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# An artificial neural network model for predicting the liquidity risk of Iranian private banks

Mahdi Khosroyani, Farzaneh Heydarpoor*, Ahmad Yaghoob-nezhad, Zahra Poorzamani

*Department of Accounting, Central Tehran Branch, Islamic Azad University, Tehran, Iran*

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**Abstract**

A highly significant financial risk is liquidity risk. Liquidity risk management is a substantial part of Basel Recommendation no. three; with regard to the importance of this risk, this recommendation directs banks to develop and implement appropriate information systems for measuring, predicting, and controlling liquidity risks. Based on its structure, size, and features, each bank manages liquidity risk using different tools and methods. This study investigated the effectiveness of artificial neural networks in predicting liquidity risk in private Iranian banks. Relying on past studies and employing accounting information, this research developed a specific structure and architecture for a multilayer perceptron neural network; then, it predicted the liquidity risk of Iranian private banks from 2009 to 2019 using neural networks plus Matlab software. The research results revealed that artificial neural networks can be used to predict liquidity risk in private Iranian banks.

Keywords: Modelling, Artificial neural networks, Liquidity risk, Accounting indicators, Private Iranian banks
2022 MSC: 68T07

## 1 Introduction

Banks function as the beating heart of the economy in the two large markets of capital and money; via providing facilities, they generate the flow of money and capital inside the society; Banks are exposed to a wide range of potential risks, ranging from those identified in the budgetary and technological structure to those related to brand reputation and those derived from the social and institutional environment [27], These risks are so diverse and occasionally grave; accordingly, the bank will be bankrupt if it does not control and manage them properly.

Liquidity management and surveillance of maturity mismatch of deposits and loans can be considered the main concerns of bank managers. Management's task becomes even more critical when the bank faces early withdrawals. The reason of this challenge is that short term deposits are the main funding resources for banks. In addition, loans are usually invested in weak liquidation assets. Too much liquidity causes an inefficient allocation of resources, while low liquidity can lead to a reduction in the deposits interest rate, a loss of market and credit, an increase of debt and, finally, to the bank's failure. In other words, insufficient liquidity can kill the bank suddenly, but too much liquidity will kill it slowly [20]. Thus, it is extremely important to handle liquidity risk prudently and evaluate it correctly by an efficient and systematic method [26].

*Corresponding author
*Email addresses:* mahdikhosro2000@gmail.com (Mahdi Khosroyani), Fheidarpoor@yahoo.com (Farzaneh Heydarpoor), yaghoobacc@gmail.com (Ahmad Yaghoob-nezhad), zahra.poorzamani@yahoo.com (Zahra Poorzamani)

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Following the financial crisis of 2007, the need to concern liquidity risk more seriously became apparent. Then, international regulatory bodies - such as the Institute of International Finance, Basel Committee on Banking Supervision [5], the Committee on European Banking Supervisors, and the Islamic Financial Services Board - developed and formulated guidelines and recommendations on the management of liquidity risk; new conditions required the Central Bank, as a regulatory and supervisory body, to draft domestic regulations to improve the structure of liquidity risk management in the banking network [15]. Therefore, with reference to clause two of article 14 of the monetary and banking law of the state, the Central Bank put the development of the minimum requirements for the management of liquidity risk of credit institutions on its agenda. In the development of the mentioned rule, the latest international regulations and standards acted as the basis, and the result was also localized with an eye to the conditions and requirements of our country. Therefore, the latest published documents around the management of liquidity risk published by the Basel Committee on Banking Supervision; particularly the document "International Framework for the Measurement, Standards, and Monitoring Liquidity Risks," together with the guideline on the management of liquidity risk published by the Islamic Financial Services Board was relied on as the basis. The directive "Minimum Requirements of Liquidity Risk Management for Credit Institutions" was finalized. This directive comprehensively elaborates on the principles of implementation, strategies, and organizational structure of liquidity risk management. And banks and financial and credit institutions were required to take the necessary actions to manage their liquidity risk [6], including creating an information system for managing liquidity risk and choosing proper methods for measuring and monitoring the level of liquidity and determining liquidity ratios and their limits [6].

## 2 Theoretical framework of the research

A private bank is owned and managed by non-governmental entities established under the law with the permission of the Central Bank; these banks are allowed to perform all authorized banking operations within the limits of the law. After the revolution in June 1979, with regard to the enactment of the Revolutionary Council, all the state's banks were declared national. The establishment of financial and credit institutions started in1997 and led to the foundation of private banks; finally, the central bank officially approved the establishment of private banks in March 1998. Table 1 presents the classification of the banks member to the state's banking network. Banks provide a type of unique service, i.e., public access to liquidity; moreover, they ought to prepare a payment mechanism in transactions to different members of society. However, different from investment experts who are analytically highly capable and able to evaluate the health and stability of financial firms and institutions like banks and other financial intermediaries, and ensure the security of the interests of investors, generally, ordinary members of the society lack this ability.

Besides, it is noteworthy that concerning the situation prevailing in the working environment of banks, a kind of public good, i.e., public access to a productive and stable system of payments, is offered and made available to everyone by a private firm, a commercial bank. Some crucial reasons traditionally made governmental bodies intervene in the activities of banks and cautionary supervision over their operations are the inability to analyze the status of banks, the failure to evaluate their health and stability, and the supply of a public good by a private firm. A method of monitoring is issuing the necessary laws and directives in order to ensure the proper functioning of banks and protect the interests of society [28].

### 2.1 Risk

Risk is often not a static element of an activity or a situation. The risk can be easily measured and decided upon if it is a static element in the said activity. However, in most issues we encounter in real life, the risk results from multiple technical, physical, behavioural, organizational, and social factors. The assortment of these factors makes risk appear as a complex challenge rather than something quickly pointed to with one movement. Therefore, conceptual tools and evaluation, decision-making, and control methods should be considered with appropriate methods for employing these devices and methods in multi-stage situations or conditions where different parties are involved [8].

In the Chinese language, risk has either of the following meaning; the first is danger, and the second is opportunity Figure 1. In other words, risk presents us with a mix of danger and opportunity. This definition may be considered relatively exhaustive. In both senses, the world of investment and nature threats and opportunities are linked, and creatures use this opportunity based on their level of consciousness and knowledge [24].

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The directive "Minimum Requirements of Liquidity Risk Management for Credit Institutions", containing 51 articles and eight notes, approved in the $1239^{th}$ session of the Money and Credit Council on 17/10/2016, became binding six months after its promulgation.

Table 1: Classification of state banking networks

| **Governmental specialized and developmental banks** | **Non-governmental commercial banks** | **Non-governmental interest-free banks** | **Non-governmental non-bank credit institutes** | **Governmental commercial banks** |
|---|---|---|---|---|
| Tose'e Taavon | Ayandeh | Resalat | Tose'e | Sepah |
| Tose'e Saderat | Eqtesad Novin | Mehr Iran | Kothar | Melli Iran |
| Sana'at va Ma'adan | Iran Zamin | | Melal | Post Bank |
| Maskan | Pasargad | | Noor | |
| Keshavarzi | Parsian | | | |
| | Tejarat | | | |
| | Khavarmianeh | | | |
| | Dey | | | |
| | Refah Kargaran | | | |
| | Sarmayeh | | | |
| | Saman | | | |
| | Sina Shahr | | | |
| | Saderat Iran | | | |
| | Gardeshgari | | | |
| | Mellat | | | |
| | Karafarin | | | |


Figure 1:

## 2.2 Banking risks

### 2.2.1 Financial risk

Financial risk arises from the employment of debts in the company [8]. Financial risk forks into two parts: The first part or specific risks, including the risk of liquidity, profitability, capital, credit, and balance sheet structure risks, if not handled well, will result in losses. The second part encompasses market risks and exchange rate fluctuations [18].

### 2.2.2 Operational risk

The risk of losses arises from errors, neglect of ethical principles, other conditions appertaining to banking operations, and lack of internal controls. When the lack of adequate controls threatens a bank's credit, operational risk arises. Some other operational risks are the risks of information and computer systems and software defects and mistakes [4].

### 2.2.3 Commercial risk

There is a connection between business risks and the bank's business environment, including macroeconomics, legal factors, and regulations of the structure of the financial sector of the payment system and systematic risk appertaining to operations. Business risk means the degree of uncertainty related to the return on an investment and the ability of the earned income to pay dividends to shareholders and pay the original and interest on the borrowed capital [4].

### 2.2.4 Events risk

Events risks encompass all external risks that can jeopardize the financial conditions of the capital adequacy and bank operations. Some of these risks are political events such as changes of governments, disruptions caused by the bankruptcy of a major bank, market crashes, banking crises, natural disasters, or civil wars. In most cases, risks of events are unexpected, so banks possibly can not anticipate them and cope with such events, except through precautionary reserves [18].

#### 2.2.5 Liquidity risk

Liquidity is generally defined as the ability of a financial firm to meet its debt obligations without incurring unacceptably large losses. An example is a firm preferring to repay its outstanding one-month commercial paper obligations by issuing new commercial paper instead of by selling assets. Thus, “funding liquidity risk” is the risk that a firm will not be able to meet its current and future cash flow and collateral needs, both expected and unexpected, without materially affecting its daily operations or overall financial condition. Financial firms are especially sensitive to funding liquidity risk [19].

The Council of European Development Bank (CEB) defines liquidity risk as follows: Liquidity risk is defined as the risk of incurring losses resulting from the inability to meet payment obligations in a timely manner when they become due or from being unable to do so at a sustainable cost.

The circular of the Minimum Liquidity Requirements of Credit Institutions issued by the Central Bank of Iran has defined liquidity risk as the credit institution’s probable inability to provide quality cash assets to pay back debts, fulfil obligations and increase assets [6].

### 2.3 Methods of measuring liquidity risk

#### 2.3.1 Analysis of financial ratios

Financial analysts employ financial ratios to delve into a company’s financial status. Financial ratios can reveal some important facts about the outcomes of operations and the financial status of a company; moreover, they provide information related to that company; therefore, specific ratios can be analyzed with regard to their purpose and applications [13].

#### 2.3.2 Analysis of time eras or gaps

A fairly well-known method of managing assets and liabilities is the analysis of time eras. This method is also applicable in the management of liquidity risk. The time era is defined in terms of net liquid assets (with high liquidity), i.e., the difference between net assets with high liquidity and highly volatile liabilities [23]. Analysis of the time era of liquidity is similar to the ladder of the maturity date of items considering the time in which the cash flow is expected to be generated (either in the form of incoming or outgoing cash flow) and items of the balance sheet are set on the steps of this ladder. In determining the total net values not getting mature simultaneously, the net values that do not match each other (do not get mature simultaneously) are determined. The bank can monitor the amount of cash available over time without getting lower-rate assets inevitably converted into cash.

#### 2.3.3 Analysis of duration gap

The duration model is another measure of interest rate risk and management of net interest income, which is obtained considering all necessary cash inflows and outflows. Duration is a weighted measure of the value and maturity time of all cash flows and the average time needed for the conversion of funds; it reveals the invested funds [4].

A positive duration gap shows that the duration of assets is more prolonged than liabilities. When the interest rate rises more, the market value of assets falls more than its value in liabilities obtained through a fall in the market value of shares and expected net interest income. Similarly, a reduction in interest rates lowers stocks’ market value with a positive duration gap. Banks can employ duration gap analysis to minimize portfolio interest rate risk by keeping the duration gap close to zero [18].

### 2.4 Introduction of the neural network model

Artificial neural networks are the ideas for information processing. It is inspired by the biological nervous system and processes information as the brain does and It is formed to act homogeneously to solve problems and learn using examples as humans do. Recent studies suggest that neural networks are a universal approximation for any nonlinear continuous function with arbitrary precision. The architecture of their brains is based on the human brain’s neural network, which consists of many linked components called neurons. The system performs nonlinear feature extraction on input data to locate an indirect relationship between input vectors and the system's target parameters. Also, weights connect different neurons in different networks, and network performance is highly dependent on weights [7].

MLP is a supervised learning algorithm that essentially consists of two main paths. The forth path, where the input vector is fed to the neural network and the output of the network is calculated. In this path, the network parameters remain constant [11]. The back path: after production of output in the previous phase, the difference between the desirable output (observed) and output calculated by the network is determined [12].

### 2.4.1 Analytical components of the neural network

The components of the artificial neural network are:

**A. Inputs and outputs:** Numbers and figures, forming one or more variables, are the inputs to the neural network. These inputs are converted into one or more output variables following the analysis and special processing. Inputs act as the independent variable, and outputs play the role of the dependent variable [17].

B. Neurons: Neurons form the main component of the artificial neural system. They are divided into three categories: input, output, and hidden neurons; they act as the input layer, output layer, and hidden or intermediary layers. Neurons or input units perform the reception of input data. Intermediary and output layers encompass information processing units. In these units, algebraic operations are conducted on the input information, and the result is sent as a new input to other units on the subsequent layers [17].

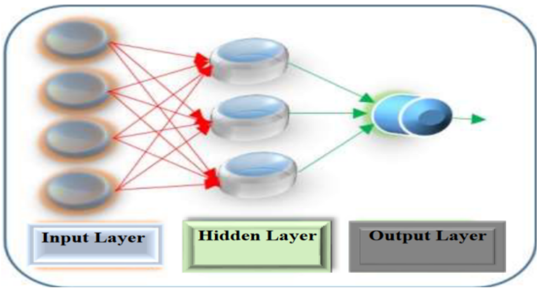



Figure 2: Layers of an artificial neural network

The number of units employed on the input and output layers depends on the explanatory and dependent variables of the model. There are no objective and precise criteria for determining the number of neurons on hidden layers [3].

### 2.4.2 Architectural styles of the neural network

The design of connections among neurons in a neural network is known as neural network architecture. Concerning architectural style, there are different types of neural networks, generally divided into static and dynamic models. In static models, the information processing path goes from data to data without any return in the units' communication system. In dynamic models, there are return paths from the data vector or vector of intermediary units to the data vector. These return paths can be compared to delay variables in the regression model; as in this situation, the outputs are subordinate both to the data and the outputs themselves.

Static networks are called "feedforward" networks, and dynamic ones are also named "feedback" or "recurrent." Therefore, the difference between feedback and feedforward networks is that in feedback networks, at least one recurrent signal goes from one neuron to the same neuron or neurons on the same or last layer.

"Perceptron nets" are a famous feedforward network, and "Hopfield nets" stand among the feedback networks. "Heming Emulative Nets" are feedforward in terms of input and output and feedforward concerning the intermediary layer [17].

## 3 Literature review

So far, no research has investigated the effectiveness of artificial neural networks in all private banks across Iran, and some few case studies have been conducted in a dozen private banks in this regard; for instance, Divandari et al. [9] is one of the first studies in Iran related to the topic of the present work; it is a case study carried out using the data of a bank, the researchers developed a suitable model for predicting and managing the liquidity of financial institutions within the interest-free banking system. In order to predict liquidity components, researchers applied neural networks with a three-layer perceptron structure. Their research revealed that the neural network is a proper tool for predicting liquidity requirements in the planned time eras. In another study by Valipour and Kargosha [29] the application of accounting ratios in predicting systematic risk was explored using an artificial neural network model across 109 companies from among the companies admitted to the Tehran Stock Exchange. The researchers finally concluded that the artificial neural network model has a more remarkable ability than the linear regression model in predicting the systematic risk of stocks using financial ratios. Faramarzi et al. [10] also investigated the possibility of modelling to predict the liquidity risk of Eqtesad Novin Bank using the accounting information of branches of this bank in Khorasan Razavi province with artificial neural network models and accounting indicators.

Among the foreign research carried out on this topic, the research of Yan and song [30] can be mentioned; this research employed an advanced neural network model and some liquidity risk indicators as input variables of the model. It attempted to identify factors affecting the liquidity risk for commercial banks; furthermore, it developed a successful model of early warning about liquidity risk. Their research time frame extended from 2000 to 2020, and a sample of Chinese commercial banks formed the geographical domain of their study. In a study carried out over five years from 2015 to 2019, Mishraz et al. [21] using accounting information from 75 Indian banks, compared the performance of artificial neural network models, logistic, and Linear Discriminant Analysis (LDA). Their research revealed that artificial neural network models are more accurate than linear discriminant analysis. Al-Duhaidahawi [2] applying the accounting information of 16 Iraqi banks collected from 2004 to 2018 plus artificial neural network models and ten accounting indices, managed to analyse financial risks (liquidity risk, credit risk, and capital risk).

## 4 Statement of the problem

In 2016, the Central Bank of the Islamic Republic of Iran composed a circular on the minimum requirements for the management of credit institutions' liquidity risk and communicated it to all banks and credit institutions. According to this circular, all credit institutions must manage their liquidity risk. Article ten of these requirements necessitates credit institutions to reduce the liquidity risk with appropriate methods of measuring and monitoring the liquidity level and via determining liquidity ratios and their limits in different scenarios based on the size, nature, and complexity of the credit institution's operations [6]. In line with the recent implementation of these requirements, the design of a suitable structure and appropriate methods for managing liquidity risk have been put on the agenda of the senior officials of the state banks. In addition, each bank uses specific methods to predict liquidity risk and needed cash independently and based on its structure and activity type [6]. As mentioned earlier, concerning the development of a model for predicting liquidity risk, the number of case studies carried out on some banks in the country is scant. The fact that a recent research priority of some banks has been the development of a model for predicting liquidity risk demonstrates this research gap; accordingly, banks support the studies carried out to meet this need to use the student research capacities across the state. Therefore, the need for conducting comprehensive studies to develop a comprehensive model for predicting liquidity risk was felt. This research investigates the effectiveness of artificial neural networks in predicting liquidity risk in all Iranian private banks.

## 5 Research methodology

This research falls in the category of experimental and applied studies as it develops the applications of accounting information using artificial intelligence around real-world issues. Private Iranian banks formed the spatial domain of the research. This research did no sampling, and all private banks in Iran were examined. Accounting information and artificial neural networks were used to model the liquidity risk; the input and output data of the model were collected using the banks' accounting data (belonging to the time era extending from 2009 to 2020). The research variables were calculated with Excel software, and the risk function was estimated using Matlab software and the neural network. Then, applying the standard criteria, the deviation of the model's results obtained from the actual information, the study examined the ability to predict liquidity risk by the neural network.

## 6 Research model

The model employed by this research is the one proposed by Asghari Oskooei [3] in the paper "The Application of Neural Networks in Predicting Time Series"; the model includes a multi-layered perceptron, together with a neuron designed as the output layer. Furthermore, Levenberg-Marquardt educational algorithm was used for training the model. The neural network system is shown as equation one and the output layer as equation two :

$$U_j = F_j(\sum U_{ij} X_i) \tag{1}$$

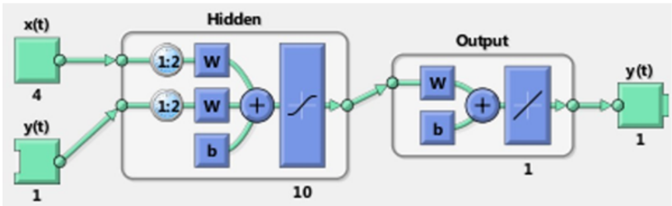
$$Z = F\left(\sum_{j=1}^{J} W_j^{(2)} F_j(\sum_{i=1}^{I} W_{ij}^{(1)} X_i)\right) \tag{2}$$

$Z$: Network output, $F$: The transfer function at the external node

$W_{ij}^{(1)}$: Weights connecting the input layer to the hidden one

$W_j^{(2)}$: Weights connecting the hidden layer to the output one (25)

The number of proper hidden layers in neural networks is experimentally determined; thus, the neural network developed for discovering the best result and the appropriate number of hidden layers was executed separately with 10, 20, 30, and 40 hidden layers and using Matlab software. The ratios approved by Thaghafi and Seif in the study titled "Identification and Measurement of Financial Ratios and Fundamental Economic Variables Affecting Banking Health and Stability in Iran" were employed by this work for determining the neurons of the neural network (accounting indices) [28]. According to Kafaei and Rahzani study , the ratio of cash assets, quick-trade securities, and short-term claims divided by short-term debts and deposits is considered the neural network's target or output neuron. Figure 1 shows the view of the developed artificial neural network [14].




Source: Research Findings

Figure 3: The model of the designed multilayer perceptron neural network

### 6.1 Variables of the model

#### 6.1.1 Input variables

$X_1$: The ratio of liquid assets divided by the total assets of the bank.

$X_2$: The ratio of term deposits divided by the total assets of the bank.

$X_3$: The ratio of term deposits affected by the interest rate divided by the total deposits of the bank.

$X_4$: The ratio of credits and granted facilities divided by the total deposits of the bank.

#### 6.1.2 Output variables

$Y_1$: The ratio of cash assets, fast-trade securities, and short-term claims divided by short-term debts and deposits [16].

### 6.2 Evaluation criteria of the model

The following two methods have been employed for the assessment of the network performance:

As announced by the website of Refah Karkaran (2019), Keshavarzi and Day banks (2022), etc.

### 6.2.1 Linear correlation coefficient

The square of the linear correlation coefficient determines the degree of correlation between two variables (calculated data and actual data); it is called the linear correlation coefficient. And it is calculated with equation three.

$$R^2 = \frac{\sum_1^n (calc - avg.obs)^2}{\sum_1^n (obs - avg.obs)^2} \tag{3}$$

avg.obs: Mean actual data, obs: actual data

n: The total number of pairs of actual data and the data calculated by the model

cals: The data calculated by the model corresponding to the actual data

The ideal value for the linear correlation coefficient is one.

### 6.2.2 Mean square error

The ideal value for MSE is zero, calculated by Equation four. A mean prediction error lower than one percent is considered good [3].

n: Number of data

$$MSE = \frac{\sum_1^n (obs - calc)^2}{N} \tag{4}$$

## 7 Research findings

Table 2 summarizes the results of the implementation of the model separately for each bank. The analysis of the model implementation results illustrated that the developed neural network had an acceptable performance in predicting liquidity risk in Iranian private banks. For instance, for Eqtesad Novin Bank, the best result is obtained when ten hidden layers are considered. The correlation coefficient in the testing stage of the model is 90%, and it shows a high correlation between the values predicted by the model and the actual ones. The amount of neural network error was measured by the criterion of mean square error; the meager value of this error (0.0041) demonstrated that the designed neural network predicted the liquidity risk in Eqtesad Novin Bank highly accurately. The results obtained for Ayandeh Bank, Iran Zameen, Parsian, Pasargad, Tejarat, Regah Kargaran, Saman, Sina, Saderat, Karafarin, Gardeshgari, and Mellat are further similar to those obtained for the Eqtesad Novin Bank. The correlation coefficient above 80% between the values predicted by the model and the real ones and the error values (mean square error) is regarded as good. Analysis of the results separately for each bank falls beyond the scope of this research; however, table 2 presents the details of these results. The remarkable ability of the artificial neural network to predict liquidity risk is evident, as it has obtained satisfactory results in all private banks, though with different intensities and weaknesses and low fluctuation. See table 2 for these results on the next page.

## 8 Discussion and conclusion

Cash is the central part of current assets in financial institutions, especially banks. The nature of financial intermediation causes banks [more than other economic units] to face financial risks, chiefly liquidity risk. Therefore, the bank should be able to access cash with decent prices quickly; the lack of liquidity will raise the liquidity risk and cause financial problems. Thereby, the managers of the credit institution attempt to apply appropriate liquidity management using various scientific methods and models of prediction. This research employed past studies' results; a group of studies dealt with suitable indicators for measuring liquidity risk in banks and credit institutions using the information of the accounting system; the other group investigated artificial neural networks or compared their efficiency with other methods for predicting liquidity risk. According to the results of the present study, artificial neural networks are a robust tool for analysing and approximating comprehensive risks. Ratios of liquidity risk measurement were selected in accordance with the results of Thaghafi and Saif [28], Kafaei and Rahzani [14], and Ansari et al. [1]; the perceptron neural network was developed according to the results of Asghari Oskooei's research [3] with four inputs and one output and Levenberg-Marquardt educational algorithm; as the number of optimal hidden layers in artificial neural networks is determined experimentally, in order to get the best results, the neural network with 10, 20, 30 and 40 hidden layers was designed separately and implemented using Matlab software. A recent need for private banks in

Table 2: Summary of research findings for private banks

| Summary of results and criteria for measuring the performance of the developed artificial neural network | | | | | | | |
|---|---|---|---|---|---|---|---|
| Bank Name | Number of hidden layers | Education | | Validation | | Test | |
| | | Mean square d error | Corre-lation coeffic-ient | Mean squared error | Corre-lation coeffic-ient | Mean squared error | Corre-lation coeffic-ient |
| Eqtesad Novin | 10 | 0.0028 | 0.89 | 0.0018 | 0.93 | 0.0041 | 0.90 |
| Iran Zamin | 10 | 0.0001 | 0.99 | 0.0001 | 0.91 | 0.0007 | 0.89 |
| Ayandeh | 10 | 0.00052 | 0.92 | 0.0012 | 0.98 | 0.0096 | 0.93 |
| Parsian | 20 | 0.0005 | 0.98 | 0.0019 | 0.95 | 0.0018 | 0.96 |
| Pasargad | 10 | 0.0009 | 0.91 | 0.0007 | 0.93 | 0.0018 | 0.89 |
| Tejarat | 20 | 0.0004 | 0.95 | 0.0006 | 0.95 | 0.0008 | 0.93 |
| Khavarmianeh | 10 | 0.1022 | 0.93 | 0.0295 | 0.88 | 0.0082 | 0.95 |
| Dey | 10 | 0.0780 | 0.93 | 0.1688 | 0.89 | 0.1041 | 0.97 |
| Refah Kargaran | 40 | 0.0001 | 0.96 | 0.0009 | 0.94 | 0.0008 | 0.86 |
| Saman | 40 | 0.0062 | 0.95 | 0.0041 | 0.89 | 0.0044 | 0.92 |
| Sarmayeh | 40 | 0.0062 | 0.97 | 0.0035 | 0.96 | 0.0322 | 0.92 |
| Sina | 20 | 0.0008 | 0.87 | 0.0004 | 0.91 | 0.0010 | 0.91 |
| Shahr | 30 | 0.0002 | 0.85 | 0.0007 | 0.65 | 0.0002 | 0.86 |
| Saderat Iran | 10 | 0.0006 | 0.89 | 0.0004 | 0.92 | 0.0004 | 0.93 |
| Karafarin | 20 | 0.0010 | 0.97 | 0.0011 | 0.94 | 0.0021 | 0.94 |
| Gardeshgari | 20 | 0.0006 | 0.82 | 0.0002 | 0.90 | 0.0003 | 0.94 |
| Mellat | 30 | 0.0004 | 0.91 | 0.0006 | 0.88 | 0.0008 | 0.90 |

Source: Researcher's findings

the area of research has been developing a model for predicting liquidity risk. The results of this study demonstrated that artificial neural networks can predict liquidity risk in private banks. Therefore, banks can employ artificial neural networks, other forecasting methods, and liquidity risk monitoring for this purpose. In addition, banks can predict liquidity risk by designing suitable software. Two folds have added to the importance of this item: The change in the Central bank's manner of treating banks' liquidity management and the Central Bank's efforts to internalize the management of liquidity inside banks. If all private banks apply this method, it will be possible to compare the status of banks with each other. Besides, the central bank of the Islamic Republic, as the institution supervising the banking network of the state, can use the results of this research to predict the monitored ratios of liquidity risk in private banks.

## References

[1] M. Ansar, Kh. Waleh Zaghard, M. Taqvi and Z. Amirhosseini, *Financial strength modeling based on risk and performance using bank accounting items*, J. Financ. Account. Audit Res. **13** (2022), no. 4, 185–209.

[2] H.M.K. AlDuhaidahawi, A. Jing, Z.S.M. Sebai and S. Abdullah Harjan, *An efficient model for financial risks assessment based on artificial neural networks*, J. Southwest Jiaotong Univer. **55** (2020), no. 33, 1–10.

[3] M.R. Asghari Oskoui, *The use of neural networks in forecasting time series*, Iran. Econ. Res. Quart. **12** (2008), 71–97.

[4] M. Barzandeh and R. Hosseini, *Income on risk management and concepts related to it*, Keshavarzi Bank Pub. **2** (2001), 125–139.

[5] Basel Committee on Banking Supervision,' Basel III: *A global regulatory framework for more resilient banks and banking systems'*, Basel, Switzerland, Bank for International Settlements, December (rev June 2011), 2011.

[6] *Communicating the minimum requirements for liquidity risk management of credit institutions*, Central Bank of I.R.I., Circular No. 96/251081 dated 09/08/2016.

[7] R. Che Mamat, A. Ramli, M.B.H. Che Omar, A.M. Samad and S.A. Solaiman, *Application of machine learning for predicting ground surface settlement beneath road embankments*, Int. J. Nonlinear Anal. Appl. **12** (2021), 1025–1034.

[8] M. Dasineh, *Effect of criteria based on accounting of profit characteristics on adverse profit risk*, Financ. Account. Audit Res. **41** (2018), 153–176.

[9] A. Diwandari, K. Louks and S.R. Mousavi, *Designing a forecasting model in the liquidity management of financial institutions in the framework of the usury-free banking system using artificial neural networks*, Manag. Perspect. Mag. **11** (2013), 23–58.

[10] F. Faramarzi, M. Lashkari and S. Bafande Imandoost, *Liquidity risk modeling using neural networks*, Int. Res. Conf. Manag. Econ. Account., 2016.

[11] S.M.R. Hashemi, H. hossanpour, E. kozegar and T. Tan, *Cystoscopy Image Classification Based on Combining MLP and GA*, Int. J. Nonlinear Anal. Appl. **11** (2020), no. 1, 93–105.

[12] S.M.R. Hashemi, H. Hossanpour, E. Kozegar and T. Tan, *Cystoscopy image classification using deep convolutional neural networks*, Int. J. Nonlinear Anal. Appl. **10** (2019), no. 1, 193–215.

[13] B. Joel, *Risk Management in Banking*, New York, John Wiley & Sons, 2002.

[14] S.M.A. Kafaei and M. Rahzani, *Investigating the impact of macroeconomic variables on liquidity risk*, J. Econ. Res. Polic. **81** (2016), 261–310.

[15] Z. Khoshnoud, T. Akbari Alashti and R. Khansari, *Designing a new guideline for liquidity risk management in the banking system of Iran*, Tehran, Research Institute of Money and Banking, 2013.

[16] M. Khosroyani and F. Heydarpoor, *Modeling to predict the liquidity risk of Iran's government banks using artificial neural networks and accounting Indicators*, Financ. Account. Audit. Res. **14** (2022), no. 55, 163–180.

[17] A. Komijani and J. Saadatfar, *Application of artificial neural network models in predicting economic bankruptcy of the registered corporations in stock market*, J. Iran. Econ. Ess. **3** (2006), no. 6, 11–44.

[18] M. Lili Dost, *Liquidity risk measurement and its relationship with profitability*, Master's thesis, Tehran, Iran's Higher Institute of Banking, 2016.

[19] J.A. Lopez, *What is liquidity Risk?*, FRBSF Economic Letter, issue oct24, Federal Reserve Bank of San Francisco, 2008.

[20] L. Matz, *Scenario analysis and stress testing*, L. Matz, P. Neu (Eds.), Liquidity Risk Measurement and Management, John Wiley & Sons Inc, New Jersey, 2007, pp. 37–64.

[21] N. Mishraz, S. Ashok and D. Tandon, *Predicting Financial Distress in the Indian Banking Sector: A Comparative Study between the Logistic Regression*, LDA and ANN Models, Global Business Review, New Delhi, 2021.

[22] B. Ostadi and P. Pezhedani Pajoh, *Presenting a model for measuring the relationship between financial risks and financial ratios*, Empir. Stud. Financ. Account. **16** (2019), no. 63, 109–127.

[23] A. Parsaian, A.R. Shirani and M. Ahmadi, *Modern Banking in Theory and Practice*, second edition, Sepah Bank, 2006.

[24] R. Raee and A. Saeedi, *Fundamentals of Financial Engineering and Risk Management*, Publications of Organization for the Study and Compilation of Humanities Books of Universities, 2015.

[25] M. Talebi and N. Shirzadi, *Credit Risk: Measurement and Management*, Tehran, Organization for Studying and Compiling Humanities Books of Universities, 2012.

[26] M. Tavana, A. R. Abtahi, Di Caprio and M. Poortarigh, *An artificial neural network and Bayesian network model for liquidity risk assessment in banking*, Neurocomputing **275** (2018), 2525–2554.

[27] G. Teles, J. J.P.C.Rodringues, R.A.L. Rabelo and S.A. Kozlov, *Artificial neural network and Bayesian network models for credit risk prediction*, J. Artif. Intel. Syst. **2** (2020), no. 1, 118–132.

[28] A. Thaghafi and V. Saif, *Identification and measurement of financial ratios and economic variables affecting the health and stability of the banking system in Iran*, Econ. Res. J. **5** (2014), no. 17, 65–111.

[29] M. Valipour, M. Kargosha, *Using accounting ratios in predicting systematic risk using artificial neural networks model*, Sec. Nat. Conf. Account. Manag. Econ., Iran, 2014.

[30] W. Yan and Y. Song, *Intelligent evaluation and early warning of liquidity risk of commercial banks based on RNN*, Comput. Intel. Neurosci. **2022** (2022), 1–12.