International Journal of Business & Economic Studies
Year: 2024, Vol: 6, No: 3, pp. 143-154
https://doi.org/10.54821/uiecd.1460617

Does Machine Learning Forecast Investor's Risk Appetite?

Makine Öğrenmesi Yatırımcının Risk İştahını Öngörür mü?

Nesrin ÖZKAN
Assoc. Prof. Dr., İnönü University
nesrin.ozkan@inonu.edu.tr
https://orcid.org/0000-0002-8674-5518

Received : 28.03.2024
Revised : 16.07.2024
Accepted : 30.07.2024
Type of Article : Research

Nurgül Ö. YALINCAKLI
MSc Candidate, Bursa Technical University
nurgulozkany@gmail.com
https://orcid.org/0000-0003-0092-4871

Keywords:

Risk Appetite, RISE Index, Forecasting, LSTM, MLP

Jel Codes:

C32, C45, G17

ABSTRACT

Risk appetite is an important indicator that is monitored with interest by financial market participants. One of the risk appetite indices is nominated "RISE risk appetite index" calculated to measure the riskiness of the Turkey market in general. There are very limited studies in the literature on RISE risk appetite, and most of them use simple econometric methods to predict the risk appetite. To the best of our knowledge, there is no study using machine learning algorithms. Therefore, it creates curiosity on how the success will be in estimating the risk appetite using machine learning algorithms. Thus, the aim of this paper is to measure the estimation success of the RISE index using Long Short-term Memory (LSTM) and Multi-Layer Perceptron (MLP). The analysis is based on a weekly frequency dataset covering the years 2008 to 2023. The results are compared as per RMSE values, and LSTM presents rather high prediction success compared to MLP. Due to the forecasting ability of BIST 100 index on RISE, the current and lagged values of BIST 100 are compared, and lagged values of BIST 100 are found to have a higher ability to estimate RISE, approximately twice as much as current values. It is expected that this valuable finding will be a guide for market participants and financial analysts to shape their investment preferences by using deep learning algorithms in predicting market expectations and to make well-directed investments.

Anahtar Kelimeler:

Risk İştahı, RISE Endeksi, Tahminleme, LSTM, MLP

Jel Kodları:

C32, C45, G17

ÖZET

Risk iştahı, finansal piyasa katılımcıları tarafından ilgiyle izlenen önemli bir göstergedir. Risk iştahı endekslerinden biri olan "RISE risk iştahı endeksi", genel olarak Türkiye piyasasının risk derecesini ölçmek için hesaplanmaktadır. Literatürde RISE risk iştahıyla ilgili sınırlı sayıda çalışma bulunmakta ve bu çalışmaların çoğu, risk iştahını tahmin etmek için basit ekonometrik yöntemleri kullanmaktadır. Bildiğimiz kadarıyla, makine öğrenmesi algoritmalarını kullanan bir çalışmaya rastlanmamıştır. Bu nedenle, makine öğrenmesi algoritmaları kullanılarak risk iştahının tahminlenmesi merak uyandırmaktadır. Bu çalışmanın amacı, RISE endeksinin tahmin başarısını Uzun Kısa Süreli Hafıza (LSTM) ve Çok Katmanlı Algılayıcı (MLP) kullanarak ölçmektir. Analiz, 2008'den 2023'e kadar olan yılları kapsayan haftalık frekanslı veri setine dayanmaktadır. Sonuçlar, RMSE değerlerine göre karşılaştırılmış olup, LSTM algoritması MLP'ye kıyasla daha yüksek bir tahminleme başarısı sunmaktadır. RISE endeksi üzerinde BIST 100 endeksinin tahmin yeteneği göz önüne alındığında ise BIST 100 endeksinin mevcut ve gecikmiş değerleri karşılaştırılmış ve gecikmeli BIST 100 değerlerinin RISE' ı tahmin etme yeteneğinin, mevcut değerlere göre yaklaşık olarak iki kat daha yüksek olduğu belirlenmiştir. Bu değerli bulgunun, piyasa katılımcılarına ve finansal analistlere, piyasa beklentilerini tahmin etmede derin öğrenme algoritmalarını kullanarak yatırım tercihlerini şekillendirmelerine ve doğru yatırımlar yapmalarına rehberlik edeceği beklenmektedir.

Suggested Citation: Özkan, N., & Yalıncaklı, N.Ö. (2024). Does machine learning forecast investor's risk appetite?. *International Journal of Business and Economic Studies*, 6(3), 143-154, Doi: https://doi.org/10.54821/uiecd.1460617

1. INTRODUCTION

Risk appetite refers to the investor's desire and tendency to engage in transactions involving various financial instruments in financial markets. In addition, risk appetite is, to some extent, a different concept from the investor's aversion to risk. Particularly, Gai & Vause (2004) argue that the difference lies in the fact that risk aversion does not show a time-dependent change and that investors differ in the point at which they will internally avoid risk. Financial difficulties and periods of macroeconomic uncertainty lead to variations in investors' risk appetite (Misina, 2005).

If we scrutinize deeper the subject, the concepts of "risk appetite," "risk premium," and "risk aversion" concepts emerge, and although these terms are sometimes used interchangeably, they represent distinct concepts. Investors dislike uncertainty surrounding the future consumption on their assets. When expressed as a willingness to take risks, risk appetite depends on an investor's level of discomfort with uncertainty and the degree of uncertainty. The level of uncertainty is determined by macroeconomic conditions. An investor's level of discomfort with uncertainty reflects their preferences for gambling. On the other hand, risk aversion is inherently internal for an investor and does not change consistently over time. These concepts differ from each other, for example, risk appetite varies over periods based on financial distress and macroeconomic uncertainties. In adverse conditions, investors demand higher expected returns for each unit of risk, leading to a decrease in risk appetite—essentially the inverse of the risk price. The price of risk, when considered alongside the amount of risk inherent in a specific asset, is the risk premium, representing the expected return for holding that asset. It is depicted in Figure 1. Distinguishing risk appetite from risk aversion is rather hard; an increase in either leads to a decrease in asset prices and an increase in the risk premium (Gai & Vause, 2006).

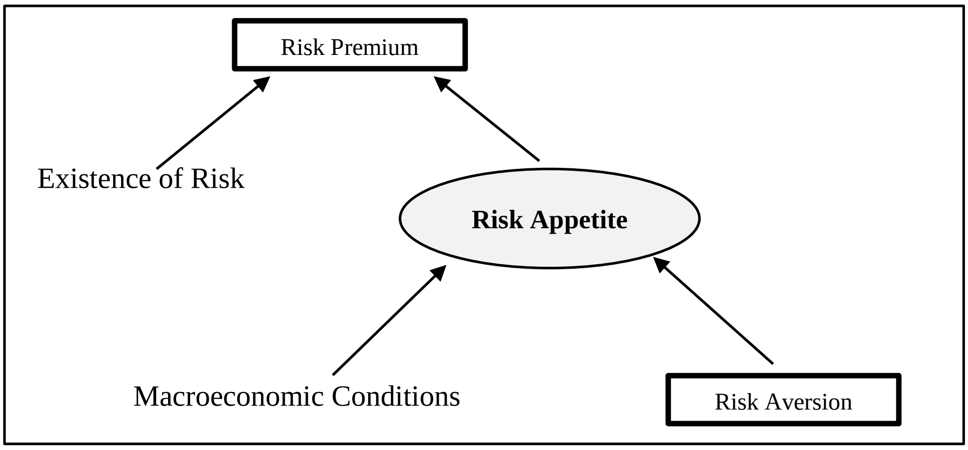

Figure 1. The Relationship between Risk Premium, Risk Aversion
Source: Gai & Vause, 2006, p.169.

Therefore, as shown in Figure 1, the two main factors fundamentally influencing risk appetite are the uncertainty stemming from macroeconomic conditions and the investor's risk aversion attitude. Considering that the investor's risk aversion attitude is an integral part and doesn't change significantly across periods, we can conclude that risk appetite is affected by the times of increased financial or macroeconomic uncertainties.

The risk appetite for financial instruments tends to rise and decline in certain periods. Behind these fluctuations, there are sometimes global and sometimes national factors. These factors can be financial and economic events, as well as political or even sociological events. These influences can sometimes affect markets in a domino effect. A decrease in risk appetite in one market can manifest as an increase in another financial market or instrument. Therefore, while global risk appetite can be measured, it is also possible to measure the risk appetite for a specific region, market, or financial instrument. However, for risk appetite measured with various indicators explaining changes in asset prices, it generally does not exhibit directly observable characteristics. In calculations, attempts are made to create a risk appetite index by combining different indicators from several markets (Hermasillo, 2008).

In this study, we aim to predict the RISE risk appetite index via machine learning methods. In the literature review, it is noticed that few studies are conducted on the RISE risk appetite, and the majority rely on basic econometric methods for prediction. As far as we know, no research has employed machine learning algorithms for this purpose. This raises curiosity about the potential success of using machine learning algorithms to estimate the

RISE risk appetite index. This study will demonstrate that machine learning algorithms can be used to predict RISE risk appetite. Therefore, it is expected to contribute to the literature by showing the prediction success of machine learning methods on the estimation of investor risk appetite. The remainder of this paper is organized as follows. Section 2 summarizes the local and international risk appetite measures. Section 3 provides the previous studies on risk appetite measures. Section 4 is the data and model, and Section 5 shows the results of the research. Section 6 concludes.

2. RISK APPETITE INDEXES

Various studies have been conducted to measure risk appetite in international markets, and different indicators have been calculated. Among these indicators, the most recognized and considered a significant measure of risk is the VIX index. The VIX index is known as the gauge of anxiety or fear arising from increased volatility in the markets, and is therefore also referred to as the "fear index." It measures the market's expectation of volatility based on S&P 500 index options. The symbol for the VIX index is the Chicago Board Options Exchange (CBOE) Volatility Index. Although the VIX is the most well-known and popular index, countries worldwide have their own calculated indices. These indices can be categorized into market-based indicators and model-based criteria. Examples of indices created based on model-based criteria include the Investor Risk Appetite developed by Gai & Vause (2005), State Street's Investor Confidence Index (ICI), Goldman Sachs Risk Aversion Index (GS), Tarashev, Tsatsaronis, & Karampatos' Risk Appetite Index (BIS), and Credit Suisse's Global Risk Appetite Index (CS). In the category of market-based indicators, VIX is at the forefront. These indicators are simple statistical measures based on implied volatility and trading variances. Others in this category include JP Morgan's Risk Tolerance Index (JPM G-10 RTI and JPM EM RTI), Merrill Lynch's Option Volatility Expectation Index (MOVE Index), Westpac Risk Appetite Index (WPRA), Dresdner Kleinwort's Total Risk Perception Index (ARPI), Merrill Lynch Risk Aversion Indicator (ML RAI), Lehman Brothers' Market Risk Sensitivity Index (MARS), and Bank of America Risk Appetite Indicator (RAM) (ECB, 2007).

Market-based measurements are focused on the measurement of market volatility, also known as market risk. The most popular risk appetite index, measured according to the expected volatility of the stock option market, is the VIX index, calculated by the CBOE. The VIX Index is closely monitored by market participants. It is calculated based on the implied volatility of the S&P 500 stock index. The calculation of this index involves using the implied volatility of buying and selling options. In its simplest form, the index represents the 30-day anticipated volatility of the U.S. stock market. It reflects the market's perception of risk. Therefore, a high index value indicates increased risk and a worsening perspective for future expectations, meaning that fear and tension in the markets may rise. Levels at 30 and above suggest that volatility may show significant increases. Hence, the VIX index is nominated as the "fear index." Figure 2 displays the graph of the VIX index for the period from 2019 to 2023. The graph apparently shows the dramatic increase in the index at the times of Covid-19 pandemic outbreak that’s because uncertainty and fear dominate all over the world and reverberate the risk appetite index values almost concurrently.

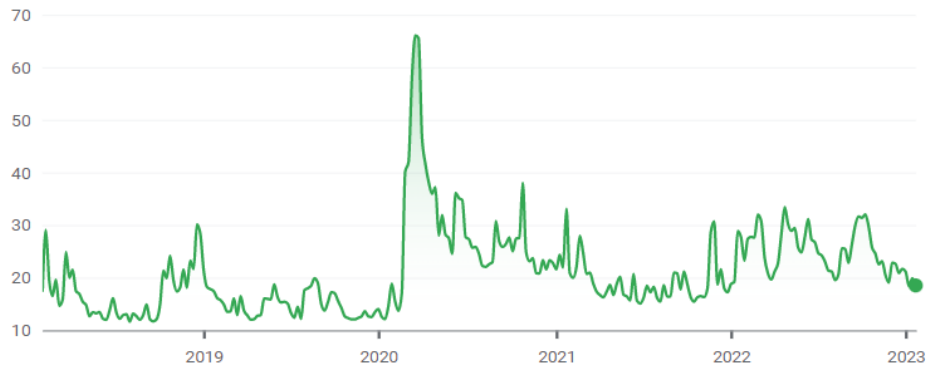

Figure 2. VIX Fear Index for the Period of 2019-2023
Source: Google Finance, 2023.

In Turkey, a collaboration between the Central Securities Depository of Turkey (MKK) and Özyeğin University has generated a risk appetite index to measure the overall market risk appetite. This index, known by abbreviation as RISE, is calculated weekly and is published on MKK's website at the end of every Friday. The data for this index goes back to 2008. The RISE index is calculated for various investor groups, including all investors, domestic investors, foreign investors, domestic individuals, domestic legal entities, domestic funds, and qualified investors. They all are regularly announced on MKK's website.

The index is calculated on the basis of the weekly changes in the portfolio values of approximately 1.7 million investors. The weekly portfolio changes are used for calculation. The calculation considers the total weekly changes in the portfolios of investors in A-type funds and equities held on Fridays. It is adjusted for changes in the BIST 100 index, and the deviation of investors' changes in the relevant week from the weighted average of the values of the previous 52 weeks is obtained. The scoring method, which assigns investors a score between 0 and 100, is used in the calculation. Subsequently, these scores are used to calculate the weighted average of investors' portfolio sizes for the relevant week relative to the market portfolio size. Finally, the result of this process is an index of market risk appetite (Saraç et al., 2016).

3. LITERATURE REVIEW

Kumar & Persaud's (2002) study is considered one of the pioneering works in the international literature on risk appetite. The authors conducted various analyses to explain the relationship between financial contagion and risk appetite and to measure the changes in investors' risk appetite. They used the spot and forward exchange rates of 17 currencies for this purpose. In calculating risk, they employed the excess returns and return volatilities of assets and computed a Risk Appetite Index (RAI) that reflects changes in an investor's risk aversion. The calculation was based on the Spearman rank correlation between expected excess asset returns and the riskiness of the asset. Empirical results suggested that the RAI could be a useful measure for understanding financial crises.

Haugen (2006) conducted research on the dependence of risk appetite on macroeconomic conditions. The results revealed statistical evidence illustrating the interaction between risk appetite and macroeconomic conditions. Baek (2006) investigated the driving and attracting factors behind portfolio investments in Asian and Latin American economies. Similar to Kumar & Persaud (2002), the author generated a risk appetite index. The findings indicated that the factors attracting and pushing foreign portfolio investments in Asian and Latin American economies were different. In Asian economies, investor risk appetite was found to be the dominant driving force behind portfolio investments. Shen & Hu (2007) aimed to measure the relationship between the risk appetites (RAI) of banks and macroeconomic variables in Taiwan. The authors conducted an analysis to explain the relationship between bank risk appetite indices and periods of financial crises or significant economic events. It is found that local crises affecting the country significantly led to a decrease in bank risk appetite. Adrian et al. (2009) examined the relationship between the VIX fear index and exchange rates of country markets that cover fourteen emerging markets and nine developed markets. Turkey was among the emerging markets in the study, and the results indicated a significant relationship between risk appetite and exchange rate changes. Pericoli & Sbracia (2009) calculated the Risk Appetite Index (RAI) using Kumar & Persaud's (2002) method with monthly data for Dow Jones Euro STOXX and S&P 500 market stocks. They concluded that RAI and CAPM yielded similar predictions when the variance of returns was sufficiently smaller than the variance of the asset's risk. Sarwar (2012) investigated the relationships between the VIX index and the national stock indices of Brazil, Russia, India, China, and the United States for the period 1993 to 2007. They found a statistically significant and negative relationship between them.

It is accurate to say that there is not an extensive literature on studies examining the RISE risk appetite since 2008. A number of research concentrates on exploring the relationships between various macroeconomic and financial indicators and risk appetite. However, there are limited studies on the determinants of risk appetite. One of the pioneering studies in this regard was conducted by Saraç et al. (2016). In this study, the authors examined the predictability of the RISE risk appetite index for the period of 2008 and 2013. The researchers found that the data on domestic investors' risk appetite were linear and did not exhibit a threshold effect. Additionally, the non-linearity of the risk appetite series of foreign investors indicates the presence of a threshold effect.

Çelik et al., (2017) conducted analyses using time series regressions for the period from 2008 to 2017, focusing on macroeconomic variables that could be used in predicting risk appetite. The results indicated that an increase in interest rates and exchange rates has a negative effect on risk appetite, while an increase in money supply and foreign exchange reserves has a positive effect. The statistically significant macroeconomic variables in the model can only explain 5% of the variation in investors' risk appetite. The remaining 95% implies the existence of other macroeconomic and financial indicators that could influence risk appetite.

Akdağ (2019) attempts to determine Turkey's financial and macroeconomic indicators influenced by the VIX index. According to the Granger causality test results, changes in the VIX fear index were found to be the Granger cause of changes in BIST 100 index, In the study by Akdağ & İskenderoglu (2019), the authors tested whether risk appetite in rising (bull) and falling (bear) markets, could be parametrically separated into regimes using the Markov Regime model. The results indicated that the RISE risk appetite could be divided into two regimes: high and low volatility. The authors noted that events such as earthquakes, economic and political crises, and terrorist incidents coincided with the high volatility regime, which they referred to as turmoil.

İskenderoğlu & Akdağ (2019) conducted a study investigating the causality relationship between risk appetite and oil prices, exchange rates, gold prices, and interest rates using weekly data from 2008 to 2015. The findings of the study indicated that changes in oil prices were sensitive to changes in investors' risk appetite in the long term. On the other hand, regarding exchange rates, it was observed that both in the long and short term, risk appetite was influenced by changes in exchange rates.

Demirez & Kandır (2020) examined the relationship between stock returns, the RISE risk appetite index, and the BIST 100 index for the period from January 2009 to January 2019. According to the regression analysis, it was concluded that the impact of changes in risk appetite on stock returns is limited. Sarı & Başakın (2021) examined the relationship between the BIST Bank Index, the RISE risk appetite index and VIX index. According to the findings, it was determined that the risk appetite index and VIX index could predict stock returns with acceptable accuracy.

Özkan (2022) investigated the relationships between the RISE risk appetite index and BIST 100, gold, and USD/TRY exchange rate during the Covid-19 pandemic period. A positive relationship was identified between the two-period lagged value of the risk appetite index and the one-period lagged values of the BIST 100 index. This finding seems to be in line with theoretical expectations.

Köycü (2022) examined the relationship between the BIST 100 index and the RISE risk appetite. The causality from the BIST 100 index to the risk appetite index was detected. Yılmaz & Yıldız (2022) examined the relationships between the volatility indices in international markets, including VIX (USA), VXN (USA), V1X1 (Germany), V2TX (Europe), and JNIV (Japan), and the RISE risk appetite index. The findings indicated that the V2TX index was the most influential fear index on the risk appetite index for all investor types.

Gemici et al. (2023) analyzed the effects of four local and five global factors on Turkey's risk appetite using weekly data from 2008 to 2022. The authors employed two nonparametric quantile-based approaches, the causality-in-quantile method proposed by Balcilar et al. (2016) and quantile-on-quantile regressions introduced by Sim & Zhou (2015) The findings unveiled the significant causal relationships between both global and local factors and risk appetite under different market conditions. Among these, local factors, especially CDS spreads, had a stronger causal impact compared to global factors. Besides the uncertainty during the pandemic crisis diminished the explanatory power of most factors. All investor groups generally experienced negative shocks, with the impact being stronger at lower and middle quantiles.

The literature review revealed that there was no study investigating whether the risk appetite could be predicted by machine learning algorithms. So, this study would be the leading one used the machine learning architectures in the prediction of the RISE risk appetite index in Turkey.

4. METHODS and DATASET

Deep learning can be defined as a machine learning method that enables digital systems to learn from vast unstructured and unlabeled data, extracting various patterns and thus making decisions. In its simplest form, it is the application of machine learning methods to big data. We observe the increasing use of deep learning algorithms in various fields such as drug discovery and medicine, natural language processing, signal processing, future prediction, the defense industry, and finance. At the core of this is the considerably successful results of deep learning architectures in these areas compared to other methods used (Doğan & Türkoğlu, 2019).

Deep learning techniques, especially within the finance domain, demonstrate superior effectiveness compared to standard econometric methods when addressing large datasets for predicting asset pricing, optimizing portfolio acquisition, managing risk, and estimating future prices and returns of financial assets. The fundamental reason for this lies in the ability of deep learning methods to detect direct but unobservable data interactions among financial data. One of the deep learning method is LSTM, which is a type of recurrent neural network (RNN) architecture that extends memory. RNN uses short-term past information and therefore has short-term memory.

LSTM, on the other hand, is an improved version of normal RNN with higher memory power, designed to facilitate capturing long-term dependencies in sequential data (Alpay, 2020). LSTM neural network was first proposed by the study of Hochreiter & Schmidhuber (1997). The network is built on the structure by constructing gates on the cell. These gates are nominated as "forget gate", "input gate", and "output gate". These gates are capable of capturing both long-term and short-term memory throughout the time steps and avoid gradient exploding. The operation of an LSTM unit can be expressed as:

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \quad (1)$$

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \quad (2)$$

$$\tilde{c}_t = tanh(W_c x_t + U_c h_{t-1} + b_c) \quad (3)$$

$$c_t = i_t * \tilde{c}_t + f_t * c_{t-1} \quad (4)$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \quad (5)$$

$$h_t = o_t * \tanh(c_t) \quad (6)$$

Where,

Input gate, i_t	: Determines which information will be updated in the cell state, c_t
Forget gate, f_t	: Controls which information will be discarded from the previous cell state, c_{t-1}
Candidate cell state, $\tilde{c}_t$	: Created by Tanh to determine the new information to be stored in the cell state.
New cell state, c_t	: Updated using the input gate and the candidate cell state
Output state, o_t	: Determines the output of the LSTM cell
Hidden state, h_t	: The output of the LSTM cell, filtered through the output gate.

Each gate (i_t , f_t and o_t) and state (c_t and h_t) is computed using specific weights (*W* and *U*) and biases (*b*), and the nonlinear activation functions σ (sigmoid) and *tanh* (hyperbolic tangent).

Multilayer perceptron (MLP), also known as a multilayered perceptron artificial neural network, is a supervised machine learning algorithm that mimics the working principle of the human brain. The multilayer perceptron artificial neural network consists of three layers: the input layer, hidden layer, and output layer. The training dataset forms the input layer from source nodes, one or more hidden layers with computation nodes, and finally, the output layer of nodes. In practice, the signal from the input nodes propagates through the MLP neural network layer by layer, as illustrated in Figure 3.

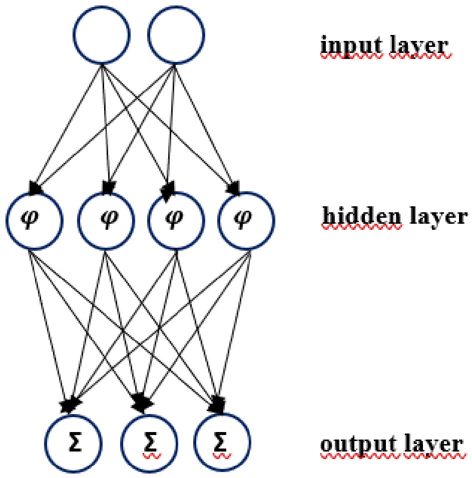

Figure 3. The Signal Flow of Typical MLP Neural Network
Source: Ting & Sim, 2017, p. 2.

MLP consists of simple neurons, called perceptron. As the weights in input nodes are calculated and the output is generated by applying a nonlinear activation function, a linear combination is formed by the perceptron through the computation of an output neuron from multiple real-valued inputs. This computation can be expressed as: (Ting & Sim, 2017)

$$y = \varphi(\sum_{i=1}^{n} w_i \ x_i + b) = \varphi(w^t \ x + b) \quad (7)$$

Where,

x : the vector of inputs

w : the vector of weights,

φ : the activation function

b : the bias

In this study, LSTM and MLP algorithms will be used for the next period price prediction of the RISE risk appetite index time series. The role of machine learning algorithms is the ability to predict the possible outcomes with higher accuracy and provide real-time predictions that allow for quick decision-making in dynamic environments. It means that enables immediate responses to changing situations. These features provide significant advantages for businesses and researchers in making strategic decisions.

Various metrics are used to compare the performance of the machine learning and statistical models. These metrics vary according to the machine learning algorithm selected, the nature of the problem, and the characteristics of the data set. These metrics evaluate the success of the model, and allow for comparison. One of these metrics is RMSE used in this study to determine the prediction performance of the models. RMSE is expressed as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2} \quad (8)$$

Here, n is the number of data points, y_i is the actual values and $\widehat{y_i}$ is the predicted values of the model. The smaller the RMSE value, the closer the model's prediction is to the actual values. When comparing LSTM and MLP models, the smaller the RMSE value indicates the better the prediction performance of the model.

In the literature, there are many activation functions that have been used in network design in neural network model. The model utilises the Rectified Linear Unit (ReLU) as the activation function, which has been chosen for its ability to introduce non-linearity while mitigating the vanishing gradient problem commonly encountered in deep networks. The network architecture includes 100 nodes per layer, with the intention of achieving a balance between complexity and computational efficiency. The Mean Squared Error (MSE) loss function is employed to quantify the difference between predicted and actual values, serving as a metric to guide the optimisation process. In order to optimise the weights of the network, we implemented the Adam optimiser, which is known for its adaptive learning rate and efficient handling of sparse gradients. The training was conducted over 50 epochs with a batch size of 150, allowing for effective learning through iterative updates and gradient adjustments. Besides, we introduced a set of hyperparameters, which we refer to as "bunker hyperparameters," with the aim of enhancing model stability and preventing overfitting. This novel approach to hyperparameter tuning provides a fortified training environment, ensuring the model's robustness in diverse scenarios.

The dataset for this study was obtained from the Central Securities Depository and Central Registry Agency (MKK). Since the data related to RISE risk appetite is published on a weekly basis, the analysis runs with weekly data. That brings the advantage of having a higher number of observations compared to monthly or yearly data. Therefore, the dataset covers weekly data from the years 2008 to 2023. The model is estimated via Python 3.

5. FINDINGS

The graph of the weekly series for the risk appetite index from 2008 to 2023 is depicted in Figure 3 below.

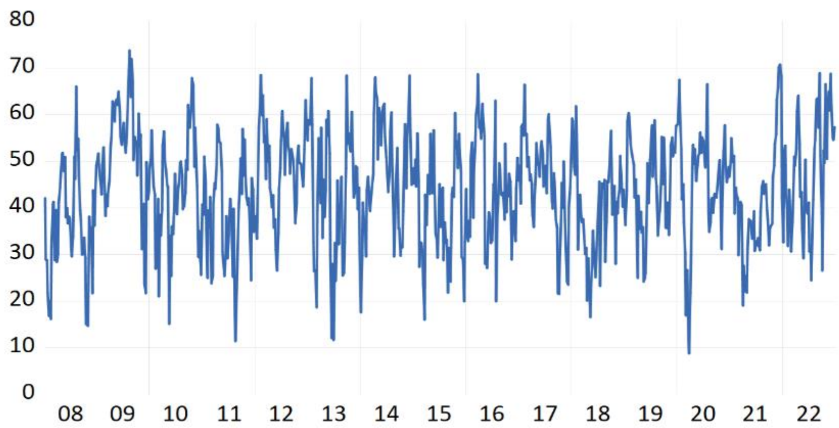

Figure 4. Weekly Chart of RISE Index (2008-2023 Period)

According to Gemici et al., (2023), there is a positive correlation between the risk appetite of investors in Turkey and portfolio flows towards Turkey, while there is a negative correlation between portfolio flows and the risk premium (CDS spreads). However, as of the 2020 pandemic period, the outlook has highly changed. The correlation between risk appetite and portfolio flows turns from positive to negative. Besides, the correlation between the risk appetite and the CDS spread is positive, and it is interpreted that the demand of investors, especially domestic investors, for Turkish stocks may have increased due to searching for a safe haven.

Before proceeding with the prediction of the RISE index, it was checked whether the series inherits unit roots. For this purpose, an ADF (Augmented Dickey-Fuller) unit root test was conducted. The results of the unit root test are presented in Table 1.

Table 1. ADF Unit Root Test and Correlogram Results

		RISE Index
ADF I (0)	**Constant**	-11.2130
	Prob.	0.0000
Test Critical Values	**1% Level**	-3.4384
	5% Level	-2.8650
	10% Level	-2.5686

Table 1 displays the results of the ADF unit root test. According to the result of the ADF unit root test, the RISE index series is found to be stationary at the 1% significance level. Table 2 shows the results of the correlogram.

Table 2. Correlogram Results

Panel B	AC	PAC	Q-Stat	Prob
1	0.7200	0.7200	407.8500	0.0000
2	0.5550	0.0750	650.1800	0.0000
3	0.3930	-0.0650	771.6400	0.0000
4	0.2740	-0.0180	830.7500	0.0000
5	0.1730	-0.0310	854.4900	0.0000
6	0.0900	-0.0390	860.8700	0.0000
7	0.0380	-0.0020	862.0000	0.0000
8	0.0000	-0.0110	862.0000	0.0000
9	-0.0350	-0.0320	862.9600	0.0000
10	-0.0590	-0.0200	865.7200	0.0000

Subsequently, the correlogram of the series was examined and Table 2 displays the correlogram for the series. When examining the correlogram, it can be observed that there is a correlation in the first differences from the partial autocorrelation function (PACF) value. In time series analysis, the PACF gives the partial correlation of a stationary time series with its own lagged values, regressed the values of the time series at all shorter lags. Values at this level cannot be used in statistical methods that involve squared errors. Therefore, it can be asserted that the ADF test might provide misleading results.

The values for the following week of the RISE index were predicted using LSTM and MLP algorithms. In order to determine the prediction success of machine learning algorithms, RMSE values were compared. RMSE is one of the standard ways to measure the error of a model in predicting quantitative data. The lower the RMSE value, the higher the measurement success of the model is considered. Figure 5 displays the error values for MLP and LSTM.

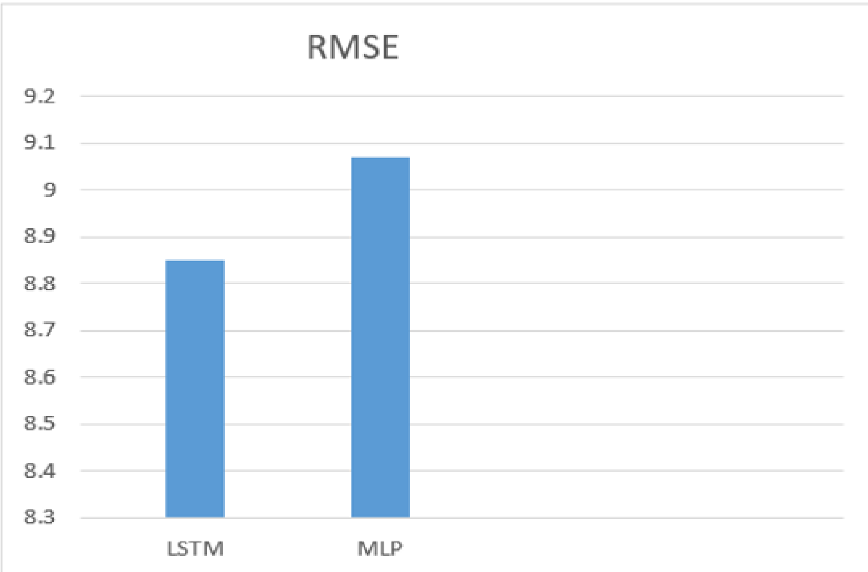

Figure 5. RMSE Values for LSTM and MLP Algorithms

In the prediction using LSTM, the mean squared error value was 8.85, whereas this value was obtained as 9.07 with the artificial neural network as seen as in Figure 5. Therefore, it can be concluded that the long short-term memory architecture provides more successful predictions in forecasting the RISE index.

In the study, there was also curiosity about the relationship between BIST 100 and RISE risk appetite index values. Köycü (2022) found a cointegration relationship between BIST 100 and the RISE index, and Özkan (2022) achieved cointegration between the two by using lagged values of RISE and BIST 100 with a one-period delay. Therefore, the relationships between BIST 100 and the RISE index were examined. Weekly RISE index data for the years 2008-2023 and BIST 100 closing data for the Fridays when the index is published were juxtaposed. By looking at the weekly changes in both data sets, labeling was done into three categories: "Increase," "Decrease," or "Stable," and movements in the same direction were analyzed.

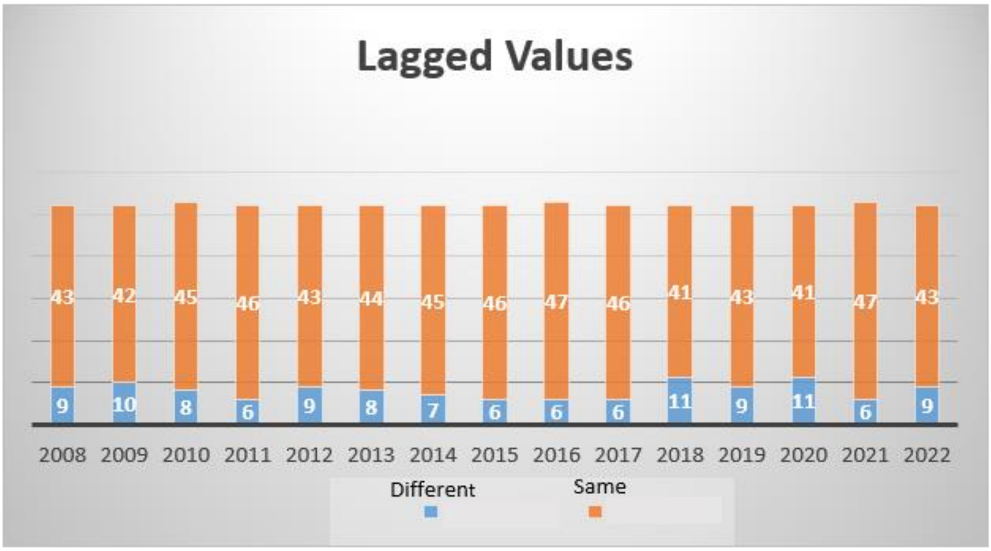

Figure 6. Compliance with the Values of Lagged BIST100 and RISE Index (2008-2023 Period)

Figure 6 shows the compliance with the values of lagged BIST100 index and RISE index. While the compliance of the same week was found to be 48.4%, it was detected at 84.5% when the one-week lagged data of BIST 100 was matched the RISE index. This value could counted as the twice times high. Accordingly, we can assert that lagged values of BIST 100 might better explain the variation on RISE. That provides valuable findings for future studies in forecasting.

5. CONCLUSION

Risk appetite is one of the leading indicators closely monitored by all market participants and institutions, to gain insights and opinions about the state of market. In this study, the predictability of the RISE risk appetite index was attempted using machine learning algorithms instead of econometric models. The weekly values of the RISE risk appetite index, available since 2008, were used until April 2023. The machine learning algorithms were implemented using Python 3 programs.

RISE risk appetite index's next-week value was predicted using two deep learning algorithms, LSTM (Long Short-Term Memory) and MLP (Multilayer Perceptron). To facilitate comparison, Root Mean Square Error (RMSE) was employed. The RMSE value for LSTM was 8.85, while for MLP, it was 9.07. The results indicated that the long short-term memory algorithm had a higher success rate in predicting the RISE risk appetite index's next-week value. In the context of the cointegration relationship between the RISE risk appetite index and BIST 100 index presented by Köycü (2022), and findings on cointegration between lagged values by Özkan (2022), the increase, decrease, and stability of both series were examined. The compliance between the values of the same week was 48.4% while it was obtained 84.5% when used the one-week lagged values of the BIST 100 index and the current value of the RISE index. This result was consistent with Özkan's (2022) finding of cointegration between the variables of two-period lagged values of RISE and one-period lagged values of BIST 100.

In this study, we enrich the existing literature by predicting the RISE risk appetite index employing the machine learning methods. The findings might help to the investors, businesses and researchers for quick investment decision-making in dynamic financial environment. For future studies, researchers are particularly advised to use lagged values related to the BIST 100 index, especially in predicting risk appetite through financial and economic variables. Additionally, it is recommended to reevaluate the predictability of the risk appetite index using different deep learning and machine learning architectures, allowing for the comparison of performance rates.

AUTHORS' DECLARATION:

This paper complies with Research and Publication Ethics, has no conflict of interest to declare, and has received no financial support.

AUTHORS' CONTRIBUTIONS:

Conceptualization, writing-original draft, editing and data collection – **NÖ**, methodology and formal analysis – **NÖY**, Final Approval and Accountability – **NÖ** and **NÖY**.

REFERENCES

Adrian, T., Etula, E., & Shin, H. S. (2010). *Risk appetite and exchange rates* (361). FRB of New York Staff Report.

Alpay, Ö. (2020). USD / TRY price prediction using LSTM architecture. *European Journal of Science and Technology*, Special Issue: 452-456.

Baek, I. M. (2006). Portfolio investment flows to Asia and Latin America: Pull, push or market sentiment?,*Journal of Asian Economics,* 17(2), 363-373.

Çelik S., Dönmez, E., & Burcu, A. (2017). The Determinants of risk appetite: Evidence from Turkey. *Usak University Journal of Social Sciences,* IASOS Special Issue, 153-162.

Central Securities Depository & Trade Repository of Türkiye (2021). *Storage Services*.

Doğan, F., & Türkoğlu, İ. (2019) Deep learning and application areas. *DUMF Engineering Journal,* 10(2), 409-445.

Financial Stability Review (2007). *ECB European Central Bank,* 167.

Gai, P., & Vause, N. (2006). Measuring investors' risk appetite. *International Journal of Central Banking*, 2(1), 167-188.

Gemici, E., Gök, R., & Bouri, E. (2023). Predictability of risk appetite in Turkey: Local versus global factors. *Emerging Markets Review,* 55, 101018.

Global Strategy Research, (2004) *Market focus,* Credit Suisse Research Institute.

Haugen, P. (2006). *Financial risk, risk appetite and the macroeconomic environment*. (Master Thesis of Science in Physics and Mathematics. Norwegian University)

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, 9(8), 1735-1780.

Illing, M., & Aaron, M. (2005). *A brief survey of risk-appetite indexes*. Financial System Review. Bank of Canada.

İskenderoğlu, Ö., & Akdağ, S. (2019). Causality analysis between risk appetite with oil prices, currency rates, gold prices, and interest rates: The case of Turkey. *Dogus University Journal*, 20(1), 1-14.

Köycü, E. (2022). The relationship between risk appetite index and BIST100 index: A study of the pre and post Covid-19 period, *Research of Financial Economic and Social Studies,* 7(1), 1-11.

Kumar, M. S., & Persaud, A. (2002). Pure contagion and investors' shifting risk appetite: Analytical issues and empirical evidence. *International Finance,* 5(3), 401-436.

Misina, M. (2005). *Benchmark index of risk appetite,* Monetary and Financial Analysis (Vol 15). Bank of Canada.

Özkan, N. (2022). Analysis of the relationship between investors' risk appetite, BIST 100, dollar exchange rate and gold prices: An investigation on Covid-19 pandemic period. *In Handbook of İşletme ve İktisadi Bilimler Metodoloji, Araştırma ve Uygulama,* (pp. 353-368). Livre de Lyon.

Pericoli, M., & Sbracia, M. (2009). Capital asset pricing model and the risk appetite index: Theoretical differences, empirical similarities and implementation problems. *International Finance*, 12(2), 123-150.

Saraç, T. B., İskenderoğlu, Ö., & Akdağ, S. (2016). Investigation of domestic and foreign investors' risk appetite: The case of Turkey. *Sosyoekonomi*, 24(30), 29-44.

Sarı, S., & Başakın, E. (2021). Analysis of BIST Bank index with data-based models. *Journal of Productivity*, (3), 147-163.

Sarwar, G. (2012). Is VIX an investor fear gauge in BRIC equity markets?, *Journal of Multinational Financial Management*, 22(3), 55-65.

Shen, D.B., & Hu, K.H. (2007). Bank risk appetite measurement and the relationship with macroeconomic factors: Case of Taiwan's banks. *International Journal of Information Systems for Logistics and Management*, 3(1), 25-39.

Ting, F.F., & Sim, K.S. (2017). Self-regulated multilayer perceptron neural network for breast cancer classification. *In 2017 International Conference on Robotics, Automation and Sciences (ICORAS)* (pp. 1-5). IEEE.

Yılmaz, T., & Yıldız, B. (2022). The relationship between investors' risk appetite index and fear indices: An empirical application with ARDL in Turkey. *Journal of Research in Economics, Politics & Finance*, 7(3), 646-676.