



## Presenting the early warning model of financial systemic risk in Iran's financial market using the LSTM model

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### ABSTRACT

The purpose of this paper was to provide an early warning model of financial systemic risk in the financial market of Iran using the LSTM model. In this study, a long short-term memory (LSTM) approach was used to predict financial risk and yield changes in the country's capital market in the period of 2011-2023. In order to model the financial risk, the profitability of the banking, insurance and leasing industry and the total capital market index along with the exchange rate, interest rate, inflation rate and production variables were used. The designed model showed that it had a high power in predicting the fluctuations and occurrence of risk in the country's financial markets. In addition, the results obtained from the evaluation of the model on the test data were used to measure the performance of the system in generalizing the network training to the test stage and the ability of the model in predicting the efficiency of the financial industry and also as a warning system.

**Keywords:** Warning model, Systemic risk, Financial markets, Long short-term memory (LSTM).

## 1. Introduction

Systemic risk is said to be the possibility of the financial system falling in crisis conditions, which is caused by the relationship between financial institutions, which is transferred between financial sectors like a domino. In most cases, investors are worried about the decrease in the value of a stock or commodity; while systemic risk has been focused on the entire market. This collapse often happens when an important company in the whole system starts to go bankrupt, the fear created ripples on other companies and they fall. These chain reactions lead to the market becoming stressed and exposed to crisis (Adrian and Brunermeier, 2016).

In general, financial systemic risk measurement criteria can be divided into two types; the first type is the criteria that measure the risk of the entire financial system when a key financial institution is at risk, and the second type includes the criteria that measure the risk of a financial institution when the entire financial system is in crisis. They calculate. Financial systemic risk is not only caused by size and mutual relationships, but may be caused by insufficient risk management, misleading accounting activities and high rewards for managers to encourage them to increase growth and productivity (Abrishmi et al., 2018).

The early warning system can be a chain of information communication systems and include sensors, event detection and decision subsystems. They work together to provide predictions and indications of disturbances that negatively affect the stability of the physical world and inform the response time of the system to prepare for the adverse event and its impact on. At least Early warning system refers to technological systems, policies and procedures that are used with the main purpose of predicting negative crisis in different environments (Gholizadeh et al., 2019). The early warning model of financial systemic risk is designed in order to notify the warning before the danger occurs and can be optimized in order to improve the level of accuracy of the early warning. Such a system is able to assess financial systemic risk due to its integrated capabilities and improves the level of development of the financial industry by providing the possibility of identifying, warning and taking timely action in the field of potential risks.

In this regard, the importance of a quick financial risk warning system can reduce the consequences of financial crises. The early warning system can be a chain of information communication systems and include sensors, event detection and decision subsystems. They work together to provide forecasts and indications of disturbances that negatively affect market stability and to announce the response time of the system to prepare for the adverse event and

minimize its impact (Akbar Mousavi et al., 2022). Early warning system refers to technological systems, policies and procedures that are used with the main purpose of predicting financial risk in different environments (Kloputan et al., 2018). There are various studies and models in the field of early warning system design. Among the methods, we can mention the Probit and Logit method, which has been discussed in the studies of Hanuk (1977), Martin (1977), and Thomson (1991) (Ahmadian, 2014). The financial risk early warning system has two more useful methods. These methods include logit, probit and signal method. Logit and probit methods are usually multiple, they are more used. The next step in the structure of the financial risk warning system model is the selection of leading indicators by referring to the colorful signs of financial risk. In addition, due to the existence of currency and financial crises in the country, the existence of an early warning system of financial risk and systemic risk has led to warning signs for policymakers and financial market activists to provide the desired guidance to prevent losses.

In the current study, in order to design a early warning system of systemic risk in Tehran, the LSTM neural network method or long short-term memory, which is a special type of recurrent neural network, is used. LSTM network has internal mechanisms called gates. These gates control the flow of information; they also specify which data in the sequence are important and should be kept and which data should be deleted; in this way, the network passes the important information along the sequence chain to have the desired output (Oyang et al., 2021).

The current paper is innovative in that it uses statistical models (dynamic conditional correlation model which is one of the methods based on multivariate GARCH and also models based on long-short-term memory) and available data. It seeks to rank the financial markets.

## 2. Literature Review

Systemic risk is the possibility of the collapse of the financial system or the failure of the entire market. This risk can originate from instability or crisis in the financial sector of the economy and spread to the entire financial system. In other words, systemic risk is caused by structural and financial connections between institutions active in financial markets such as banks, insurance, leasing, and the stock market (Huang et al., 2019).

Several definitions of systemic risk have been proposed in the financial literature. The most important feature considered in these definitions is that the financial institution should be considered as a system. Because if the institution becomes insolvent

and fails against the created credits, or if the financial institution is unable to pay its obligations, this issue has an important effect on the financial system and leads to a worsening of the situation (Gang Jin et al, 2022).

In a financial institution, if the value of the equity is less than the value of the debts created by that institution, in this situation, if the economy is in a stable and suitable state, the financial institution should primarily increase the value of the equity by increasing the capital. Shares or declare bankruptcy. In a situation where this lack of capital occurs at a time of economic crisis, the important point is whether the government will have the ability and power to solve this problem and finance the company in order to increase capital or not. In crisis situations, companies and institutions that have a higher systemic risk lead to a severe and greater contagion of the crisis to the entire financial markets. The sum of the systemic risk of all institutions represents the total potential of lack of capital in the economy. Therefore, in this situation, the government may provide it to reduce the pressure of the systemic crisis (Rahimi Baghi et al., 2018).

Systemic risk is usually considered as a risk that may affect the financial system as a comprehensive and complete system (De Bennet and Hartmann, 2002).

The origin of systemic risk in the economy may be from the banking industry or other financial markets. Therefore, crisis or systemic risk may have occurred based on economic shocks or systemic dependence between financial markets and have been transferred to the entire system. Risk contagion between financial markets may take place through different channels (Berati et al., 1402).

Change in investors' expectations

- 1) Payment systems for payments with large figures
- 2) Off-exchange operations (mainly related to derivatives)
- 3) Interbank markets.

The risk warning system is considered as an experimental tool for macroeconomic fault finding, which aims to develop a warning system before the occurrence of macroeconomic damages. That is, an effective early warning system makes preventive policy action possible and the need for actual monitoring can be reduced. The main logic of the idea of early warnings is that some economic indicators show a behavior that is different from their trend in financial stability before the occurrence of a financial crisis. Therefore, studying the trends of these variables can indicate the occurrence of a crisis or the continuation of the stability process. The warning system in the world was first raised after the currency crises of European countries in 1992-1993, the crisis

of Latin American countries in 1994-1995, and more seriously after the crisis of East Asian countries in 1997-1998. In this field, in addition to the International Monetary Fund, which is the leader of this method, some universities and central banks have also conducted research. Therefore, some recent works in the related literature have predicted financial crises. In this context, a wide range of indicators have been identified and tested as leading indicators. The economic crisis of 2008-2009 drew attention to the early warning literature again (Kalami et al., 2018).

The rapid warning system can be a chain of information communication systems and include sensors, event detection and decision subsystems. They work together to provide predictions and indications of disturbances that negatively affect the stability of the physical world and inform the response time of the system to prepare for the adverse event and its impact on minimize (Gholizadeh et al., 2021).

Early warning systems refer to technological systems, policies and procedures that are used with the main purpose of predicting negative crisis in different environments. There are various studies and models in the field of early warning system design. Probit and logit methods can be mentioned among the methods. The early warning system has two methods that have more applications. These methods include logit-probit and signal method. The logit-probit method is usually multiple, they are more used. The next step in the structure of the warning system model is the selection of leading indicators by referring to the colorful signs of the crisis in the first step (Zhang and Wei, 2023).

Sayadanya Tayibi et al. (2009) explained a warning system to identify financial crises in Iran. In this research, a warning system was explained to identify financial (banking and money) crises, so that this warning system should send a signal now that a crisis is likely to occur in the future. First, warning indicators include GDP growth, inflation, real interest rate, stock market index, effective exchange rate and official and unofficial exchange rate deviation, ratio of foreign debt to foreign assets, ratio of current accounts to GDP through the method A signal is selected and then these variables are measured through logit model and neural network.

Yu et al. (2010) proposed a multi-scale neural network model and showed that compared to traditional neural networks, network models have higher forecasting accuracy for systemic risk in financial markets.

Iturriaga and Sanz (2015) combined a multilayer perceptron and self-organizing mapping to build a neural network model to study the bankruptcy problem in the United States. This model can predict the probability of bank failure three years in advance and has a higher prediction accuracy. However, financial

forecasting based on artificial neural networks (ANN) has the following problems. First, possible overfitting of an ANN degrades the predictive ability of the model outside of the training set. Second, the gradients may disappear or explode in the optimization process, which makes the ANN unable to learn effectively. In recent years, deep learning has continued to develop, and some deep learning methods, such as LSTM neural network, have been gradually applied in financial forecasting.

Di Persio and Honchar (2016) used LSTM neural network to predict Google stock price trends and the results showed that LSTM neural network has advantages in predicting financial time series.

Yang and Wang (2019) used the LSTM neural network to research the forecasting of three different maturities of 30 global stock indices and found that the forecasting accuracy was significantly improved compared to BP and SVR. The advantage of deep learning methods over traditional machine learning is that they can adapt better to complex nonlinear and high-dimensional data.

Ouyang et al. (2021) designed a financial systemic risk warning model in China. In this study, an LSTM neural network model was proposed to study China's systemic risk early warning. Based on the data mining of public opinion index, the desired network was built and used as a training set to be included in the early warning model to test the effect of early warning. The results show that: (1) network public opinion is the non-linear Granger causality of systemic risk. (ii) LSTM neural network has strong generalization capability. The early warning effects have been significantly improved. (iii) Compared with the BP neural network model, SVR model and ARIMA model, the LSTM neural network early warning model has a higher accuracy rate, and its average prediction accuracy for systemic risk indicators is improved in the short, medium and long term.

Qolizadeh et al. (2021) designed a quick warning system for the financial crisis in Tehran Stock Exchange with a decision tree approach. According to the results obtained from various data, it was determined that the most important variable for predicting the crisis in the Tehran Stock Exchange in the weekly data was the occurrence of the financial crisis in the past period. Therefore, it can be claimed that the fall of the stock index is more affected by the value of the index in the previous period than by external shocks such as exchange rate, gold and oil shocks. It was also found that the accuracy of crisis detection for all trees is the same and equal to 81.82%. That is, out of 44 crises that occurred during the mentioned period (includes 1121 weeks), 36 crises could be identified and predicted by the mentioned methods.

Saeedi Aghdam et al. (2022) presented a stock price forecasting model using deep learning algorithms and its application in stock pricing of Islamic banks. In this research, an attempt has been made to present a model based on which the movement of the target stock price can be predicted with high accuracy. Based on this, a hybrid model for predicting stock price movements using artificial neural network is presented. For the statistical sample, the top companies of the stock exchange have been selected in the second quarter of 2019. Then, for this purpose, 32 variables were calculated. These variables are input to the model and have been optimized with the help of artificial neural network algorithm. The results show that the model has performed much better in predicting the movement trend of stock prices and is more accurate compared to traditional methods.

Namaki et al. (2022) analyzed the level of systemic risk of Tehran Stock Exchange companies using the complex systems approach. This research analyzed the structure of the local topology of financial institutions in the financial network on the level of systemic risk of the twenty most active companies of the Tehran Stock Exchange from the beginning of 2013 to the end of 2017, using the measure of conditional differential value at risk (CoVaR $\Delta$ ). First, to calculate the conditional correlation matrix, the dynamic conditional correlation multivariate GARCH model (DCC-MVGARCH) was used and the minimum spanning tree (MST) was created. Then, the topological characteristics of the financial institutions network in the financial network were calculated and the relationships between the characteristics and systemic risk were investigated. By quantifying the relationship between the local topology structure and the level of systemic risk with panel data regression analysis, it can be found that there is a significant relationship between the closeness centrality of the node, the strength of the node and the degree of the node with differential conditional risk value and therefore the level of systemic risk. Studies show that financial institutions with greater centrality have a higher level of systemic risk, and also financial institutions with less node power and smaller node degree have a higher level of systemic risk. However, with the data examined in this research, no significant relationship was found between the betweenness centrality of the node and the level of systemic risk of the institutions.

Khoonsarian et al. (2023) predicted the price with LSTM artificial neural network and portfolio selection model of financial assets and digital currencies. Finding solutions for price prediction, forming an optimal stock portfolio and achieving more profit are the basic goals of financial market participants. The purpose of this research is to predict the price of

financial assets such as several stocks, gold, coins and a number of digital currencies using the LSTM neural network model and then form the optimal stock portfolio by calculating the rate of return, risk and the Sharpe criterion. The data used is from the archives of the Tehran Stock Exchange website, the website of the gold, coin and currency information network, as well as the website of buying and selling digital currencies. The time series of the prices of the investigated assets is between 2017 and 2020. Also, Python programming language and Geffy software were used to build the model and analyze the data. In the end, it was found that the LSTM neural network model is capable of predicting the price of financial assets with a very low error rate in each asset, and according to the Sharpe criterion obtained for each financial asset and the correlation matrix, stocks, banks, stocks, and digital currencies. Tron, Tether and Bitcoin will allocate more shares in the proposed portfolio.

### 3. Research methodology

Long-short-term memory networks are a special type of recurrent neural networks that have the ability to learn long-term dependencies. These networks were first introduced by Hachreiter and Schmidhuber in 1997. In fact, the purpose of designing Long-short-term memory networks were to solve the problem of long-term dependence, memorizing information for long-term periods, the default and normal behavior of recurrent neural network with long short-term memory and their structure is such that the information They learn very well that this feature lies in their structure. All recurrent neural networks are in the form of a repeating sequence (chain) of modules (units) of neural networks in the network. Standard recurrent neural networks, these recurrent modules have a simple structure, and contain only one hyperbolic tangent layer. The recurrent neural network with long-short-term memory also has such a sequence or chain-like structure, but the recurrent module has a different structure to Instead of having only one neural network layer, they have 4 layers that interact and communicate with each other according to a special structure (Shi et al., 2015).

The major change of LSTM compared to previous models is in the activation calculation method. Activation in stage t is calculated based on four types of gates, which include information gates, forgetting gates, exit gates and known cell gates. The input of the information gate is in the form of equation (1) (Saeidi Aghdam et al., 2022):

$$i_t = \sigma(W_{ia} \cdot h_{t-1} + W_{ix} \cdot x_t) \tag{1}$$

Where  $\sigma$  is a non-linear function like sigmoid function.  $W_{ia}$  and  $W_{ix}$  are respectively the matrices that connect

$h_{t-1}$  with  $h_t$  and  $x_t$  with  $h_t$ . Also, the input of the forget gate and the input of the output gate will be in the form of equations (2) and (3):

$$f_t = \sigma(W_{fa} \cdot h_{t-1} + W_{fx} \cdot x_t) \tag{2}$$

$$o_t = \sigma(W_{oa} \cdot h_{t-1} + W_{ox} \cdot x_t) \tag{3}$$

The input of the cell gate is also calculated as equation (4):

$$C_t = (f_t \cdot C_{t-1} + i_t \cdot k_t) \tag{4}$$

Where  $C_{t-1}$  is the cell status information from the previous step and  $k_t$  is considered as equation (5):

$$k_t = \tanh(W_{ca} \cdot h_{t-1} + W_{cx} \cdot x_t) \tag{5}$$

So that the hyperbolic tangent function was a tangent function. At the end, the activation in stage t is presented in the form of equation (6):

$$h_t = o_t \cdot \tanh(C_t) \tag{6}$$

In order to calculate the systemic risk index of the financial market, statistical data such as expected yield and final deficit for each financial market is needed. As mentioned, in order to estimate the marginal expected shortfall, the dynamic conditional correlation approach has been used. In order to estimate this index, the yield information has been used, that rit and rmt respectively represent the logarithmic yield of each financial industry and the total index on day t. The relationship between these components is as follows (Barati et al., 2023).

$$R_{mt} = \mu_{mt} + \sigma_{mt} \varepsilon_{mt} \tag{7}$$

$$R_{it} = \mu_{it} + \sigma_{it} \rho_{it} \varepsilon_{mt} + \sigma_{it} \sqrt{1 - \rho_{it}^2} v_{it} \tag{8}$$

Where  $\varepsilon_{mt}$  and  $v_{it}$  respectively represent the yield disturbance statements resulting from the estimation of univariate GARCH models for the total index and yield of each financial industry. The terms  $\mu_{mt}$  and  $\mu_{it}$  represent the conditional mean,  $\sigma_{mt}$  and  $\sigma_{it}$  represent the conditional standard deviation, and finally  $\rho_{it}$  is the dynamic conditional correlation of each financial industry with the total index resulting from the use of dynamic conditional volatility models.

### 4. Estimation of the model

In the first part, the estimation of the systemic risk index of the financial markets has been discussed. The statistical population of the current study included the banking, insurance, leasing and capital market industries in the period of 2011-2023. The variables

used included daily stock returns and items in balance sheets and financial statements. The statistical information related to the research sample has been extracted from Rahavard Navin software and the website of Tehran and Kodal Stock Exchange Organization.

#### 4-1 Descriptive statistics

One of the important issues regarding the variables used in the calculation of systemic risk has been the investigation of their statistical characteristics such as the average, standard deviation and their correlation with the return of the index of the entire financial markets. Table (1) shows the descriptive statistics of the variables during the period of 2011 to 2023. Based on the obtained results, it was observed that the highest average return is related to the banking industry and the lowest is related to the insurance industry. Comparing the average efficiency of the statistical population with the index, it was observed that the efficiency of the studied statistical population was lower than the overall market index, but the amount of fluctuations and dispersion in them was more than the standard deviation index in the overall index.

In order to estimate the systemic risk using the final expected deficit index, the conditional dynamic

correlation approach is used. For this purpose, the moving average autocorrelation model with 2 and 2 intervals was used to estimate the average yield equation, and the conditional variance threshold model with 1 and 1 intervals was used for the variance equation. The optimal number of breaks was selected based on Schwartz's information statistic. The results of the estimation are reported in table (2).

In order to calculate and represent the marginal expected shortfall, the values of conditional mean, conditional variance and also the estimated correlation coefficient have been used. Table (2) shows the estimated parameters for the mentioned values. It should be noted that the significance of the used series was assessed and checked using the Dickey-Fuller test and the variables used are at the significance level. In table (3), based on the values calculated for systemic risk using the expected final deficit method, as well as the conditional value at risk, financial markets are ranked.

According to the obtained results, it was observed that the estimated systemic risk criterion for financial markets was such that the statistical value of risk was the highest in the insurance industry and the lowest in the leasing industry.

**Table 1. Descriptive statistics of variables**

Variable	Average daily return	standard deviation	correlation
Market Index	0.015	0.009	
Banking Index	0.008	0.012	0.411
Insurance index	0.0004	0.019	0.369
Leasing index	0.007	0.024	0.523

**Table 2. Estimation results of conditional dynamic correlation model**

	ARIMA				Volatility		
	AR(1)	AR(2)	MA(1)	MA(2)	ARCH(1)	GARCH(1)	GJR(1)
Banking Index	0.24	0.15	-0.28	0.17	-0.15	0.47	-0.09
Insurance index	0.79	-0.25	-0.32	0.29	-0.08	0.52	-0.17
Leasing index	0.64	-0.19	-0.41	0.33	-0.15	0.34	-0.12

**Table 3. Comparison of financial markets ranking based on systemic risk based on marginal expected shortfall**

Financial Markets	marginal expected shortfall average
Market Index	0.028
Banking Index	0.027
Insurance index	0.035
Leasing index	0.021

In the following, data pre-processing is discussed, in which data is prepared for deep learning operations and includes the steps of data cleaning, data unification, data transformation, and data purification. In the continuation of this step, only the features that

are considered for the purpose of neural network learning, in this research, the efficiency feature of the financial industry has been selected. According to different methods, there are different models, and in this research, the model of long-short-term memory

networks has been used. To train the model, first the data was divided into two parts, the training data is 80% of the data and the test data is 20% of the data. In fact, the training data is the data set. Which is needed to learn the model. The number of input and output nodes in the neural network can be determined by the mapping presented to the network in this research due to the presence of 5 independent variables (inflation rate, exchange rate, interest rate, production and efficiency gap) and a dependent variable. (systemic risk) the number of nodes in the input layer is 5 and the number of nodes in the output layer is one; But the only way to determine the number of hidden layers and the number of nodes in each layer as well as the type of transformation function is trial and error; In such a way that if the number of hidden layers and the number of neurons in each layer are not enough, the network cannot properly converge to an optimal solution, and if their number is more than necessary, the network will suffer instability. The steps of the research are presented as follows:

**Primary data:** In this research, the real data collection of the efficiency of each financial industry from the statistical sources of Tehran Stock Exchange in the period of 2011 to 2023 was used.

**Data normalization:** Data normalization is a process to standardize them, and by normalizing the data, they are coordinated. In fact, it is one of the most important parts of model implementation, especially when using data. To train them, the input data is normalized.

**Adding time steps to the data:** In this step, the input data should be converted into a 3D array into a recurrent neural network model with long-short-term memory. First, the data is created in a time interval of 50 samples, and finally, the data is converted into a three-dimensional presentation with 50 samples.

**Creating a recurrent neural network:** Creating a recurrent neural network model with long-short-term memory is widely used for sequence prediction and it has been proven to be very effective. The reason for the proper performance of this model is that the recurrent neural network with long short-term memory, it is able to store past information and does not forget information. The recurrent neural network with long short-term memory has three gates, which are:

**Input gate:** Input gate adds information to the state of the cell.

**Oblivion gate:** removes information that is no longer needed by the model.

**Output gate:** The output gate in a recurrent neural network with long-short-term memory selects the information to be shown as output.

Cross library is used to implement the mentioned artificial neural network models. An important feature

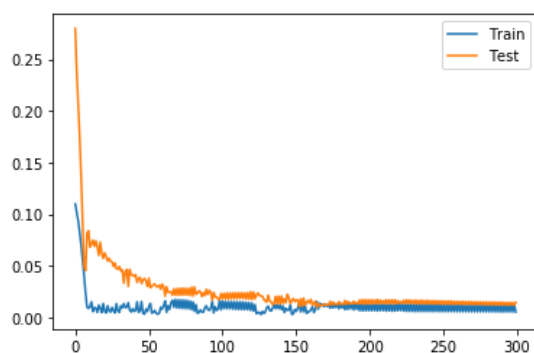
in the Cross library is adding layers step by step, instead of defining the model at once. In this way, the number of layers and their type can be easily changed; A characteristic feature that will be very useful during neural network optimization. A multi-layered perceptron neural network consisting of two hidden layers is created, 100 nodes (or neurons) are used in each of the hidden layers, and the continuation optimizer is used to update the weights. This algorithm will replace the standard gradient descent algorithm due to the better performance of the continuation optimizer compared to the gradient descent algorithm, this method has gained double popularity among machine learning activists. After fitting the model on the training data, the test data is used to evaluate its performance. The results obtained from the evaluation of the model on the test data are used to measure the performance of the system in generalizing the network training to the test stage and the capability of the model. It was used in forecasting the systemic risk of the financial industry and also as a warning system.

In the following, the mean square error is used to analyze the efficiency of the system. The error or the difference between the target and the output value obtained by using the value of the mean square of the error is minimized. All Errors The use of mean squared error is very common and provides an excellent general error measure for numerical predictions. Compared to the equivalent absolute mean error, mean squared error tends to penalize large errors. As can be seen in table (4), the recurrent neural network model with long-short-term memory has reached the highest accuracy of the average squared error. After analyzing the model of long-short-term memory networks, it was predicted that the systemic risk will gradually increase every day.

**Table 4. Model evaluation results**

Model	MSE of Learning data	MSE of Testing data
LSTM	2.38%	2.86%
ANN	3.12%	3.94%
Logit	4.89%	5.14%

The obtained results indicate that the LSTM model has higher accuracy and power in estimation and forecasting than the neural network model and also the logit regression model and can be used as a quick warning system before the crisis and the spread of systemic risk between markets. Finance to be used. The results of comparing the predicted and observed flow data for the one-day prediction model are shown in graph (1).



**Graph 1. Comparison of one-day flow values of real and predicted values in the validation stage**

After the implemented neural network models have been evaluated on the training data, fit and on the test data, backtesting is used to evaluate the model. In fact, backtesting is a process that It is the algorithm implemented to predict the variables, on historical data and with the aim of measuring the accuracy of the model in predicting the real results, the backtest method presented in this method is a simple method. The results show that in some places the real value is close to the predicted value, and this is while the model has accurately predicted the general trend of variable fluctuations such as going up or down. The research findings indicate that the recurrent neural network model with long-short-term memory can be somewhat effective in predicting risk trends.

## 5. Conclusion

In this article, the early warning model of financial systemic risk in the financial market of Iran was presented using the LSTM model. Systemic risk has a new concept that is considered a contagious risk, that is, the collapse of one financial market will lead to the collapse of other financial markets. Due to the direct or indirect connection between various markets, systemic risk has risk contagion effect among financial markets; on the other hand, as risk continues to accumulate within the financial system, the intermediary efficiency and resource allocation efficiency of financial markets are gradually reduced, systemic risk will cause damage to the real economy huge destruction. In this study, a long short-term memory (LSTM) approach was used in the period of 2011-2023. In order to model the financial systemic risk, the profitability of the banking, insurance and leasing industry and the total capital market index were used along with the exchange rate, interest rate, inflation rate and production variables. Deep learning methods are rapidly evolving and new and innovative algorithms are being implemented in this field. On the other hand, the popularity of the financial market is

growing rapidly, which encourages researchers to use the method. Find new ways to predict using new techniques. New techniques help not only researchers but also investors and anyone who deals with this financial market to predict asset price changes. It is considered as a challenging activity in predicting financial time series. A correct prediction of the change in the price of a financial asset can bring a lot of profit to investors. Due to the complexity of the financial market data, it is very difficult to develop efficient models for prediction. According to the presented model in this research and comparison with the proposed methods together, it was concluded that the LSTM model's error criteria perform better than the neural networks and time series methods. Based on the obtained results, it is suggested that the use of new approaches in predicting and designing financial systemic risk in financial markets will be effective and will be able to provide warnings before the occurrence of financial crisis. Also, paying attention to the state of macroeconomic variables has had a great impact on the occurrence of financial crisis in the country's economy and financial markets.

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