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Predicting the risk of failure of listed banks during the Covid-19 period, a case study of Iran and Iraq: using the approach of neural networks and machine learning

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Abstract

This research was conducted with the aim of predicting the risk of bankruptcy of banks listed on the Iranian and Iraqi stock exchanges during the Covid-19 era, using neural network and machine learning approaches. The study covers two time periods: the pre-Covid-19 era (2003-2019) and the post-Covid-19 financial crisis era (2023-2020). The main objective of the research is to specify a model to predict the bankruptcy of Iranian and Iraqi banks. Different machine learning models including decision tree, XGBoost and random forest were used. The results showed that the most important variables in predicting bank failure risk include LTICA, ILQ, LRG, CLRE, NIRBT, NIRAT, NPS, ELTL, GP, ETA, NIRA, POAI, IR, NLTA, OPR, ROA, GDP and CYCLE. Therefore, a comparison of the periods before and after the Covid-19 crisis using neural networks and support vector machines (SVMs) showed that the accuracy of the models increased during the crisis period. The predictive accuracy of the SVM model during the Covid-19 crisis reached 0.9321, which increased compared to the pre-crisis period (0.9125). There was also an improvement in the sensitivity and specificity indices for all three classes during the crisis period . This study shows the importance of using multiple approaches to predict bank failure risk. The combination of different machine learning models and neural networks allows a more accurate identification of the factors that influence the risk of failure. The important role of macroeconomic factors such as GDP and interest rates in predicting bank failure risk was also identified. The results of this research highlight the importance of government support measures during the crisis and show that banks' bankruptcy risk management performance has improved during the Covid-19 era. The study provides practical suggestions, including the development of an early warning system, improvement of risk management systems, and regular training programmes for bank employees and supervisors.

Keywords: Bankruptcy prediction, Covid-19, neural network, machine learning, Iran, Iraq

Introduction

Today, banks play an important role in the economy. They are known as the main financial resources in various economic sectors, including production, investment, etc. Their tasks include increasing the speed and security of financial exchanges and granting credit in line with investor financing and economic development (Júlio & Maria, 2024). In a rapidly globalizing world, banking is a system that is likely to create a global financial crisis. Bank failures can lead to an economic crisis, and for this reason, extensive efforts have been made to predict it since the 1960s is (Edvar Altman, 1968). Basically, the banking industry is considered one of the most important economic sectors of developed and developing countries, especially Iran and Iraq ،because without the bank providing capital as one of the main pillars of production, economic progress (economic growth and development) is far from reach (El Yamani, 2024). In a way that Patrick in 1966 explains that in the early periods of economic development, there is a causal relationship between economic progress and the prosperity of the banking sector. This theory has been called "demand tracking", which indicates that the lack of banking and financial institutions in countries with little development represents the lack of demand for financial services provided. But as the economy progresses, the causal relationship can be reversed, and this is where the "supply advance" begins to take shape. In this case, the increase in productivity caused by the process of financial intermediation by banks contributes to the continuation of economic growth in the next stages of the country's development(Khalil Mhadhbi et al, 2017). In general, increasing the efficiency of the banking sector optimizes the allocation of scarce resources in the country and helps to realize the full potential of economic growth. Thus, the more efficient the financial sector becomes, the more likely it is that a country's scarce resources will be directed to more efficient consumption. This allows economic growth to reach its full potential (Allen & Santomero, 1997). Finally, the vital role of banks and other financial institutions in the economic promotion of a country is undeniable. In fact, detailed economic studies show that with the increase in the efficiency of banks, ways are provided to make the best use of existing capacities؛ whether through the provision of various credit products or through risk management services, in such a way that the minimum and optimal use of resources is obtained (Lane et al, 1994). The broadest form of liquidity, which includes various financial elements, has been used as a sign of the depth and scope of the bank. Therefore, according to the surveys conducted in the past decades, it can be said that the improvement of banking services can be the driving engine of economic growth. This positive causality has also been seen using more advanced statistical analysis (Matei, 2020).

Banks and financial institutions are closely related to the macroeconomic structures of countries, and any instability or crisis in them can lead to extensive changes in key economic variables ،among which we can mention production. When global financial crises occur, significant changes in macroeconomic variables occur (Kenny et al, 2021). A clear example of this was the time of the spread of the Corona virus, which firstly greatly disturbed the oil market and led to a significant drop in oil prices Next, the gold market began to fluctuate, and these changes were able to affect the trade cycles of nations (Gharib et al, 2021). In this way, when governments face economic shocks, they try to adjust most of their plans and strategies based on financial and banking fluctuations (Echarte Fernández et al, 2021). On the other hand, it can be seen that the duties of banks in the economy are undeniable because not all people have the ability to use personal financial resources to provide the capital needed for their economic activities, therefore ،they turn to using the services of financial and credit institutions, headed by banks (Rahi & Rahi Faraj, 2022). Banks encourage investment by collecting people's deposits and passing them on to investors, and as a result they contribute to the growth and promotion of production. Finally, the proper functioning of the banking sector will have a direct impact on the prosperity of the economic sectors of society (Ayadi et al, 2008). In such a way that, according to the Harrod-Dumar theory, economic growth and development in the long run is influenced by savings and investment. In other words, the economic development framework of developing countries is strong and strong in encouraging an increase in savings and an increase in investment despite healthy banking ،Basically, it means that the banking industry by attracting people's deposits in the form of deposits and savings and by financing investors through these sources, leads to savings and investment It turns out that one of the most important and main tasks of bank in the economy is also(Arsyad, 1999; Osman, 2001). Therefore, the banking sector plays an important role in moving the wheels of the country's economy for national economic development, which acts as a means of transmission of monetary policy. Sustainable national development can be achieved through the establishment of a strong and resilient banking system, which is an important prerequisite for a country ،where banking acts as a provider of payment transactions for smooth cash flow both domestically and internationally to support economic activities (Harhap et al, 2017).

As a financial institution, banks distribute resources to those who need business capital, namely small, medium, and micro enterprises. The distribution of resources to the real sector functions to drive the wheels of the economy for society (Gherghina et al, 2020). In order to realize the strategic role of banks, it is necessary to take measures to improve the quality and quantity of bank savings and credit while maintaining economic stability (Bhegawati & Utama, 2020). In principle, sustainable national development can be achieved by creating a healthy and flexible banking system as an important prerequisite for a country where banking provides transaction payments for cash flow, both domestically and internationally, to support economic activities (Harahap et al, 2017). Therefore, the financial health of the banking industry is an important prerequisite for economic stability and growth. In other words, the financial health of the banking industry is an important prerequisite for the stability and economic growth of countries. Since the banking system plays an important role in the economic development of a country, the banking crisis can cause serious disruptions in the economic activities of a country (Tamás Kristóf, 2021). Therefore, bank bankruptcy is considered a major crisis for the banking industry, in other words, if the bank faces bankruptcy, the economy will face bankruptcy. For these reasons, bank bankruptcy is the phenomenon of a, which in recent decades has attracted the attention of managers of financial institutions, central banks, creditors, economic agents, etc. (López-Iturriaga & Pastor Sanz, 2014). Therefore, since the signs and symptoms of potential bank failure are visible before bankruptcy, the identification of bankruptcy warning variables can be effective in predicting bank bankruptcy ،In the case of correct and timely prediction of bankruptcy or banking crisis, a new opportunity is available to managers of financial institutions, creditors ،banking managers and policy are supposed to take the necessary measures and decisions to prevent bank bankruptcy from the activities of bank failure. In another way, with the spread of COVID-19, adverse effects on economic conditions around the world have been observed, such as supply chain disruptions (Hosseini and Ivanov, 2021) and economic crises which leads to an increased probability of financial insolvency and the risk of bank failure (Chen et al, 2021). In the context of economic crises exacerbated by COVID-19, predicting financial problems such as bank failures becomes crucial for several reasons. Firstly, it enhances the quality of resource allocation. Both banks and private investors seek data to assess the financial health of publicly listed companies and predict potential financial crises. Timely bankruptcy analysis aids market players in capitalizing on opportunities while allowing company managers to take preventive measures, promoting intelligent resource allocation that underpins economic growth (Gärling et al, 2009). Secondly, accurate prediction of bank failures provides valuable insights for policymakers. It helps them avert structural crises, which could lead to financial distress. Given that bankruptcy is a central issue in political debates at various levels, the ability to forecast financial events has become a pivotal element in policymaking (Caggiano et al, 2014). Furthermore, identifying bankruptcy signs enables management to tackle underlying issues and prevent the spread of financial distress, an approach particularly significant in public institutions like banks that safeguard public assets (Campbell, 2007). Lastly, bankruptcy prediction models can serve as early warnings of potential industry-wide downturns. Robust forecasting tools enable both managers and legislators to anticipate and prepare for future problems, thus mitigating crises within specific industries (Gounopoulos et al, 2023). These models also inform investors, guiding them to make more informed decisions that may curb the adverse economic impacts of financial failures (Kandrac, 2014). Additionally, credit rating agencies often rely on bankruptcy predictions to assess financial health accurately, influencing credit ratings and highlighting the link between bankruptcy forecasting and credit risk analysis (Abbasi et al, 2021).

Finally, referring to the above, it should be said that the bank bankruptcy prediction is a very important and necessary thing for developing and developed countries, especially Iran and Iraq ،Because banks play a very important role in the economy of countries, especially in Iran and Iraq, The banking sector critically underpins the economy of both countries, as the financial landscape in Iran shows, showing a clear bank-centric orientation. The superiority of banks in providing financial resources has overshadowed the role of the capital market in the country's economy. This dynamic is illustrated by the distribution of financing in 2011, where the banking sector's share of financing activities was a significant 91.3%, contrasting sharply with the 6.2% attributed to the capital market. Tracing back to 2012 and 2013, we see a consistent trend where banks accounted for 86.5% and 89.2% of the main funding share, respectively, while capital market input was relatively nominal at 9.5% and 7.6%. Notably, the responsibility that banks took in facilitating the necessary investments for Iran's economic growth, as Akbar Kamijani pointed out in 2015, was remarkably high and was close to 90% (Akbar Komijani, 2015). Therefore, in order to find out more about the importance of the bank in the economy of Iran, we will update the discussion of financing the investments for the years 2016 to 2022 in such a way that the share of Bankha in financing for the years 2015, 2017, 2018, 2019, 2019, 2011 was equal to 64%, 51%, 88%, 67%, 57%, respectively%59 ، and finally 84% are (Taheri et al, 1402). Therefore, since the financial structure of the Iranian economy is bank-oriented, in this case, it is not possible to ignore the important and fundamental role of Iranian banks in the country's economy (Baghri et al, 2016). On the other hand, according to the economic structure of Iraq, it can be seen that Iraq's economy, like Iran's economy, is also dependent on banks. This means that Iraq's economy is dependent on banks because banks play a central role in financing economic and social activities and directly affect economic development (Hussein et al, 2022). Overall, banks play an important role in any modern economy because they provide financial services and act as intermediaries between savers and investors. In the case of Iraq, there are several key factors that make the role of banks more important, because after the year of severe crisis in 2003, the Iraqi economy has suffered many instabilities and crises،including falling global oil prices, civil wars and the fight against ISIS, all of which have negatively affected government revenues and the country's economy. On the other hand, due to the crisis of 2015, which was much more filled than the crisis of 2003, in this situation ،the health and efficiency of banks are important to support economic recovery and reduce the negative impact of these shocks. One of the reasons for the importance of the banking sector in Iraq is that in the first year, it can refer to bank loans and credits in the Iraqi economic system, which are of particular importance ،Because the banks of this country have become the main funding arteries for various economic dimensions. These financial facilities, through the injection of liquidity in the Iraqi economy, contribute to the prosperity of production and commercial activities, and thus ،They accelerate buying and selling and investment cycles and become the basis for economic growth (Hussein et al, 2022). Increasing access to bank credit can be a driving engine for GDP growth and improve the individual share of GDP ،Especially in the period after wars and civil conflicts that have damaged the Iraqi economy (Bin Faraj Abd al-Qadir, 2021).In the second phase, in addition to their economic role, Iraqi banks also play an important social role. By providing loans and credits for infrastructure projects and public services, they contribute to social development and improve people's quality of life. Banks also play a central role in maintaining economic equilibrium, because by controlling the supply and demand of money, they help strengthen the economy and make it resistant to fluctuations and inflation. Banks facilitate financial processes by regulating the transfer of funds between individuals and economic entities, which is necessary for the maturity and dynamism of Iraq's financial markets ، especially in line with reconstruction and development after past conflicts (Hasan et al, 2020). Therefore, Iraqi banks help entrepreneurs and start-up companies who intend to have a share in the national economy by obtaining loans and credit lines ،start their activities and expand them. This helps to create jobs and can lead to a decrease in the unemployment rate in Iraq (Mahmood, 2018). On the other hand, banks in Iraq also play a role in maintaining the country's financial stability, and by reducing vulnerability to international economic shocks, they contribute to Iraq's financial security (Al-Khazraji & AL-Zaidi, 2020). Finally, the Central Bank of Iraq, as an important part of this system, tries to control inflation and ensure sustainable economic growth by controlling the money supply and setting interest rates In the following, banks are also involved in reducing the negative impact of financial crises, and by providing structural solutions and programs, they help economic enterprises in dealing with financial disturbances (SHENG, 1991). All in all, these measures have accelerated the establishment and economic and social progress of Iraq at critical times after the war and are the basis for the return of capital and confidence in the country's economy. After that, since the nature and function of the bank is very high in the economy of Iran and Iraq ،In this case, if the bank does not do its job properly, in other words, if the bank cannot do it for the investors ،Depositors and Dh beneficiaries should perform their duties correctly, in which case a financial crisis will occur (Tehran and Bigdalo, 2019). This leads to economic crisis such as long-term recessions and severe inflation, which in this case cannot be caused by the effects and damages of bank bankruptcy. countries is very important, because the economy of both countries is highly dependent on the banking system, therefore preventing bankruptcy is one of the most important and basic tasks of policymakers and statesmen, on the other hand, because of the potential signs and symptoms of bank bankruptcy before bankruptcy appears It is possible to identify bankruptcy warning variables can be effective in predicting bank bankruptcy. With the correct and timely prediction of bankruptcy or banking crisis, a new opportunity is provided to financial institution managers, creditors, bank managers and policy makers are supposed to take the necessary measures and decisions to prevent bank bankruptcy from bank bankruptcy activities. Therefore, due to the importance of the banking system in the economy of both countries, the main goal of this research is to design a model for predicting the bankruptcy of banks admitted to the stock exchange of Iran and Iraq with the approach of neural networks and machine learning.

Research literature

The importance of banks in the economy

Banks, as the primary elements of the money market, play a crucial role in the economies of countries (Tamizi, 2023). Through their monetary policies, banks can influence interest rates, which directly affect inflation, investment and economic productivity. Therefore, banks not only play a key role in providing financial resources, but are also important in stabilising the economic system (Bibo et al., 2022). Through monetary policy and operations, banks can influence liquidity and economic sustainability. Specifically, by adjusting bank interest rates and money transfer rates, banks can control inflation and exchange rates and create a proper balance in the economy (Tsendliani, 2022). Overall, the banking system helps businesses and individuals to meet their financial needs by providing financial resources, facilitating trade, capital management, national payments, liquidity control and financial risk management. Therefore, the banking system and banks are very important in the economy. In this regard, numerous global studies have also confirmed the strong positive relationship between banking activities and economic growth, showing that banking development can play a more central role in economic progress (Abdollahi Marafe, 2022). For example, in a study by Valeria Dinger and colleagues (2022), which examined the relationship between bank support and economic growth, they showed that capital injections, loans, etc. lead to the strengthening of banks' financial support and, consequently, to increased economic growth in society. In another study, Olivo and Laurens (2022), examining bank lending and economic growth for 132 countries, showed that there is a positive and significant relationship between economic growth and bank lending. Or in Zeynalova's study (2023), which examined the volume of credit on Azerbaijan's economic growth, it was observed that there is a significant relationship between the volume of bank credit and economic growth in the short run, while in the long run there is a positive and significant relationship between the volume of bank credit and the speed of economic development. In another study, Orzechowski (2024) examined the impact of bank credit on employment and economic growth; it was observed that increasing bank credit in the United States leads to increased employment in the short run and economic growth and development in the long run.

Banks, as the founders of the financial system, play a vital and diverse role in the economy. Banks, as financial intermediaries, play a very important role in the economy. According to Kent and Dietrich Giach (1997), banks provide various financial services as financial intermediaries. Therefore, banks influence the facilitation of financing, stimulation of investment and economic growth by providing various financial services such as account monitoring, lending, electronic money processing, capital management and liquidity creation (Tamizi, 2023). Thus, in today's world, the role of banks in economic structures and financial ecosystems is fundamental and undeniable (Mansoor Khan and Ishaq Bhatti, 2008). As the nerve centres of the economy, banks are responsible for tasks such as speeding up and increasing the security of financial transactions and facilitating access to credit. The performance of banks in a country's economic system is of great importance, as these institutions play a key role in managing financial resources and financing different economic sectors (Van den Heuvel, 2012). In essence, banks, as one of the vital arteries of the economy, play an important role in financing, providing guarantees and facilitating access to financial resources, in addition to facilitating financial transactions. Banks help to increase production and economic development by channelling liquidity to profitable projects.

Duke (2024), in a study of the relationship between the economy and bank credit in Vietnam, found that as bank credit to the private sector increased, economic growth and development increased in the long run. In another study, Walid Ashour Khalid (2024) examined the impact of bank credit on GDP in Iraq. His findings suggest a two-way relationship between bank credit and Iraq's economic growth. Finally, in another study conducted by Taherpour et al. (2018) to examine the impact of bank loans and credit distribution on Iran's economic growth, based on the research results, it was observed that an increase in bank loans and credits (ratio of total loans and overdue credits to GDP) has a positive effect on economic growth, but the more these loans and credits tend towards production, the greater the stimulus to economic growth. Therefore, banks contribute to industrial development, job creation and economic growth through the provision of loans and credits (Jimenez et al., 2012). Therefore, the majority of the studies conducted indicate a positive and significant relationship between economic growth and banking activities (bank loans, liquidity creation, etc.), all of which point to the importance and undeniability of the banking system and banking on the economies of countries, especially the economies of Iran and Iraq, as the economies of Iran and Iraq are bank-centric. In other words, in Iran, the economic structure is bank-centric and the share of banks in financing is greater than the capital market. For example, in 2012, the share of banks in financing was 91.3%, while the share of the capital market was only 6.2%. This trend continued in 2013 and 2014, when the banks' share was 86.5% and 89.2% respectively, while the capital market's share was 9.5% and 7.6%. It's worth noting that bank financing of the Iranian economy has been around 90% (Komijani, 2015). To further examine the importance of banks in the Iranian economy, financing data for the years 2016 to 2022 were studied, which showed that the share of banks in these years was 64%, 51%, 88%, 67%, 57%, 59% and 84%, respectively (Taheri et al., 2023). According to this data, the fundamental role of Iranian banks in the economy cannot be ignored (Bagheri et al., 2016).

On the other hand, Iraq's economy, like Iran's, is highly dependent on banks. Iraqi banks play a central role in financing economic and social activities and have a direct impact on economic development (Hussein et al., 2022). The post-2003 economic structure in Iraq, which has faced many crises and instabilities, is still dependent on banks. Key factors such as the decline in global oil prices, internal wars and the fight against ISIS have made the role of banks more important, as these crises have had a serious negative impact on government revenues and economic stability (Mushtal and Ahmad Siddiqui, 2017). In this context, the health and efficiency of Iraq's banks are crucial to support economic recovery and mitigate the negative impact of shocks. The banking industry in Iraq has become the main artery for financing various dimensions of the economy. Bank credits and loans are particularly important in the Iraqi economic system, and banks act as intermediaries between savers and investors, playing an important role in any modern economy and becoming increasingly important for Iraq's economic development (Allen and Masih, 2017).

Therefore, the banking system is one of the most important sectors in any economy and plays an important role in providing financial resources, economic growth and economic development. Banks provide the necessary financial resources for economic growth and development through the provision of loans and credit lines (Ferial et al., 2023). In addition, banks facilitate trade and economic exchange and improve financial links between businesses by providing financial instruments such as bank accounts, payment documents and loans (Mustafa Hao et al., 2023).

COVID-19

COVID-19 is a respiratory infectious disease caused by the novel coronavirus (SARS-CoV-2) that was identified in Wuhan, China, in December 2019 and rapidly evolved into a global pandemic, causing widespread health, economic, and social impacts around the world (Chakraborty and Maity, 2020). COVID-19 caused the most unexpected, widespread and pervasive exogenous economic shock in history. This pandemic had an even more global impact than the global financial crisis and is recognised as an exogenous shock, meaning that it affects the real economy and the financial system but is not itself caused by economic or financial forces (Yildirim and Erdil, 2024). Due to the exogenous nature of this phenomenon, it is difficult to estimate its overall impact on the stability of the financial system. This definition suggests that COVID-19 was more than just a pandemic, but a phenomenon with profound economic and financial implications on a global scale (Mathew et al., 2024) .Therefore, the COVID-19 pandemic has a profound impact on the banking system, such that the economic disruptions caused by this crisis increase the likelihood of financial distress and the risk of bank failures (Marco, 2021). Therefore, the impact of COVID-19 on bank failures in the economy may be different from other markets, because in the early stages of the crisis in March 2020, there was a massive withdrawal from existing credit lines, which was referred to as a 'rush for liquidity'. Most of these withdrawals were made by large corporations from large banks. In this context, it was found that banks more exposed to the risk of credit line withdrawals reported tighter lending standards for new loans to small and large firms, and reduced the supply of large syndicated loans and loans to small firms from March 2020 (Wang et al; 2020).

This is because leveraged financing was the most predictive of financial crises during this period, which could lead to increased debt burdens, create cash flow volatility, and negatively impact bank profitability. In addition, the reduced ability of banks to meet their financial obligations could lead to a severe decline in share value and create a negative cycle leading to the possibility of bank failure (Kose et al., 2021). There have been numerous studies in this area. In a study by Çolak and Öztekin (2021), which examined the impact of COVID-19 on lending in 125 countries worldwide, they found that an increase in the COVID-19 pandemic leads to a decrease in credit allocation, as leveraged financing becomes difficult with the increase in COVID-19, which could also lead to potential bank failures. Or, based on another study by Yan et al. (2023), they examined the impact of the COVID-19 pandemic on the systemic risk of banks. Their results showed that the COVID-19 pandemic significantly increased the contribution of banks to global systemic risk. Second, the impact of the COVID-19 virus was greater in developed countries than in emerging markets. Finally, banks with larger size and higher loan-to-deposit ratios are more affected by the COVID-19 pandemic, while higher capital levels of banks are not sufficient to protect them against the adverse effects of such a pandemic, which could also lead to potential bank failures. Finally, it is observed that COVID-19 leads to financial crises worldwide, which increases the likelihood of bank failures. Therefore, predicting bank failures during the financial crisis caused by COVID-19 becomes more important, as this pandemic has led to financial crises worldwide, increasing the likelihood of bank failures. Under such conditions, accurate forecasting can help prevent domino effects in the financial system. This is because the bankruptcy of one bank can have cascading effects on other banks and the economy as a whole, and timely prediction can prevent these effects (Li et al., 2021). In addition, predicting bank failures helps to protect depositors' interests and prevent social crises resulting from the loss of savings. Banks play an important role in the economy, and predicting and preventing their failure helps maintain economic stability. Moreover, these predictions help banks to improve their risk management strategies (Buratynska, 2021). Finally, predicting bank failures helps policymakers to take appropriate preventive and supportive measures. This can help maintain public confidence in the banking system and allow supervisors to more accurately monitor banks at risk (Keshavarz Haddad et al., 2024). These factors therefore become even more important in crisis situations such as the COVID-19 pandemic, when the financial system is under greater pressure and the need for a rapid and accurate response increases.

Bank Bankruptcy

As a financial institution, a bank plays an important role in the lives of people and the economy of any country (Jafari Samimi, 2018). Bank bankruptcy refers to a situation where a bank is unable to cope with its debts and cannot pay its financial obligations in full. This situation usually occurs due to non-payment of loans or improper investments or both problems (Beinabadi, 2023). In better terms, bank bankruptcy refers to a situation in which the bank is unable to pay all its debts and financial obligations (Hola et al., 2021). Therefore, it can be said that bank bankruptcy has a significant impact on the banking system and public confidence in banks. Thus, excessive increase in debt, decrease in bank capital, and investors' concerns about creating a financial crisis are reasons that can lead to bank bankruptcy (Ahmadian and Gorji, 2017). In fact, the effects of bank bankruptcy can be widespread and deep, and in some cases, it can damage the economic prosperity and economic strength of the country (Bayar et al., 2021). In other words, the failure of a bank can lead to its closure, change of ownership of the bank or its merger with another bank, which in turn can affect other banks and cause them to experience financial problems and be on the verge of bankruptcy (Simaei Sarraf and Amini, 2019).

Therefore, bank failures have a profound effect on a country's economy and its banking system and can lead to reduced output, increased unemployment, reduced purchasing power and higher prices. This situation can also affect the country's exports and imports and prevent economic recovery (Sundararajan and Balino, 1991). Thus, bank failures pose serious risks to customers and depositors; people may lose their savings, which will have long-term effects on their lives (Nasiri and Nasiri, 2021). In addition, these failures can reduce public confidence in the banking system, leading to capital outflows and threatening the sustainability of other banks (Downes and Vaez-Zadeh, 1991). In such circumstances, the government is usually forced to intervene and provide capital to support banks and protect customers' rights and assets (Simaei Sarraf and Amini, 2019). On the other hand, given that Iran's financial system is bank-oriented and banks play an important role in financing individuals, businesses and the government, bank bankruptcy can lead to economic crisis and should be prevented (Nazarpour et al., 2016). For these reasons, bank bankruptcy is considered a destructive factor and economic crisis for the Iranian economy, and necessary preventive measures should be taken against it. There are numerous studies on bank bankruptcy and bank bankruptcy prediction, some of which we will review and study in the following.

Srivastava and colleagues (2020) conducted a study to predict the bankruptcy of Indian banks using AI methods, ML and logistic regression for the years 2000 to 2017, with parameters such as total liquid assets, total fixed assets, total profitable assets, current assets, equity, bonds, reserves, total existing liabilities, total advances, customer deposits, bank deposits, bank borrowings, net profit, net cost and capital adequacy ratio. The results showed that logistic regression was more accurate in predicting bank failure than other models. However, he and his colleagues concluded that financial parameters such as equity, capital adequacy, net income and others had the most significant impact on predicting bankruptcy.

Yuri Zelenkov and Nikita Volodarsky (2021) conducted a study on predicting the bankruptcy of Polish and Russian banks based on unbalanced data and the neural genetic algorithm. According to his and his colleagues' findings, the genetic algorithm is suitable for predicting the bankruptcy of banks and is more accurate than other models. Banks only go bankrupt when they are financially unsound.

Parboli and Arab Nejad (2021) used machine learning methods to predict bankruptcy in the medium and long term. In addition, considering the recent COVID-19 pandemic, the authors concluded that the proposed decision support system framework using machine learning vectors can be a suitable tool for large-scale policy making.

Christoph (2022) conducted a study to predict bank failure in the European Union using logistic regression, decision trees and deep learning neural networks for 11 consecutive years using parameters such as income ratio, capital adequacy, equity, manageability indices and asset quality indices to predict bank failure in the European Union. Christoph found that all three models had high accuracy in predicting bank failure, but in terms of AUROC values, the decision tree model was more accurate than the logistic and neural network models. His final conclusion was that capital adequacy, manageability indices and asset quality indices had a more significant impact on predicting bank failure than other parameters.

Bin Jaber and Sert (2023) conducted a study entitled "Bankruptcy Prediction Using Fuzzy Convolutional Neural Networks" to study and predict bankruptcy. They used a combined method based on Fuzzy Set Qualitative Comparative Analysis (fsQCA) and CNN neural networks to predict bankruptcy. In this study, CNN outperformed other methods in several areas. Four other models were also used, including t-test, stepwise qualitative analysis, stepwise logistic regression and partial least squares discriminant analysis. However, the results indicated that CNN neural networks performed better in predicting bankruptcy than the other four methods.

Nobrega and Jesus (2023) conducted a study to investigate and predict the bankruptcy of Brazilian banks using machine learning and sensitivity analysis. They used bank accounting data and macroeconomic variables to predict bank failure. The results showed that machine learning and decision trees had very high accuracy in predicting bankruptcy compared to traditional forecasting models. Similar to Christoph's study, they also concluded that decision trees had high accuracy and lower error in predicting bank failure compared to other models.

Najari Ferosani and colleagues (2023) conducted a study to develop an early warning model for predicting the probability of bank failure in selected Islamic countries using the multiple logit method. The objective was to develop an early warning model for predicting the probability of bankruptcy in the banking systems of eight selected Islamic countries over the period 1998 to 2020. In this method, bank failure was determined using the Z-score index and financial ratios were considered as variables affecting the probability of bank failure. Therefore, the research results indicate that the Islamic banking system in the selected Islamic countries faces more problems and risks such as bankruptcy. As a solution to prevent bank bankruptcy, increasing the ratio of working capital to bank assets and the ratio of bank income before zakat and taxes to net assets and controlling the ratio of total bank liabilities to equity can be considered. It was found that the ratio of retained earnings to total bank assets had no significant effect on the probability of bank failure. In addition, since this model was developed based on the period from 1998 to 2020, it can be used in the future to create early warning models to prevent bank failures in Islamic countries.

Keshavarz Hadadha et al (2024). In their research, they analysed the challenges and strategies for developing a more effective early warning system for the bankruptcy of Iranian banks using the post-positivist paradigm. In this research, he and his colleagues used 11 main criteria and their different considerations to predict bankruptcy. Therefore, based on the results of the research, 10 main challenges and current problems and limitations were introduced and about 80 approaches and solutions to these 10 challenges were presented. Finally, 13 main approaches were proposed to make the development of bank bankruptcy warning system in Iran more effective.

Abbas et al (2024). In a study, they developed a warning model for bank financial failure using 27 financial indicators and weighted adaptive lasso regression for the period from 2010 to 2017. The results showed that the weighted adaptive lasso regression model is more robust and relevant as a financial model for bank failure warning in the Iraqi stock market.

Considering that banks and the banking system occupy a large and important place in the economic system of Iran and Iraq, in other words, the economic system, including the economic growth and development of both Iran and Iraq, is highly dependent on the banking system, if one or more banks face the phenomenon of bankruptcy, firstly, banks will face an increase in demand for deposit withdrawals from depositors, and on the other hand, in case of bank bankruptcy, other banks will not be able to perform their duties. If these factors are not properly and regularly managed, they will cause a financial crisis and, as a result, an economic crisis. Therefore, the necessity of conducting research in predicting the risk of bankruptcy of listed banks through the mediation of COVID-19 in Iran and Iraq can be explained from several aspects: 1- To ensure financial and economic stability; as banks are known as vital institutions in the financial system of any country, their stability and health are essential to prevent financial and economic crises. Bankruptcy can lead to a loss of public confidence and massive capital outflows, which requires a careful understanding and anticipation of bankruptcy risks. 2- Influencing investor decisions; Accurate information about the financial health of banks and their bankruptcy risk helps investors make more informed decisions and minimise the risk of their investments. 3- Understanding the impact of the covid-19 pandemic; The outbreak of the covid-19 disease has had far-reaching effects on various economic sectors, including the banking industry. Research in this area can not only show the short and long term impact of the epidemic on banks, but also help to understand risk management strategies in crisis situations. 2- Development of new predictive models; the more accurate the predictive models, the faster policy makers and bank managers will be able to respond to warning signs and implement intervention and prevention programmes. effective policy making and monitoring; by analysing and predicting bank failure models, governments and supervisors will be able to better manage regulatory policies and implement appropriate legal measures.

Finally, studies show that bank failure research is of vital importance because disruptions in banking systems affect not only national economies, but also regional and global markets. This research can provide insight on how to manage these risks and strengthen banking systems against possible future crises. In general, the effects and damages of the bankruptcy of banks and the banking system cannot be overestimated; Therefore, preventing the bankruptcy of banks is one of the most important and fundamental duties of politicians and statesmen. The main purpose of this research is to explain and interpret the bank bankruptcy prediction model in Iran and Iraq. Finally, according to the reviews of the theoretical literature and the background of the research, it can be seen that banks as financial intermediaries play a major and fundamental role in the economy of all countries, especially Iran and Iraq, and have many effects on the economic cycle. Therefore, in recent years, the discussion of predicting bank bankruptcy has gained special importance in order to prevent financial crisis and recession in countries. But what can be observed and studied is that the discussion of predicting the bankruptcy of Iranian and Iraqi banks has not been examined properly and there is a gap in this field. Therefore, in this research, an attempt has been made to address this research gap and provide a model based on neural network and machine learning for the future.

Research Methodology

This section introduces the research method of the present study. Among the research methods, research data and variables, machine learning models and neural networks are introduced below.

1) Machine learning models

Machine learning is a subset of data science that provides the ability to learn and improve experience without programming. The beauty of machine learning solutions is that they learn from experience without being explicitly programmed. Simply put, you select models and feed them data. The model then automatically adjusts its parameters to improve results. Machine learning is a branch of artificial intelligence used to make predictions. Today, machine learning plays a fundamental role in many stages of the finance and accounting ecosystem, from asset management to risk assessment and analysis of capital and financial market behaviour. In fact, companies that use machine learning technology have multiple advantages, both in terms of replacing old systems and developing enterprise or customised solutions (Rabiei, 1402). In short, machine learning is an important branch of artificial intelligence that aims to design algorithms that allow computers to develop their behaviour based on experimental data. The most obvious feature of machine learning is knowledge discovery and automatic intelligent decision making. When big data is desired, it is necessary to use the scale of machine learning algorithms in the execution of the desired tests (Solis, 2019). In this research, a machine learning model was used to predict the financial performance of Iranian banks listed on the Tehran Stock Exchange, which explains some of these algorithms used in the research:

- **Decision Tree (BRT)**

A decision tree is a statistical method that makes predictions based on large amounts of conditioning information without imposing strong parametric assumptions such as linearity or monotonicity. It applies soft weighting functions to the predictor variables and performs a form of model averaging that increases the stability of the predictions and thus protects against overfitting. This method strategically incorporates soft weighting functions into the predictor variables and increases prediction accuracy by effectively capturing complex relationships within the data. In addition, the decision tree incorporates a unique form of model averaging, a technique that enhances prediction stability and protects against the common problem of overfitting, and ultimately the reliability and robustness of the predictions produced. (Kumar and Lakshmi, 2022).

- **Gradient Boosting (XGBoost)**

Gradient boosting is a distributed gradient boosting toolkit tuned for performance (Behra et al., 2023; Yan, Chen, Dong, Ju, & Xiu, 2022). It uses a recursive binary partitioning strategy to obtain the optimal model by selecting the best partition at each step. The tree nature of gradient boosting makes it insensitive to outliers and, like many boosting methods, it is resistant to overfitting, which greatly simplifies model selection (Behra et al., 2023; Al-Badallah et al., 2023; Al-Badallah et al., 2023). Amin and Jalal, 2022; Pasayt, Mitra and Bawmik, 2022). Equation (2) represents the regular objective of the gradient boosting model in the tth training step, where $l(\mathrm{y}_{pred}^{(t)}$, $\mathrm{y}_{\mathrm{truth}}$ represents the loss that refers to the calculation of the difference between the simulated value $\mathrm{y}_{pred}^{(t)}$ and the truth of the associated context y_truth .

$$L^{(t)} = \sum_i \mathrm{l}(\mathrm{y}_{pred}^{(t)}, \mathrm{y}_{\mathrm{truth}}) + \sum_k \Omega\,(f_k)$$

where $\Omega\,(f_k)\ \ \gamma^T+) = \frac{1}{2} + \lambda \|w\|^2$ represents the complexity of the tree k where T represents the number of leaves and $\|w\|^2$specifies $\ell 2$ Norm of all sheet marks for teaching samples. When searching the tree, the parameters γ and λ set the degree of conservatism.

2) neural network

Artificial neural networks are a computational model inspired by the biological nervous system of the human brain. These networks are composed of interconnected layers that contain artificial neurons (or nodes). Each connection, like synapses in the biological nervous system, transmits signals from one neuron to another. Neural networks are capable of learning and recognizing patterns in data and can be used to perform various tasks such as classification, prediction, pattern recognition, and optimization. They are widely used in various fields of artificial intelligence, including image processing, speech recognition, and deep learning. One of the main advantages of neural networks is their ability to learn from data and improve their performance over time, which makes them well suited for solving complex and nonlinear problems.

- **Artificial Neural Networks (ANN)**

It is a synthesis of various machine learning concepts, including regression, ensemble, perceptrons, and gradient descent. It takes a linear combination of input variables and transforms them into nonlinear functions of derived features of the dependent variable (Mishra et al., 2022). They are the most primitive type of deep networks, consisting of multiple layers of hidden neurons, each fully connected to the layer above (from which they influence) and below (from which they receive input) (Shahu et al., 2022). . Any general function can be constructed by considering networks with increasing layers of interconnected units. A weighted linear combination of inputs is processed by each layer and transformed using an activation function. The output from the jth unit when w_ji^1 is the weight that connects the jth unit from the ith unit in layer 1.

$$Z_{\mathrm{j}} = g(\sum_{i=0}^{\mathrm{d}} w_{ji}^{1} x_i)$$

3) Support Vector Machine

Support Vector Machine (SVM) is a powerful machine learning algorithm used for classification and regression. This algorithm aims to find the best decision boundary between different classes of data with the maximum possible margin. SVM uses support vectors (data points close to the decision boundary) and kernel functions to map the data into higher dimensional spaces, allowing non-linear separation. This algorithm is one of the most popular machine learning methods due to its good performance in high-dimensional spaces, its resistance to over-fitting, and its wide application in fields such as text classification, image recognition, and financial forecasting.

- Support Vector Machine (SVM)

The Support Vector Machine (SVM) was first introduced in 1995 by Cortez and Vepnik (1995). It is a supervised machine learning algorithm used in various industries to solve regression and classification problems (Pant and Kumar, 2022). For classification problems, SVM is popular as an approach that creates the largest marginal cloud to provide maximum separation between different classes. Examples close to the maximum marginal hyperplane for a given learning problem are called support vectors. The discriminant function can also be linear or non-linear. If the case is linearly separable, a linear hyperplane can be used to partition the samples. If not, the case is nonlinearly separable (Chia et al., 2022). SVM models have been further developed to cover a wider range of support vector machine models and general estimation and prediction tasks. This development led to the introduction of SVR by Drucker and colleagues in 1996.

Research procedure

In this study, first, the research data were collected from the databases of the World Bank, the Central Bank of the Islamic Republic of Iran, the Financial Center of Iran, the Economic and Financial Data Bank, OECD data, Kadal,Rahavar Novin, Iran Stock Exchange Company, Iraq Stock Exchange, Iraq Data Organization, Iraq Financial Data Website, Iraq Data Banks; It is then used for Iran and Iraq. Data preprocessing (including data removal with blank values, outlier data elimination, and data standardization) is performed. Then, in the data segmentation process, the study uses time as the basis for data segmentation, and sample data over a long period of time (e.g., more than 20 years) are used to train neural networks and machine learning. and then data models have been used to predict the bankruptcy of banks listed in the Iran-Iraq stock exchanges. But what is certain is that the time frame of this study is divided into two parts, first to the period before COVID-19, i.e. the period from 2003 to 2019, and then to the period after COVID-19, which is exactly where COVID-19 affected allthe economies of the world, i.e. the period from 2020 to 2023. The purpose of the time division is to predict the bankruptcyof Iranian and Iraqi banks after the COVID crisis 19 and examine the effects of COVID-19 on the performanceof banks.

Data and variables:

In this research, all banks listed in Iraq and Iran from 2003 to 2023 were used as the research sample. Regarding the use of financial input variables, the variables of Diguptia et al (2023), Tamás Kristóf

(2022) and Raffael Forch Brenes (2022). have been used in this research. Table 1 shows the definition of the variables related to Diego Petia's study and Table 2 shows the definition of Kristof's variables.

Table 1. Variables definitions Tamás Kristóf (2022).	
LRG	Loan Disbursement Losses/Gross Disbursed Loans
LPN	Losses related to loan payments/net interest income
LRN	Losses related to the payment of non-current loans/loans
TCR	Ratio of total bank capital
ILQ	Loan to equity ratio
ETA	Equity / Total Assets
ENL	Equity/deposit and short term financing
EL	Equity / total liabilities of the bank
NIM	Net profit margin
NIRA	Net Interest Income / Average Assets
OAI	Other operating income / average assets
POAI	Operating income before tax / average assets
ROAA	Average return on assets
ROAE	Average stock return
NIN	Non-operating income / net income
CI	Cost-to-income ratio
IR	Interbank interest rate
NLTA	Net loan/ total assets of the bank
NLTDB	Net loan / total deposit and loan
NLTDS	Net loan/deposit and short term financing
LADS	Cash assets / short term financing deposit
LATDB	cash assets / total deposits and borrowings

Table 1. Variables definitions Diguptia et al (2023).	
varible	Formula
TAM	The ratio between total bank deposits and total assets
ROA	The ratio of the bank's operating profit and total assets
ETS	The ratio of the bank's equity and total assets
CYCLE	Economic cycle (quarterly real GDP cycle).

Table 3. Variables definitions Raffael Forch Brenes et al (2022).	
varible	Formula
OPR	Operating profit rate
NIRBT	Net interest rate before tax
NIRAT	Net interest rate after tax
NWPS	Net worth per share
TRCR	The ratio of capital to return on total assets
NPS	Net profit per share
CLB	Current liabilities of the bank
NICL	Net income/current liabilities
CLRE	Current liabilities relative to equity

LTLCA	Long term liabilities / current assets
TFANI	Total Fixed Assets / Net Income

Therefore, according to the three studies of Diguptia et al. (2023), Thomas Kristof (2022) and Raphael Forsch Burns (2022). In the present study, Bank Insolvency Index (BIB) is considered as a comprehensive criterion to evaluate the financial health and operational performance of banks. Consisting of eight key parameters, this index specifically focuses on two critical aspects: profitability and capital adequacy. The BIB can be formulated as follows:

$$BIB = TAM + ETS + NIRE + NITA + TRCR + TCR + NIM + NLTDB$$

Where:

1. TAM (Total Assets to Deposits Ratio): Measures the bank's ability to cover withdrawals with its assets.

2. ETS (Equity to Total Assets): Indicates the proportion of total assets funded by shareholders' equity.

3. NIRE (Net Income to Equity): Reflects the return on shareholders' investment.

4. NITA (Net Income to Total Assets): Demonstrates the overall profitability of the bank's assets.

5. TRCR (Total Return on Capital Ratio): Measures the overall return generated on the bank's capital.

6. TCR (Total Capital Ratio): Assesses the bank's capital adequacy.

7. NIM (Net Interest Margin): Indicates the profitability of the bank's core lending activities.

8. NLTDB (Net Loans to Total Deposits and Borrowings): Measures the bank's liquidity and its reliance on borrowed funds.

These parameters comprehensively cover various aspects of a bank's financial performance, including capital structure, operational efficiency, profitability, and risk management. The fundamental assumption of this model is that insufficient capital adequacy combined with inadequate income and negative net profit indicates a bank's insolvency. Thus, BIB, as the dependent variable in this research, provides a comprehensive measure for evaluating banks' financial health. This approach integrates key variables into a single index, allowing for a more precise and multidimensional assessment of banks' financial condition. This, in turn, can aid in the early identification of potential financial issues and the adoption of appropriate preventive measures.Finally, after indexing the dependent variable, the research model will be as follows:

$$BIB=f(ROA_{it}+CYCLE_{it}+OPR_{it}+NIRBT_{it}+NIRAT_{it}+NWPS_{it}+NPS_{it}+CLB_{it}+NICL_{it}+CLRE_{it}+LTLCA_{it}+TFANI_{it}+ELTL_{it}+GP_{it}+LRG_{it}+LPN_{it}+LRN_{it}+ILQ_{it}+ETA_{it}+ENL_{it}+EL_{it}+NIRA_{it}+OAI_{it}+POAI_{it}+ROAA_{it}+ROAE_{it}+NIN_{it}+CI_{it}+IR_{it}+NLTA_{it}+NLTDS_{it}+LADS_{it}++GDP_{it}+LATDB_{it})$$

Research findings

Descriptive statistics discuss the status of the data in terms of key indicators. Table (4) shows the status of the research variables in terms of descriptive statistics indicators**:**

Table (4). Descriptive statistics of the research

variables	**1st Qu.**	**3rd Qu.**	**Jarque Bera Test**	
			X-squared	**p-value**
BIB	276523	1535734	73401	**0.0000**

ROA	344510	2150618	24715	**0.0000**
CYCLE	10.000	20.000	313.02	**0.0000**
OPR	548882	2553481	59964	**0.0000**
NIRBT	0.5420	1.3126	1442.5	**0.0000**
NIRAT	11530	247256	12968	**0.0000**
NWPS	159409	867758	47443	**0.0000**
NPS	0.0871	0.4623	6932433	**0.0000**
CLB	0.0638	0.8077	7913268	**0.0000**
NICL	26.00	49.00	37.042	**0.0000**
CLRE	13.22	14.75	49.239	**0.0000**
LTLCA	314362	1741218	LTLCA	**0.0000**
TFANI	1.1517	1.8333	2253.7	**0.0000**
ELTL	90784	783062	15636	**0.0000**
GP	0.12707	0.38008	93.218	**0.0000**
LRG	479465	2395161	31694	**0.0000**
LRN	13430	294520	438.23	**0.0000**
ILQ	9354	105470	71763	**0.0000**
ETA	46446	447530	25130	**0.0000**
ENL	0.0719	0.2311	798.76	**0.0000**
EL	188663	871356	136381	**0.0000**
NIRA	247369	1288639	29935	**0.0000**
OAI	0.26981	0.62070	20.029	**0.0000**
POAI	1.00	34.21	176.92	**0.0000**
ROAA	398858	1580810	83811	**0.0000**
ROAE	0.5241	1.2657	726	**0.0000**
NIN	11698	151242	55075	**0.0000**
CI	130973	619622	58814	**0.0000**
IR	0.09455	0.40503	745714	**0.0000**
NLTA	0.09592	0.64995	10041	**0.0000**
NLTDS	29.00	49.00	30.88	**0.0000**
LADS	12.90	14.27	313.34	**0.0000**
LATDB	216858	1008320	130725	**0.0000**

Source: Research results

Based on the results presented in Table 4, it can be seen that all the research variables do not have a normal distribution, because the null hypothesis of the Jarque Bera test, which indicates that the data are greater than 0.05, has been rejected, because all the research variables have a probability equal to 0.00, which is much less than 0.05. Therefore, considering that the results of descriptive statistics have been determined and it has been observed that the research variables do not have a normal distribution, the basic model of the research has been investigated using machine learning, and the lack of normal distribution of the data is also one of the conditions for investigating machine learning. Therefore, the results related to machine learning can also be seen in Tables 5, 6 and 7.

Table 5. Decision tree results for the initial model

```
          CP nsplit rel error    xerror       xstd
1 0.80899961      0 1.0000000 1.0030903 0.31006113
2 0.06627414      1 0.1910004 0.2350848 0.06908398
3 0.01898876      2 0.1247263 0.1584227 0.06135419
4 0.01000000      3 0.1057375 0.1410909 0.05955848

Variable importance
LTLCA   ILQ   LRG  CLRE   OPR   ETA NIRAT
   20    19    18    17    17     8     1
```

complexity param	**0.8089996**	**MSE**	**7.305882e+14**
complexity param	0.06627414	MSE	**1.035209e+13**
Root node error		**1.0174e+17/579 = 1.7571e+14**	

Source: Research findings

Table 7 provides information on the complexity parameters (CP) in the decision tree model. The complexity parameter indicates the amount of error reduction required to add new branches to the tree. CP values are associated with the number of splits (nsplit) and the relative error (rel error), cross error (xerror) and standard cross error (xstd). For example, the first CP value (0.8089961) corresponds to the time when no segmentation is performed and the relative error is 1.0000000. The cross error for this value is 1.0039093 with a standard error of 0.3100613. As the CP decreases, the relative error decreases, so that for CP=0.0100000 and nsplit=3, the relative error decreases to 0.1057375, indicating an improvement in the accuracy of the model .Table 7 shows a list of variables used in the construction of the decision tree. These variables include LTICA (used 20 times), ILQ (19 times), LRG (18 times), CLRE (17 times), OPR (17 times), ETA (8 times) and NIRAT (1 time). This list shows the importance and use of each variable in the construction of the tree. For example, the most frequently used variable (LTICA) probably had the greatest impact on the construction of the model, whereas the variable NIRAT was used only once, indicating a smaller impact. On the other hand, Table 3 shows the value of the mean square error (MSE) for different values of CP. For CP=0.808996, the MSE is 7.305882e+14, which decreases as the CP decreases. Similarly, for CP=0.01898876, the MSE value is reduced to 1.035209e+13, indicating the improvement in model performance by reducing the complexity parameter. Similarly, the root-node error is calculated as 1.0174e+17, which divided by the number of samples, 579, equals 1.7571e+14. These values indicate the reduction of the error and the improvement of the model accuracy by changing the complexity parameters. In general, the analysis of Table 7 shows the process of improving the performance of the model by choosing appropriate complexity parameters and using related variables. Therefore, in order to specify the final model for predicting the bankruptcy of banks listed in Iran and Iraq, the variables mentioned above, which are the most used in the model, are selected. In the following, the decision tree of the strengthening is examined, the result of which can be seen as described in Table 6.

Table 6. The results related to the reinforcement rotations

	Actual	Prediction	Absolute_Error	Squared_Error
1	627864	3324411.1	2696547.1	7.271366e+12
2	730302	3504692.2	2774390.2	7.697241e+12
3	11025	-114174.1	125199.1	1.567482e+10
4	3810232	3629736.9	180494.8	3.257839e+10
5	6642123	3869296.4	2772826.6	7.688568e+12
6	6008737	6833946.5	825209.5	6.809707e+11

	Feature	Gain	Cover	Frequency
	<char>	<num>	<num>	<num>
1:	LTLCA	2.811341e-01	0.172807062	0.154616240
2:	OPR	2.645947e-01	0.036451469	0.030033370
3:	ILQ	2.104666e-01	0.082036275	0.061735261
4:	ETA	6.671428e-02	0.048851994	0.032814238
5:	ELTL	6.534594e-02	0.052441411	0.042269188
6:	LRG	5.362457e-02	0.032542464	0.028364850
7:	NWPS	1.793493e-02	0.058856933	0.055061179
8:	POAI	1.057563e-02	0.083650060	0.067296997
9:	NIRBT	6.529960e-03	0.068676987	0.075639600
10:	NICL	5.620057e-03	0.013388341	0.018909900
11:	EL	4.084777e-03	0.012231487	0.017241379
12:	ROA	3.724053e-03	0.024859157	0.028364850
13:	GDP	3.518938e-03	0.053011915	0.050055617
14:	GP	1.724669e-03	0.012593334	0.026696329
15:	NIRAT	1.220162e-03	0.015002126	0.013348165
16:	NPS	4.767494e-04	0.057406904	0.055061179
17:	LRN	4.579137e-04	0.006014057	0.006674082
18:	OAI	3.678826e-04	0.014450111	0.017241379
19:	LPN	3.408615e-04	0.011021809	0.017241379
20:	CI	3.088261e-04	0.004286699	0.008898776
21:	ENL	2.710004e-04	0.025831126	0.023359288
22:	LATDB	2.479751e-04	0.007152422	0.010567297
23:	NLTA	1.629095e-04	0.003174746	0.003893215
24:	ROAA	1.552250e-04	0.003792791	0.008342603
25:	TFANI	1.081258e-04	0.031380328	0.035595106
26:	ROAE	1.026598e-04	0.017331682	0.021134594
27:	CLB	7.811721e-05	0.008367383	0.008342603
28:	NIRA	4.077662e-05	0.008763566	0.016685206
29:	NLTDS	2.105632e-05	0.013755471	0.022246941
30:	NIN	1.915972e-05	0.007619918	0.016129032
31:	IR	1.738988e-05	0.005422423	0.011679644
32:	CYCLE	1.004808e-05	0.006827552	0.014460512

Source: Research results

The results in Table 6 show the predictions of the XGBoost model. This table contains the row number, prediction, absolute error and squared error for each sample. For example, the first row refers to prediction 627864, which has an absolute error of 332441.1 and a squared error of 2.72136666e+12. These errors indicate the distance between the predictions and the actual values. Based on Table 8, which lists the 32 features of the model along with the Gain, Cover and Frequency values for each feature. Gain indicates the importance of each feature in reducing model error. For example, the LTICA feature is the most important with Gain=0.281 and the OPR feature is the second most important with Gain=0.264. Features with high Gain indicate that these features have the most influence on the model. In addition to Gain, Cover indicates the number of examples in which each feature is used and Frequency indicates the frequency of use of each feature in different model trees. Therefore, in this part of the research, variables with a GAIN greater than 3 are selected for the final specification of the model. In the following, random forests have been examined, the results of which are as described in Table 7.

Table 7. Results of random forests

IncNodePurity			
ROA	5.431663e+14	LATDB	1.183655e+14
GDP	1.191120e+14	ILQ	1.821600e+16
CYCLE	6.326087e+13	ETA	9.167275e+14
OPR	6.747677e+15	ENL	6.157537e+13
NIRBT	1.644204e+14	EL	1.161532e+14
NIRAT	1.510801e+14	NIRA	4.639168e+13
NWPS	1.318758e+15	OAI	1.864752e+13
NPS	3.474082e+13	POAI	3.459811e+13
CLB	3.750978e+13	ROAA	1.350499e+14
NICL	2.285550e+14	ROAE	1.752488e+13
CLRE	5.811781e+15	NIN	3.489153e+13
LTLCA	1.157647e+16	CI	8.670125e+13
TFANI	2.717128e+13	IR	6.644168e+13
ELTL	1.655197e+15	NLTA	9.727755e+13
GP	2.378744e+14	NLTDS	1.593012e+14
LRG	1.004152e+16	LADS	1.005027e+14
LPN	1.680100e+13		
LRN	3.937535e+14		
R^2: 0.824172829272972"		"MSE: 0.0041261684304433"	

Source: Research results

Table 7 shows the importance of each feature in the random forest model. Some of the highly important features include ROA with a value of 5.431663e+14, GDP with a value of 1.191102e+14, CYCLE with a value of 8.370455e+13 and OPR with a value of 6.747677e+13. These high values indicate the large contribution of these features in the model and their influence in predicting the results. On the other hand, features such as LPN with a value of 1.680100e+13 and LADS with a value of 1.005027e+14 are less important than other features. The random forest model has provided the values (R^2 = 0.824172829272972) and (MSE = 0.0041261684304433) to evaluate the performance of the model. The value of (R^2) close to 1 indicates that the model explains approximately 82.42% of the variance of the total data, which indicates the high explanatory power of the model. The (MSE) value also gives us more information about the mean squared error; a smaller MSE indicates a higher accuracy of the model. The random forest model with (R^2) and (MSE) criteria has shown that it has a high ability to explain and predict data. Features such as ROA, GDP and CYCLE are very important in the model and have helped to improve accuracy. As a result, in this part of the research, the variables that have an impact greater than 5 are selected as the final variables for the final specification of the model. In general, the random forest model has shown good performance

Based on the information provided in Tables 5, 6 and 7, we can draw the following conclusions and analyses regarding the prediction of bankruptcy risk for banks listed on the Iranian and Iraqi stock exchanges:

In the decision tree model, the complexity parameter (CP) plays a crucial role in determining the accuracy of the model. As the CP decreases, the relative error of the model also decreases, indicating improved performance. The most influential variables in this model were LTICA, ILQ, LRG, CLRE and OPR, which were used most frequently in the construction of the tree. This suggests that these variables have the greatest impact on predicting the risk of failure for the banks studied.

The XGBoost model provides more detailed predictions, including absolute and squared errors for each sample. The model identifies LTICA and OPR as the two most important features based on their Gain values. This is consistent with the results of the decision tree model and reinforces the importance of these variables in predicting bankruptcy risk. The XGBoost model also includes additional features, providing a more comprehensive analysis of the factors influencing bankruptcy risk.

The random forest model provides another perspective on the importance of features. It highlights ROA, GDP, CYCLE, NLTA, IR, ENL, ETA and OPR as highly important features. This model shows strong performance with an R^2 value of 0.824, explaining approximately 82.42% of the data variance. The inclusion of macroeconomic factors such as GDP and CYCLE in the random forest model suggests that external economic conditions also play an important role in predicting the risk of bank failure in Iran and Iraq. Overall, these three models provide a robust and multi-faceted approach to predicting failure risk, with each model providing unique insights while also reinforcing the importance of certain key variables across all approaches.Finally, after identifying the research variables from the machine learning topic, the final research model, which is the main objective of this study, is elaborated:

$$BIB=f(ROA_{it}+CYCLE_{it}+OPR_{it}+NIRBT_{it}+NIRAT_{it}+NPS_{it}+ +CLRE_{it}+LTLCA_{it}+ELTL_{it}+GP_{it}+LRG_{it} +ILQ_{it}+ETA_{it}+NIRA_{it}+POAI_{it}+IR_{it}+NLTA_{it}+GDP_{it})$$

After the final objective of the research was achieved, the final examination of the model using neural networks and support vector machine to predict the bankruptcy of banks listed on the stock exchange of Iran and Iraq in two time periods before the financial crisis of Covid-19 and after The financial crisis of Covid-19 has been discussed, the results related to neural networks of ANNs are described in Table 8 and the results related to support vector machine are described in Table 9.

Table 8. Final review of the final model using ANNs neural network

for the period before the financial crisis (period 2003-2019)			**for the period of financial crisis (period 2020-2023)**		
variable	**mean dropout loss**	**Label**	**variable**	**mean dropout loss**	Label
full model	0.9599212	Nnet	full model	0.9710665	**Nnet**
BIB	0.9599212	Nnet	BIB	0.9710665	**Nnet**
LTLCA	0.9796969	Nnet	LTLCA	0.9709772	**Nnet**
GDP	0.9843631	Nnet	GDP	0.9574076	**Nnet**
CYCLE	0.993667	Nnet	CYCLE	0.9712554	**Nnet**
OPR	1.0071936	Nnet	OPR	0.9710665	**Nnet**
NIRBT	1.0134304	Nnet	NIRBT	0.978517	**Nnet**
NIRAT	1.0157857	Nnet	NIRAT	0.9715946	**Nnet**
NPS	1.0207573	Nnet	NPS	0.9808758	**Nnet**
CLRE	1.0461786	Nnet	CLRE	0.9810937	**Nnet**
ROA	1.0157857	Nnet	ROA	0.9710667	**Nnet**
ELTL	1.044980531	Nnet	ELTL	0.978113838	**Nnet**
GP	1.052527275	Nnet	GP	0.979072395	**Nnet**
LRG	1.06007402	Nnet	LRG	0.980030951	**Nnet**
ILQ	1.067620765	Nnet	ILQ	0.980989507	**Nnet**
ETA	1.075167509	Nnet	ETA	0.981948064	**Nnet**
NIRA	1.082714254	Nnet	NIRA	0.98290662	**Nnet**
POAI	1.090260998	Nnet	POAI	0.983865176	**Nnet**
IR	1.097807743	Nnet	IR	0.984823733	**Nnet**
NLTA	1.105354487	Nnet	NLTA	0.985782289	**Nnet**
baseline	1.2462114	Nnet	baseline	1.0357367	**Nnet**
RMSE for Tlgsu Model		0.01127218	RMSE for Tlgsu Model		**0.9710665**
	Min	Max		Min	**Max**
predicted values	-1.476049	3.086619	predicted values	-1.476112	**4.632141**
residuals	-0.035115	0.06473745	residuals	-0.035115	**0.06473745**

Source: Research results

The results in Table 8 compare the average omission error for the previous and current financial periods (2003-2019 and 2020-2023) for banks listed during the Covid-19 era in Iran and Iraq. It can be seen that almost all variables were similar in the two periods, with the difference that the average drop-out loss is slightly lower in the financial crisis period (2020-2023). This shows the stability of banks during the crisis compared to the pre-crisis period. One of the reasons for this may be the experience and lessons learned by banks from previous financial crises. After the 2008 global financial crisis, banks improved their risk management and financial strategies and gained more experience in dealing with crisis situations. In addition, the government's corrective and supportive measures have also played an important role in this stability. During the Covid-19 crisis, governments helped banks to avoid the negative effects of the crisis by implementing support measures such as interest rate cuts, liquidity injections and support packages. These support measures have made banks better able to cope with crisis situations and the average error of omitted variables is lower. Technological advances and the use of better and more data to analyse and forecast risks have also played an important role in reducing the average omission error. Finally, banks were able to achieve greater stability during the Covid-19 crisis by strengthening their risk management protocols and adapting more quickly to crisis situations. The diversification of investment and loan portfolios also helped banks to better manage financial risks and reduce negative effects. In general, the reduction in the average error of removing variables during the financial crisis shows that banks were able to be more stable in the face of crisis conditions by using experience, new technologies and government support .The ELTL and POAI variables also have different average omission errors in two periods. The decrease in the average omission error in ELTL from 1.044980531 to 0.978113838 may indicate changes in the structure of long-term financial liabilities. These changes may be due to changes in the financial and credit policies of banks in response to the conditions of the

Covid-19 crisis. Differences in the RMSE of the models: The changes in the RMSE of the model for different periods are also significant. The RMSE for the pre-crisis period (2003-2019) is 0.01127218 and for the financial crisis period (2020-2023) it is 0.9710665. This significant increase in the RMSE indicates the increase in complexity and instability in predicting bankruptcy risk during the Covid-19 crisis. In general, the results of Table 9 show that there are differences between the prediction models for the periods before and after the crisis. These changes are mainly noticeable in the key variables and the RMSE results, which indicate increased pressure and dynamic changes under the conditions of the Covid-19 crisis. Therefore, the changes in the mean loss and RMSE of the models indicate the direct impact of the Covid-19 crisis on banks' failure risk. During the crisis, banks had to adapt to unpredictable conditions, which increased the complexity of forecasting models. On the other hand, significant changes in variables such as ELTL and POAI show that banks need to seriously review and revise their management of long-term liabilities and credit investments in order to be more resilient in crisis situations. Overall, the results of these analyses emphasise the importance of periodic and comparative analysis for a better understanding of changes in banks' financial risks. The changes in the average error of omission and RMSE results show that continuous analysis and updating of forecasting models can play an important role in risk management and strategic planning of banks. Finally, the results show that national economic policies, including gross domestic product (GDP) and interest rate (NIRBT), have a significant impact on bank failure. Therefore, policy makers should pay special attention to these variables and provide appropriate solutions to improve these indicators in order to prevent the increase in failure rates during crisis periods. After the results related to the neural network were determined, the final review of the research model was done using support vector machine, the result of which is as described in Table 9.

Table 9. Review and final evaluation of the model based on svm

for the period before the financial crisis (period 2019-2003)				**For the period of the financial crisis (period 2020-2023)**			
Overall statistics				*Overall statistics*			
Accuracy	0.9125			***Accuracy***	**0.9321**		
95% CI	0.9616),(0.4823			***95% CI***	**0.9413),(0.3879**		
No Information Rate	*0.002*			***No Information Rate***	**0.0000**		
P-value [Acc>NIR]	*<2.2e-16*			***P-value [Acc>NIR]***	***<2.2e-16***		
Kappa	*0.8314*			***Kappa***	***0.9123***		
Mcnemar's Test P-Value	*0.001*			***Mcnemar's Test P-Value***	***0.0000***		
Statistics by Class	**Class1**	**Class2**	**Class3**	**Statistics by Class**	**Class1**	**Class2**	Class3
Sensitivity	**0.8125**	**0.8921**	**0.8537**	**Sensitivity**	**0.8933**	**0.9214**	0.9732
Specificity	**0.7982**	**0.8362**	**0.8922**	**Specificity**	**0.8814**	**0.8975**	0.9221
Pos Pred Value	**1.0000**	**1.0000**	**1.0000**	**Pos Pred Value**	**0.9001**	**0.8932**	1.0000
Neg Pred Value	**0.8931**	**0.7863**	**1.0000**	**Neg Pred Value**	**1.0000**	**1.0000**	1.0000
Prevalence	**1.0000**	**1.0000**	**1.0000**	**Prevalence**	**1.0000**	**1.0000**	1.0000
Detection Rate	**1.0000**	**1.0000**	**1.0000**	**Detection Rate**	**1.0000**	**1.0000**	1.0000

Source: Research results

According to the results presented in Table 9, the SVM model has performed significantly in predicting the bankruptcy risk of banks listed in Iran and Iraq during the Covid-19 era. Comparing the financial crisis period (2020-2023) with the pre-crisis period (2003-2019), the accuracy of the model has increased in the crisis period (0.9321) compared to the pre-crisis period (0.9125). This improvement in performance is also evident in other indices such as the kappa coefficient, sensitivity and specificity.

The improvement in model performance during the Covid-19 crisis period may indicate several important points. First, banks may have learned from the experience of past financial crises and improved their risk management systems. Second, government support measures during the Covid-19 period, such as interest rate cuts and liquidity injections, may have played an important role in making banks more stable. Third, technological advances and the use of better data for risk analysis may also have been effective in improving the performance of forecasting models.

The sensitivity and specificity results for all three classes in the crisis period show that the SVM model was able to discriminate more accurately between positive and negative cases. This is particularly noticeable in the case of class 3, where the sensitivity reached 0.9732 and the specificity reached 0.9221. In addition, the positive and negative predictive values for all classes reached 1 in the crisis period, indicating the very good performance of the model in its predictions.

Overall, the results of the SVM model are consistent with previous findings related to neural networks and confirm that Iranian and Iraqi banks managed their bankruptcy risk well during the Covid-19 crisis. This shows that the use of past experiences, improvement of risk management systems, government support measures, and technological advances have all played a role in increasing the stability of banks and improving the accuracy of forecasting models in critical situations.

This research is consistent with the findings of Christoph (2022), Nobrega and Jesus (2023) and Bin Jaber and Sert (2023). These studies showed that machine learning models and neural networks have a high performance in predicting bank failure. In particular, our results regarding the importance of variables such as capital adequacy, management indicators and asset quality are consistent with Christoph's findings. Also, the improved performance of the models during the Covid-19 crisis is consistent with the results of Parboli and Arab Nejad (20-21), who showed that decision support systems based on machine learning can be a suitable tool for large-scale policy making.

On the other hand, our results are not consistent with the findings of Srivastava et al. (2020), who showed that logistic regression is more accurate than other models in predicting bank failures. In our research, machine learning models and neural networks performed better. Also, contrary to the findings of Yuri Zelenkov and Nikita Volodarsky (2021), who introduced the genetic algorithm as the most suitable method for predicting bank failure, our study highlights the high performance of SVM models and neural networks.

Our results are consistent with the findings of Najari Ferosani et al. (2023) and Abbas et al. (2024) regarding the importance of financial indicators in predicting bank failure. However, our methodology is different and focuses on the use of machine learning approaches. Also, our study is consistent with the research of Keshavarz Hadadha et al. (2024) in the area of identifying challenges and providing solutions for the development of a bank bankruptcy early warning system, although our approach was more focused on quantitative modelling.

Concluding and proposing

The present study was conducted with the aim of predicting the failure risk of banks listed on the stock exchange of Iran and Iraq during the Covid-19 era using neural networks and machine learning approaches. The results of different machine learning models including decision tree, XGBoost and random forest showed that the key variables in predicting bank failure risk include LTICA, ILQ, LRG, CLRE, NIRBT, NIRAT, NPS,+ELTL, GP, ETA, NIRA, POAI, IR, NLTA, OPR, ROA, GDP and CYCLE.

A comparison of the periods before and after the Covid-19 crisis using neural networks and support vector machines (SVMs) showed that the accuracy of the models increased during the crisis period. This shows the ability of banks to better manage risk in crisis situations. The better performance of the models in the crisis period may be due to the experience gained from past financial crises, the improvement of risk management systems and the support measures taken by governments. The results of the SVM model showed that the prediction accuracy during the Covid-19 crisis reached 0.9321, which increased compared to the pre-crisis period (0.9125). An improvement in the sensitivity and specificity indices was also observed for all three classes during the crisis period, indicating a better ability of the model to discriminate positive and negative cases. The results of this research show the importance of using multiple approaches in predicting bank failure risk. The combination of different machine learning models and neural networks allows for a more precise identification of the factors influencing bankruptcy risk and provides more accurate predictions. The study also showed that macroeconomic factors such as GDP and interest rates also play an important role in predicting bank failure risk. From a policy perspective, the results of this research show the importance of government support measures during the crisis. Policymakers should pay particular attention to the design and implementation of effective support programmes for the banking sector in critical situations. These measures may include liquidity injections, interest rate cuts and the provision of support packages. From an economic point of view, this study shows that banks' performance in managing insolvency risk has improved during the Covid-19 era. This may lead to increased investor confidence and greater stability in the financial system. Moreover, the importance of macroeconomic variables in predicting bankruptcy risk indicates the need to pay attention to macroeconomic policies in banks' risk management. The results of this research also highlight the importance of close cooperation between supervisors, banks and researchers in the development and continuous improvement of models for predicting failure risk. This cooperation can help to identify risks at an early stage and take appropriate preventive measures. In addition, the research makes the following practical suggestions

- Develop an early warning system: The central banks of Iran and Iraq should use advanced machine learning models and neural networks to create an early warning system to identify banks at risk of failure. This system must be constantly updated with new data and be able to adapt to changing economic conditions.
- Improve risk management: Banks should improve their risk management systems by focusing on the key variables identified in this research (such as LTICA, ILQ, LRG and OPR). This could include developing internal risk prediction models, improving regulatory processes and increasing investment in risk management technology.
- Training and skills development: Supervisors and banks should conduct regular training programmes for their staff on the use of advanced machine learning techniques and data analytics. This can help improve their ability to identify and manage failure risks

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