerçek hayata ilişkin olguları sembolize eden verinin işlenerek anlamlı ve karar verilebilecek bir forma başka bir deyişle bilgiye, bilgilerin de yatırım kararına dönüştürülmesi sürecinde istatistik ve ekonometrik modeller aracılıyla yapılan finansal analizlerin, hızlı, ekonomik ve detaylı bir biçimde yapılabilir olması gerekliliği yeni analiz yöntemlerinin doğmasına yol açmıştır. Finansal öngörüde, bilgi işleme sürecinde kullanılan yöntemler ise; genel olarak gruplama ve regresyon analizi yöntemleri ve volatilite yöntemleri; olasılık dağılımının belli parametrelere bağlı olduğu otoregresyon analizi gibi parametrik istatiksel teknikler; Friedman testi ve Spermanın sıra korelasyon testi ve kovaryans tahmini gibi olasılık dağılımının belli parametrelere bağlı olmadığı parametrik olmayan istatiksel teknikler olarak sıralanabilir.

Finansal belirsizlik ve maliyetleri azaltan doğru tahminlerin başarılı sonuçları beraberinde getireceği ve böylece hem yatırımcılar hem de hükümetler açısından ortaya çıkacak sorunların ve maliyetlerin azaltılmasında da önemli rol oynayacağı ve fayda fonksiyonlarının en üst düzeye çıkabileceği gerçeği son yıllarda finansal verilerin yapısına oldukça uyum gösteren ve bilgisayar teknolojilerine dayanan çeşitli yapay zekâ teknolojileri de yaygın olarak kullanılmaya başlanmasına neden olmuştur (Henrique, Sobreiro, & Kimura, 2019). Yapay Sinir Ağları (ANN) yöntemi ve türevleri; öğrenebilme, genelleme yapabilme, eksik, hatalı, kusurlu ve hatta yanlış verilerle çalışabilme yeteneği olduğundan; sınıflandırma, optimizasyon, örüntü tanıma işlemlerinde ve özellikle doğrusal olmayan zaman serilerini tahmin etmede oldukça başarılı sonuçlar vermiş ve bu talepleri karşılaması nedeniyle ön plana çıkan bir yöntem olmuştur (D. Cheng, Yang, Xiang, & Liu, 2022). Kurumsal finans alanındaki, finansal simülasyon, yatırımcı davranışı tahmini, finansal değerlendirme, kredi onaylama, hisse ve varlık portföy yönetimi, halka arzların fiyatlanması ve optimal sermaye yapısının belirlenmesi gibi yapay sinir ağları teknolojisi kullanılarak üretilmiş uygulamaların yine yapay sinir ağları teknolojisi ile geliştirilebileceği örneklenmiştir (J. Hsieh, Chen, & Lin, 2019; C. Lin, Chang, & Sun, 2024).

Menkul kıymet borsasında işlem gören finansal varlıkların fiyat hareketlerinin yönünün tahmin edilmesinde elde edilecek doğru öncül göstergelerin, siyasi olaylar, genel ekonomik koşullar, temel ekonomik veriler, savaşlar, doğal felaketler ile bu şartlar altında yatırımcıların beklentileri, gibi birçok değişkenden etkileneceği açıktır. Ancak bu bileşenlerin basitleştirilerek modele dahil edilmesi, doğrusal olmayan yüksek frekanslı verilerin işlenmesi ancak yapay zekâ teknolojilerinin geleneksel yöntemlere karşı sağladıkları öngörü üstünlükleri ile aşılabileceği yapılan çalışmalar ile ispatlanmıştır. Aynı zamanda kullanılan hibrit modeller ile tekniklerin tek tek kullanılmasından doğan dezavantajlar da ortadan kaldırılmaya da çalışılmaktadır. Bu nedenle bu tür çalışmaların sayısı giderek artmaktadır (J. Cheng, Tiwari, Khaled, Mahendru, & Shahzad, 2024; Oyewole et al., 2024).

Doğrusal stokastik regresyon modelleri, değişkenler arasındaki önemli detayları anlayabilir ve açıklayabilirlerse diğer modellere göre avantajlı olabilirler. Ancak üzerinde çalışılan problemdeki değişkenler arasındaki ilişki doğrusal olmadığında doğrusal modeller yetersiz kalmaktadır. Bu noktada, doğrusal olmayan ilişkiler için uygun ağ yapısı belirlendiğinde AI modelleri başarılı tahminler yapabilmektedir.

Bu çalışmada, girdi değişkeni olarak kullanılacak değişkenler Logit ve Probit modelleri kullanılarak belirlenmiş ve doğrusal olmayan tahmin modellerinden biri olan AI modelleme tekniği ve bir makine öğrenmesi modeli olan derin öğrenme modelleme tekniğiyle, Ocak 2001-Ocak 2022 döneminde ISE100 endeksinin değerinin tahmin edilmesi amaçlanmıştır. Türkiye'de ve dünyadaki hisse senedi piyasalarının veya başka bir deyişle borsaların büyüklüğü ve gelişimi bu konuda yapılacak çalışmalarda yön vermiştir. Derin öğrenme ağ mimarisi kullanılarak oluşturulan LTSM ağında kullanılan aktivasyon, katman ve nöron ve döngü sayıları değiştirilerek en iyi sonuca ulaşılmaya çalışılmıştır. Model tasarımı yapılarak uygun bulunan ağ mimarileri ve yedi adet makro ekonomik değişken kullanılarak ISE100 değeri modellenmiştir. Tahmin edilen modeller hem kendi içinde değerlendirilmiş hem de Logit ve Probit analizi yapılarak performans karşılaştırmaları yapılmıştır. Logit ve Probit analizinde de ISE100 endeksi bağımlı değişken; Dolar Kuru (TL/$), Para Arzı, Üretici Fiyat Endeksi, Sanayi Üretim Endeksi, Altın Fiyatları (TL/Gr), Aktif Tahvilin Faiz Oranı ve Brent Petrol Fiyatı olmak üzere yedi adet bağımsız değişken kullanılmıştır.

Tahmin edilen makine öğrenme yöntemi olan derin öğrenme modelleri (LTSM) kendi içlerinde tutarlı bir yapı ve iyi bir öngörü performansı göstermişlerdir. Logit ve Probit modelleri ile yapılan öngörü karşılaştırmasında ise derin öğrenme tekniğinin bu yönteme göre daha iyi bir performans gösterdiği sonucuna varılmıştır. Ayrıca, finansal krizlerin tahmini konusunda derin öğrenme tekniğinin yönteminin Logit ve Probit yöntemlerine göre daha başarılı olduğu en dikkat çekici noktadır.

Dünya genelinde finansal piyasalar ve borsalara ilişkin tahminlerde derin sinir ağları veya derin öğrenme modellerini kullanan çalışma sayısı oldukça azdır. Türkiye hisse senedi piyasasının yönünü tahmin etmek için yapılan birkaç çalışmada yapay sinir ağları yöntemi kullanılmış fakat derin öğrenme modeli kullanılmamıştır. Bu çalışmada, Logit ve Probit analizleri ile derin öğrenme modelinin ISE100 endeksinin yönünün tahmininde kullanılmasının ve analize dâhil edilen makro ekonomik değişkenlerinin sayısı ve çeşidinin fazla olmasının çalışmaya özgünlük kattığı düşünülmektedir.