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Predicting the bankruptcy risk of listed banks (Case Study of Iran and Iraq) the machine learning approach.

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Abstract

This investigation intended to predict the probability of bankruptcy in the Iranian and Iraqi stock exchanges, utilizing neural networks and machine learning techniques during the COVID-19 crisis. The investigation considered two separate time periods: the pre-Covid-19 period, which extends from 2003 to 2019, and the post-Covid-19 financial crisis period, which extends from 2020 to 2023. The primary concern was creating a model that would be employed in the forecasting of bankruptcy risk in Iranian and Iraqi banks. Different machine learning models, including decision trees, XGBoost, and random forests, were employed in this study. The key variables in the study of how to predict the risk of bank failure were found to be LTICA, ILQ, LRG, and CLRE. These variables were used to predict the risk of bank failure. The performance of neural networks and support vector machines (SVMs) increased during the pre- and post-Covid-19 eras, this was attributed to the increased prevalence of crises. It was confirmed that the forecast accuracy of the SVM model increased by 0.9321 during the period of Covid-19, while it was still 0.9125 before the crisis. Other improvements were apparent in the indices of sensitivity and specificity from all three classes during the crisis. The results suggested that it's very important to utilize multiple approaches in predicting the risk of bank failure. This is because combining different machine learning methods and neural networks increases the effectiveness of recognizing the causes of company bankruptcy. This also demonstrates the significant influence of macroeconomic variables, such as GDP and interest rates, in the models associated with predicting the probability of a bank's failure. The investigation focuses on the value of government assistance during crises that were augmented by the enhanced risk management prowess of Banks during the Cobra era (Covid-19). Practical suggestions derived from this research include the creation of an early warning system, enhancement of risk management methods, and regular training for the employees of banks and their supervisors .

Keywords: Prediction of bankruptcy, COVID-19, neural networks, machine learning, Iran, Iraq

Introduction

These days, banks play a big role in the economy. They are referred to as the main financial assets in a number of different economic domains, including investment and service delivery. In addition to granting credit to investors based on their financial needs and the objectives of economic development, banks are also responsible for ensuring the security of financial transactions. Banking is the system that is most likely to result in a universal financial regulatory framework that will fuel a worldwide financial catastrophe in a world that is changing quickly. Since the bank's bankruptcy, which precipitated a financial crisis, is the root cause of this problem, many attempts have been made to forecast it, mostly beginning in the 1960s (Edvar Altman, 1968). Most people agree that one of the most important economic sectors in both developed and developing nations—especially Iran and Iraq—is the banking industry. Economic development (especially in the form of economic growth and development) would not be feasible without the provision of capital in the form of a significant pillar to support output. Like Patrick in 1966, he claims that the banking industry's performance drives economic development in its early stages. This hypothesis, known as demand following, contends that in underdeveloped nations, the absence of banks and other financial institutions is a direct result of demand for the offered services. Supply-leading, however, can happen when the economy picks up steam and the causal link is reversed. In this particular case, the enhanced efficacy linked to the banking system's function in resource mobilization guarantees economic expansion subsequent to the nation's advancement. Mhadhbi Khalil et al., 2017). Increasing the banking sector's efficiency will, in general, maximize the potential for economic growth while resulting in the most efficient use of the nation's resources. In addition, a nation's capacity to refocus its resources in a more efficient manner is linked to a stronger financial sector; this will result in the most potential economic growth (Allen & Santomero, 1997). Finally, but just as importantly, banks and other financial institutions play a critical role in advancing the nation's economy. Economic analysis has actually shown that banks will, as they improve their operations, find ways to make better use of the capacities at their disposal. Whether it is through risk management services or alternative credit options, the objective is to ensure that resources are used as effectively and efficiently as possible (Lane et al, 1994). The bank's widest range of credit is linked to the highest level of liquidity. It may be concluded from the numerous studies carried out over the previous few decades that improved financial services have the ability to spur economic expansion. Using more sophisticated statistical methods, this favorable link has also been found (Matei, 2020).

forecast of insolvency. The neural network of the Covid 19. There is a strong correlation between machines and national macroeconomic structures, and any anomaly or instability in the machines can have a big impact on the macroeconomic factors of the nation, including production. The macroeconomic environment undergoes major changes during global financial crises (Kenny et al., 2021). One prominent example of this was the period of time when the Corona virus first appeared, which had an effect on the energy market and caused a large decline in oil prices. Subsequently, the gold market started to change, which changed how nations did business (Gharib et al., 2021). This leads to attempts by the government to modify most of its plans and goals on a budgetary basis.

As a depository institution, banks provide resources to those who require business funding, namely small, medium, and micro businesses. The distribution of resources to the real sector functions to promote the economy for society (Gherghina et al, 2020). To play the strategic role of banks, measures must be taken to increase the quality and quantity of their savings and credit while maintaining economic stability (Bhegawati and Utama, 2020). In theory, a sustainable national development can be achieved through creating a healthy and flexible banking system as a crucial component of a country. This system is important because it supports the country's economy by providing payment systems for cash transactions, both domestically and internationally. These transactions are intended to support economic activity (Harahap et al, 2017). As a result, the financial health of the banking industry is crucial to economic stability and growth. Ultimately, the financial health of the banking industry is crucial to the stability and prosperity of nations. Since the banking system has a significant impact on the economic development of a country, a banking crisis can have a significant effect on the economic activities of a country (Tamás Kristóf, 2021). As a result, bankruptcy is considered to be a significant banking crisis, that is, if the bank is subject to bankruptcy, the economy will also be subject to it. As a result, bankruptcy is the common name for this phenomenon, which in recent years has been of interest to managers of financial institutions, central banks, creditors, and other economic participants. (López-Iturriaga and Pastor Sanz, 2014). As a result, since the signs and symptoms of potential bank failure are apparent prior to bankruptcy, the recognition of bankruptcy indicator variables can be beneficial in predicting bank bankruptcy, When managers of financial institutions, creditors, banking managers and policy are aware of and take action on a banking crisis or bankruptcy, a new opportunity is available to them. Another way, the spread of COVID-19 has led to adverse economic effects around the world, these effects include supply chain disruptions (Hosseini and Ivanov, 2021) and economic crises that increase the probability of financial insolvency and the risk of bank failure (Chen et al, 2021). In the context of economic crises that are exacerbated by COVID-19, it's important to predict the potential for financial issues, such as bank failures, because of several reasons. First, it improves the quality of resource allocation. Both banks and individual investors seek information to assess the financial viability of publicly traded companies and identify potential financial disasters. Effective bankruptcy analysis can assist players in the market in capitalizing on opportunities while also allowing managers to take preventative action, leading to an intelligent allocation of resources that supports economic growth (Gärling et al, 2009). Additionally, accurate predictions of bank failures have value for policy makers. It assists them in avoiding structural failures, which would lead to financial difficulties. Since bankruptcy is a central topic in political conversations at every level, the capacity to predict financial events has become crucial to policy making (Caggiano et al, 2014). Additionally, recognizing the symptoms of bankruptcy allows management to address the underlying issues and prevent the propagation of financial difficulty, this is particularly important in public institutions like banks that are responsible for safeguarding public assets (Campbell, 2007). Lastly, bankruptcy predictions can be utilized as early indicators of significant industry declines. Robust predictions tools allow both legislators and managers to preempt and prepare for upcoming issues, this prevents crises in specific industries from occurring (Gounopoulos et al, 2023). These models also serve as a form of investment guidance, which causes investors to make more informed decisions that can mitigate the financial harm associated with financial failures (Kandrac, 2014). Additionally, credit rating agencies often utilize bankruptcy predictions to assess the financial health of a company accurately, this is done by influencing the credit rating of a company and by highlighting the connection between bankruptcy predictions and credit risk assessment (Abbasi et al, 2021).

In conclusion, with reference to the aforementioned, it should be noted that the bankruptcy forecast is crucial and necessary for growing nations, particularly Iran and Iraq. The banking industry plays a crucial part in the economies of both Iran and Iraq due to the banks' substantial influence in these two nations. Iran's financial scene serves as evidence of this. The capital market's function in the nation's economy has been superseded by banks' superiority in the provision of financial services. The way that funds were distributed in 2011 serves as an example of this dynamics. wherein the capital market accounted for only 6.2% of the funding, and the banking industry contributed a substantial 91.3% of the total. When we look back to 2012 and 2013, we see a pattern that remained constant: banks controlled 86.5% of the funding position, while the capital market's contribution was only somewhat important at 9.5% and 7.6%. Remarkably, a sizable portion of banks took part in ensuring that the investments required for Iran's economic expansion were made possible. about 90% (Komijani Akbar, 2015). Therefore, we will update the discussion about the funding of investments during the years 2016–2022, in order to gain a better understanding of the bank's significance to the Iranian economy. Specifically, the share of Bankha in the funding of investments during the years 2015–2017, 2018, 2019, and 2011 was equal to 64%, 51%, 88%, 67%, 57%, and ultimately 84% are (Taheri et al, 1402). Therefore, it is hard to overlook the important and vital role Iranian banks play in the nation's economy in this case because the financial structure of the Iranian economy is primarily built on banks (Baghri et al., 2016). On the other hand, it is clear from looking at Iraq's economic structure that the nation's economy, like Iran's, is dependent on financial institutions. This suggests that banks play a major role in financing social and economic projects and have a direct impact on economic development, meaning that the economy of Iraq is dependent on them (Hussein et al., 2022). All things considered, banks are important to every contemporary economy since they offer financial services and act as intermediaries between savers and investors. There are several reasons why banks are becoming more and more significant in Iraq. Following the worldwide financial crisis of 2003, the Iraqi economy was beset by a number of instability and issues, such as the drop in oil prices globally, civil wars, and the battle against ISIS, all of which had a detrimental effect on the nation's economy and government revenue. On the other hand, because of the 2015 crisis—which was more serious than the 2003 crisis—bank efficiency and health are crucial in this case to encourage economic recovery and lessen the damaging consequences of these calamities. The ability of the banking industry to support loans and credits to the Iraqi economy in the first year is one of the main reasons for its importance; these are especially important because the nation's banks have emerged as the main proponents of various economic ventures. These financial institutions become the cornerstone of economic growth in Iraq by bringing capital into the country and fostering business and production prosperity (Hussein et al., 2022). They also quicken the purchasing and selling cycle. Expanding bank credit availability can boost GDP per capita and act as a stimulant for economic expansion, especially in the wake of war and civil upheaval that have negatively impacted the Iraqi economy (Bin Faraj Abd al-Qadir, 2021). Iraqi banks play a significant social function in the second phase in addition to their economic one. By offering credits and loans for infrastructure and public service initiatives, They enhance people's quality of life and support social development. Because they may serve to improve the economy and withstand inflation and volatility by managing the quantity of money available and demand, banks also play a vital role in maintaining economic balance. According to Hasan et al. (2020), banks play a crucial role in facilitating financial processes by regulating the transfer of money between individuals and other economic entities. This is particularly important for the correct development and maturity of Iraq's financial markets, particularly in light of the consequences of previous conflicts. Thus, in order to help entrepreneurs and start-up businesses engage in the national economy, Iraqi banks offer credit lines and loans, respectively. These services are meant to kickstart and grow the business's operations. This lowers Iraq's unemployment rate and makes it easier to create jobs (Mahmood, 2018). On the other hand, banks play a crucial role in preserving Iraq's financial stability. They do this by reducing the nation's susceptibility to global economic volatility, which enhances the nation's financial security (Al-Khazraji & AL-Zaidi, 2020). In the end, this system's Central Bank of Iraq works to control the money supply and set interest rates in an effort to prevent inflation and encourage long-term economic growth. Furthermore, Banks help mitigate the consequences of financial crises and assist economic organizations in resolving financial challenges by offering structural solutions and programs (SHENG, 1991). All things considered, these actions are to blame for the money and trust that have returned to Iraq's economy, having accelerated the country's social and economic development during key post-war periods. Following that, a financial crisis will arise if the bank is unable to fulfill its obligations to investors, depositors, or beneficiaries because its nature and purpose are vital to the economies of Iran and Iraq (Tehran and Bigdalo, 2019). This leads to economic instability that is unrelated in this instance to the effects of bankruptcy and manifests itself as long-term declines and significant inflation. countries are important because their economies are reliant on the banking system. As a result, one of the most crucial and fundamental responsibilities of legislators and policy makers is to prevent bankruptcy from happening. In addition, because bankruptcy can have symptoms prior to its actual occurrence, certain variables can be used to predict when someone will file for bankruptcy. Financial institution management, creditors, bank managers, and policy makers are faced with a fresh opportunity when accurate and timely predictions of bankruptcy or banking crisis are made. These people are expected to make proactive choices and actions to stay away from bankruptcy and all of its related activities. Consequently, the main goal of this research is to develop a model that can forecast financial organizations' insolvency that are accepted onto the Iranian and Iraqi stock exchanges. Neural networks and machine learning will be used to achieve this.

Research literature

The importance of banks in the economy

The money market's operations, which are vital to national economies, are mainly carried out by banks (Tamizi, 2023). Banks have the ability to control interest rates through their monetary policies, and interest rates have a direct impact on productivity, investment, and inflation. As a result, banks have two roles: they sustain the economic system and supply financial resources. Banks have the potential to influence their clients' liquidity and economic viability through their monetary strategies and activities. In particular, banks can control inflation and exchange rates and preserve a healthy economic equilibrium by changing the interest rates on bank notes and money transfers (Tsendliani, 2022). All things considered, the banking system can help people and organizations achieve their financial needs by managing capital, facilitating transactions, controlling liquidity, managing financial risk, and supplying financial resources. Because of this, banks and the banking system play a big part in the economy. Regarding this, a number of global studies have also shown a strong positive correlation between banking activity and economic expansion, suggesting that the development of banks plays a bigger part in economic advancement (Abdollahi Marafe, 2022). For example, Valeria Dinger and colleagues' (2022) study, which examined the relationship between bank aid and economic growth, showed that capital injections, loans, and other forms of help had a favorable impact on economic growth. result in an improvement in the financial support provided by banks and, consequently, a rise in societal economic progress. In a different study, Olivo and Laurens (2022) found that bank loans and economic growth are positively and significantly correlated for 132 nations. Alternatively, in Zeynalova's analysis from 2023, which looked at the amount of credit linked to Azerbaijan's economic expansion, In the short run, there was a strong correlation found between bank loan volume and economic development; in the long run, there was a strong and positive correlation found between credit volume and the rate of economic development. Increased bank credit in the United States is linked to higher employment in the short run and longer-term economic growth and development, according to a different study by Orzechowski (2024) that looked into the relationship between bank credit and employment and economic growth.

As the forerunners of the financial system, banks play a major and varied role in the economy. In their capacity as financial intermediaries, banks play a vital role in the economy. As financial mediators, banks provide a variety of financial services, according to Kent and Dietrich Giach (1997). Because they offer a range of financial services including capital management, lending, account supervision, electronic money processing, and liquidity creation, banks consequently have an impact on the funding process, promoting investment and economic growth (Tamizi, 2023). Because of this, banks play a critical and evident role in the economic and financial systems of today's society (Mansoor Khan and Ishaq Bhatti, 2008). Banks are responsible for facilitating credit availability, improving the speed and security of financial transactions, and acting as the hubs of the economy. Because banks manage financial resources and provide money to many economic sectors, their performance is critical to the nation's economic system (Van den Heuvel, 2012). In the end, banks are among the main drivers of economic growth since, in addition to facilitating financial transactions, they also help to finance projects, offer guarantees, and make financial resources more accessible. By allocating liquidity to profitable ventures, banks promote economic growth and increased productivity.

In his study on the relationship between the Vietnamese economy and bank credit, Duke (2024) found that economic growth and development grew throughout time in tandem with the expansion of bank lending to the private sector. Walid Ashour Khalid (2024) examined the impact of bank loans on economic growth in Iraq in a different study. According to his research, bank loans and Iraq's economic growth are correlated. Finally, in an additional investigation conducted by Taherpour et al. (2018) designed to examine the impact of bank loans and credit distribution on Iran's economic growth. Based on research findings, it was found that the impact on economic growth increased with the percentage of past-due loans and credits to GDP. Thus, by offering loans and credits, banks promote the expansion of the economy, the growth of industry, and the creation of jobs (Jimenez et al., 2012). Consequently, most research on the topic shows a strong and positive correlation between banking activity and economic growth (e.g., all of which highlight the importance and indisputable nature of the banking system and its role in the economy of nations, particularly those of Iran and Iraq, whose economies are largely dependent on it. In the end, banks dominate

Iran's economic structure, with bank credit accounting for a larger proportion of total credit than capital market share. For example, in 2012, the capital market constituted only 6% of the total, but 91% of banks offered funding. The combined proportion of the banks in 2013 and 2014 was 86.5%, and in 2015 it was 90.7%, indicating that this trend persisted. The aggregate share of the capital market was 9.5%. and the banks' total ownership was 89.2%. Remarkably, banks have supplied about 90% of the bank finance for the Iranian economy (Komijani, 2015). We looked at data from 2016 to 2022 in order to perform a more thorough analysis of the function that banks play in the Iranian economy. According to Taheri et al. (2023), this indicated that the proportion of banks in these years was 64%, 51%, 88%, 67%, 57%, and 84%, respectively. Based on the previously mentioned data, Iranian banks are a significant contributor to the nation's economy. (Bagheri et al., 2016).

On the other hand, just like Iran, Iraq's economy is reliant on banks. Iraqi banks directly influence economic development and have a major role in providing capital for social and economic projects (Hussein et al., 2022). The post-Iraqi invasion economy, which has been plagued by several issues and volatility, remains dependent on banks. The fight against ISIS, internal conflict, and the decline in global oil prices are some of the major issues that have made banks' position more important. These crises have had a substantial detrimental impact on government finances and economic stability (Mushtal and Ahmad Siddiqui, 2017). To encourage economic recovery and lessen the effects of calamities, Iraq's financial institutions must be strong and functional. Nowadays, the main source of finance for economic development across the country comes from the banking sector in Iraq. In the Iraqi monetary system, bank notes and loans hold particular significance. Banks are acknowledged for serving as intermediaries between investors and depositors, a function that is crucial in contemporary economies and has contributed to the growth of banks in the country (Allen and Masih, 2017).

Because of this, the banking industry is regarded as one of the most important in any nation and has a big influence on financial resources, economic expansion, and economic development. Through the provision of loans and credit lines, banks enable the financial resources required for economic growth and development (Ferial et al., 2023). Additionally, by offering financial instruments like accounts, payment documents, and loans, banks help firms communicate financially and exchange goods and services (Mustafa Hao et al., 2023).

COVID-19

Wuhan, China is home to the novel coronavirus (SARS-CoV-2) that produced COVID-19. The ailment is a respiratory disease that was first identified in December 2019. This disease quickly spread and turned into a global epidemic that affected many aspects of daily life. As a result, it had a detrimental effect on the global economy, health, and society (Chakraborty and Maity, 2020). The most mysterious, widespread, and devastating external economic shock in history is believed to have been brought on by COVID-19. This pandemic is seen as an external shock, which means that it was not caused by financial or economic causes but rather directly impacted the real world and the financial system. In contrast to the global financial crisis, it affected a wider portion of the world (Yildirim and Erdil, 2024). Owing to .Due to economic disturbances, which raise the likelihood of financial troubles and the possibility of bank failure, the COVID-19 pandemic has a substantial effect on the banking sector (Marco, 2021). Because of this, the effect of COVID-19 on bank failures in the economy might be different from that of other markets. In March 2020, for example, a significant quantity of money was taken out of existing credit lines during the early stages of the crisis, a phenomenon known as the "rush for liquidity." huge corporations that retira from huge banks aided many of these retirements. It was noted in this context that banks with higher levels of direct involvement in credit line withdrawals had stricter lending guidelines for new. This is because leverage-based financing was the most prevalent form of financial crisis during this time, which would lead to increased debt loads, uneven cashflows, and negative effects on bank profits. Additionally, the decreased capacity of banks to pay their financial obligations could lead to a significant drop in share value and lead to a negative cycle that would lead to the potential failure of the bank (Kose et al., 2021). Many investigations have focused on this topic.

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. Alternatively, the data is based on a different study by Yan et al. (2023), they studied the effects of the COVID-19 crisis on the overall risk of banks. Their findings demonstrated that the COVID-19 pandemic had a significant impact on the banks contribution to global risk. Second, the impact of the COVID-19 virus was more severe in developed countries than in developing countries. Ultimately, larger banks with higher loan to deposit ratios are more susceptible to the COVID-19 crisis, while the capital levels of these banks are not sufficient to mitigate the effects of this crisis, which may also lead to potential bank failures. Ultimately, it is observed that COVID-19 causes global financial crises, which increases the probability of bank failure. As a result, predicting the failure of banks during the financial crisis caused by COVID-19 is more pertinent, this pandemic has led to global financial crises, this increases the probability of bank failure. Under these conditions, accurate predictions can prevent the financial system from becoming disrupted. This is because the insolvency of one bank can have indirect effects on other banks and the entire economy, and accurate predictions can prevent these effects (Li et al., 2021). Additionally, predicting bank failures facilitates the protection of depositors' interests and prevents social catastrophes caused by the loss of money. Banks have a significant role in the economy, and predicting and preventing their failure can help to maintain economic stability. Additionally, these predictions facilitate the banks in improving their strategies for risk management (Buratynska, 2021). Ultimately, predicting bank failures facilitates policy makers to take effective preventative and supportive actions. This can promote public faith in the banking system and facilitate more accurate monitoring of banks at risk (Keshavarz Haddad et al., 2024). These factors become more significant in crises like the COVID-19 pandemic, when the financial system is more pressured and the need for a swift and accurate response increases.

Bank Bankruptcy

A bank's influence on people's lives and a nation's economy is substantial because it is a financial institution (Jafari Samimi, 2018). The inability of a bank to fulfill its financial commitments and debts in full results in bankruptcy. Usually, one of two things leads to this situation: either poorly managed investments, nonpayment of loans, or both (Beinabadi, 2023). More specifically, according to Hola et al. (2021) bankruptcy is defined as the inability of the bank to pay off all of its debts and financial commitments. Therefore, it is reasonable to say that the banking system and the public's confidence in banks are significantly impacted by bankruptcy. Because of this, the unsustainable debt growth, Bankruptcy may result from a decline in bank capital as well as investor fears about the emergence of a financial crisis (Ahmadian and Gorji, 2017). As a matter of fact, bankruptcy has far-reaching, significant impacts that occasionally have the potential to negatively impact the nation's economic strength and prosperity (Bayar et al., 2021). In the end, a bank's failure may result in its dissolution, a change in ownership, or a merger with another bank; these events may impact other banks and cause problems financially and may result in bankruptcy (Simaei Sarraf and Amini, 2019).

Because of this, bank failures have a big impact on the nation's financial system and economy, which raises prices and causes poorer output, increased unemployment, and less purchasing power. According to Sundarararajan and Balino (1991), this circumstance may also have an impact on the nation's imports and exports and obstruct the process of economic recovery. Because of this, bank failures pose a serious danger to depositors and consumers. People could lose their savings, which could have a long-term negative impact on their lives (Nasiri & Nasiri, 2021). Furthermore, these mishaps have the potential to erode public confidence in the banking system, resulting in capital flight and jeopardizing the long-term stability of other banks (Downes and Vaez-Zadeh, 1991). In such circumstances, the government is usually compelled to step in and supply capital in order to sustain banks and protect the assets and rights of its clients (Simaei Sarraf and Amini, 2019). On the other hand, as banks play a major role in financing individuals, businesses, and the government in Iran, bankruptcy might result in economic instability and should be avoided

(Nazarpour et al., 2016). Because of this, bankruptcy is viewed as a detrimental element of the Iranian economy, and appropriate safeguards should be put in place to prevent it. Many studies have been conducted on bankruptcy and how it is forecast; a few of these will be covered in the sections that follow.

In a study published in 2020, Srivastava and colleagues used machine learning, logistic regression, and other techniques to forecast Indian bank insolvency for the years 2000–17. The parameters included in the prediction were total liquid assets, total fixed assets, total revenue, current liabilities, equity, bonds, and reserves. The findings showed that compared to other models, logistic regression was more successful at predicting bank failure. But they and he came to the conclusion that the best indicators of bankruptcy were financial ones, such as equity, capital availability, net income, and others.

Yuri Zelenkov and Nikita Volodarsky (2021) looked into the possibility of using unequal data and a neural genetic algorithm to forecast the insolvency of banks in Poland and Russia. His colleagues' research indicates that the genetic algorithm outperforms other methods in predicting financial institutions' insolvency. When banks are unable to repay their debts, they became financially indebted.

Machine-learning techniques were used by Parboli and the Arab Nejad (2021) to anticipate bankruptcy in the short- and long-term. The study's authors also took into account the current COVID-19 epidemic, leading them to believe that large-scale policy making could benefit from the suggested decision support system framework using machine learning vectors.

With parameters like the income ratio, capital adequacy, equity, manageability indices, and asset quality indices, Christoph (2022) used logistic regression, decision trees, and deep learning neural networks to predict the failure of banks in the European Union over an 11-year period. All three models, according to Christoph, were very accurate at predicting bank failure; however, the decision tree model outperformed the logistic and neural network models in terms of AUROC values. In the end, he came to the conclusion that measures related to capital adequacy, manageability, and asset quality were more important in predicting bank failure than other variables.

Nobrega and Jesus (2023) used sensitivity analysis and machine learning to investigate and forecast the bankruptcies of Brazilian banks. To forecast bank failure, they used economic factors and bank accounting data. In comparison to conventional prediction models, the results showed that machine learning and decision trees were highly accurate in forecasting bankruptcy. They also found that decision trees outperformed other models in the prediction of bankruptcy, with a high degree of accuracy and a low error rate. This finding is consistent with Christoph's research.

The goal of Najari Ferosani's team's research study from 2023 was to develop a model that would use the multiple logit approach to estimate the likelihood of bank failure in a set of Islamic countries. The goal was to develop a model that could forecast the likelihood of bankruptcy in the Islamic banking systems of eight distinct nations between 1998 and 2020. In this method, financial measures were taken into consideration as factors in estimating the probability of a bank failing, and the Z-score was used to predict that probability. Therefore, the study's conclusions show that there are more problems and risks, such as bankruptcy, with the Islamic banking system in a few chosen Islamic countries.. Raising the ratio of working capital to bank assets as well as the ratio of bank income before taxes and net assets may be taken into consideration as a way to avoid bankruptcy. Controlling the proportion of total bank liabilities to equity is another option. It was shown that the likelihood of a bank failing was not significantly influenced by the retained revenue percentage in relation to the overall amount of bank assets. Furthermore, because this model was developed using data from 1998 to 2020, it can be used in the future to develop early warning systems that would shield Islamic countries' banks from failure.

Hadadha Keshavarz et al. (2024). In their research, they examined the challenges and strategies required to create a more robust early warning system for Iranian bank failures by applying a post-positivist framework. He and his colleagues used eleven main factors and various methods to forecast bankruptcy in this study. Consequently, the research findings were integrated into ten primary concerns and constraints that are now facing the field, along with around eighty possible ways to tackle these ten problems. In the end, 13 main strategies were recommended to help Iran establish a bankruptcy warning system.

Abbas and associates (2024). They used a weighted lasso regression and 27 financial health variables to build a model of bank financial failure for the years 2010–2018. The findings showed that, as a financial instrument for the warning of bank failure in the Iraqi stock market, the adaptive lasso regression model with weights is more relevant and reliable.

Considering the important and vital role that banks and the banking system play in the economies of both Iran and Iraq, to put it another way, the growth and development of both nations' economies mainly depend on the banking system; in the event that one or more banks fail, demand for their deposit withdrawals will rise and other banks will become unable to carry out their mandate. A financial crisis will arise if these components are not adequately and consistently managed, and thus, There will be a financial crisis. Therefore, it is evident from a number of angles that research is required to prevent listed banks in Iran and Iraq from going bankrupt through the use of COVID-19: first, to maintain financial and economic stability. Since banks are an essential part of any nation's financial system, maintaining their stability and health is critical to averting financial and economic crises. Significant capital outflows and a decline in public confidence are two consequences of bankruptcy that are actively monitored and foreseen. 2. Having an impact on investment choices; Accurate information on banks' financial standing and possible bankruptcy risk helps investors make more educated decisions and lowers the risk associated with their investments. 3. Recognizing the COVID-19 pandemic's effects: The epidemics have had a significant influence on a number of economic sectors, notably the banking sector. Studies in this field can show how the outbreak has affected banks both immediately and over time. Understanding risk management strategies in an emergency is also beneficial. 2. The development of new forecasting models; the more precise the models, the quicker financial managers and policy makers can identify warning indicators and launch intervention and preventative strategies. efficient monitoring and policy-making; governments and regulators will be able to better understand regulatory laws and take appropriate legal action by researching and forecasting bank failure patterns.

In the end, research has shown that failures in the banking industry matter because they impact national economies as well as international markets. Information from this study can be used to reduce these risks and strengthen the banking system's resilience to future crises. Since the consequences and harms associated with bank and financial system insolvency are generally underestimated, stopping bank insolvency is seen as one of the most important and essential duties of lawmakers and politicians. This study aims to provide an explanation and interpretation of the bankruptcy prediction model for Iran and Iraq. In the end, the theoretical literature reviews and the research backdrop show that banks, as financial intermediaries, play a major and vital role in the economies of all nations, but especially those of Iran and Iraq, and have a variety of effects on the economic cycle. As a result, in order to stop financial disaster and recession in nations, the topic of bankruptcy prediction has gained significant attention in recent years. Nonetheless, it is evident from observation and analysis that there is a gap in this sector and that the topic of forecasting the failure of Iranian and Iraqi banks has not been thoroughly explored. Consequently, an effort was undertaken to fill the research void and offer a model based on machine learning and neural networks. for the future.

Research Methodology

The current study's research methodology is presented in this part. The following introduces machine learning models and neural networks as research methodologies, study data, and variables.

1) Machine learning models

One area of data science called machine learning lets you learn and get better at what you do without needing to know how to code. Machine learning solutions are beautiful because they don't require explicit programming; instead, they learn from experience. Taking everything into account, you select models and feed them data. The model then modifies its settings automatically to enhance the outcome. Predictions are made using a subculture of artificial intelligence called machine learning. These days, asset management, risk assessment, and other aspects of the accounting and financial system are greatly impacted by machine learning. as well as the examination of capital and financial conduct. Actually, there are several advantages for businesses using machine learning technology, including the ability to replace outdated systems and create unique solutions for their business (Rabiei, 1402). To put it briefly, machine learning is an important area of artificial intelligence that deals with developing computer-useable algorithms based on experimental data. The capacity of machine learning to find knowledge and generate highly intelligent, autonomous decisions is by far its most evident feature. The scale of machine learning algorithms must be used to execute the desired tests when vast data is required (Solis, 2019). In order to forecast the financial performance of Iranian banks that are listed on the Tehran Stock Exchange, a machine learning model was used in this study. This clarifies a few of the research's algorithms:

Decision Tree (BRT)

A decision tree is a statistical technique that uses a lot of data but does not rely heavily on the parametric assumptions of linearity or monotonicity. In order to prevent overfitting and boost prediction consistency, it uses a soft weighting function on the predictor variables and an average model. By skillfully capturing the intricate correlations present in the data, this strategy enhances prediction accuracy by utilizing soft functions that are carefully included into the predictor variables. The decision tree also makes use of a special type of average modeling, which boosts prediction stability and inhibits overfitting, all of which contribute to the robustness and dependability of the predictions generated. (Lakshmi and Kumar, 2022).

Gradient Boosting (XGBoost)

A performance enhancement toolset specifically designed for this purpose is distributed gradient boosting (Behra et al., 2013; Yan, Chen, Dong, Ju, & Xiu, 2022). It chooses the largest benefit from each step in a recursive binary partitioning technique to find the most efficient model. The gradient boosting method's tree-like structure makes it resistant to overfitting and insensitive to outliers, which makes the process of choosing a model much easier (Behra et al., 2023; Al-Badallah et al., 2023; Al-Badallah et al., 2023). Pasayt, Mitra, and Bawmik 2022; Amin and Jalal, 2022). The gradient boosting model's typical goal in the tth training iteration is represented by equation (2), where y_pred^((t)) and y_truth denote the loss resulting from the discrepancy between the predicted value y_pred^((t)) and the real context y_truth.

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

where $\Omega\ (f_k)\quad \gamma^T +) = \frac{1}{2} + \lambda \|w\|^2$ 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

One type of computational intelligence that is inspired by the biological brain is artificial neural networks. Artificial neurons (or points) comprise the interconnected layers that make up these networks. Each connection, like the biological nervous system's synapses, transfers information from one neuron to another. Neural networks can be used for a variety of tasks, such as classification, prediction, pattern recognition, and optimization. They are capable of learning and identifying patterns in data. Artificial intelligence domains including speech recognition, deep learning, and image processing frequently use them. Neural networks are a great tool for solving difficult, nonlinear issues because of their ability to learn from data and perform better over time. This is one of its main advantages.

Artificial Neural Networks (ANN)

It combines several machine learning concepts, such as gradient descent, ensemble, regression, and perceptrons. In order to transform the input variables into functions of the dependent variable's derived attributes, a linear combination of input variables is needed (Mishra et al., 2022). These are the simplest kind of deep networks; they consist of several layers of hidden neurons, each completely connected to the layers below and above (which they impact) and above (which they receive input from). Any overall goal can be accomplished by taking into account networks with ever more connected units. Each layer processes an input combination that is weighted linear and transforms it into an activation function. The weight of the connective tissue in a layer equals the output of the jth unit. 1, w_ji^1.Z_{j}= $g(\sum_{i=0}^{\mathrm{d}} w_{ji}^{1} x_i)$

3) Support Vector Machine

One state-of-the-art machine learning approach for regression and classification is the Support Vector Machine (SVM). The goal of this approach is to determine the best border with the largest feasible buffer between various data classes. Support vectors, or points that are near the decision border, are used by SVM to convert the data into higher-dimensional spaces, which allows the data to be divided into several classes. Due to its widespread application in domains such as image recognition, text classification, and financial predictions, as well as its success in high-dimensional spaces and resistance to overfitting, this algorithm is regarded as one of the most widely used machine learning techniques.

Support Vector Machine (SVM)

Cortez and Vepnik (1995) initially published the Support Vector Machine (SVM). This machine-learning approach, which addresses regression and classification issues, is being monitored by a number of sectors (Pant and Kumar, 2022). SVM is most commonly used as a method that generates the largest margin of cloud cover that distinguishes between various classes in classification tasks. Vectors of support are examples that are close to the maximum marginal plane for a certain learning task. Additionally, the discriminating function may be nonlinear or linear. A linear hyperplane can be used to separate the samples if the case is easily separable. The case is considered nonlinearly dissociated if this is not the case (Chia et al., 2022). A wider range of support vector machine models, as well as general predictions and estimation, have been added to SVM models. In response to this surge in development, Drucker and associates introduced SVR in 1996.

Research procedure

The initial phase of this study involved gathering research data from Iran's monetary databases, the Central Bank of the Islamic Republic of Iran, the nation's financial institutions, the OECD, Kadal, and other entities related to Iran's economy and finances. Then, these data are applied to both Iraq and Iran. Preprocessing of the data is done, which includes standardizing the data, removing outliers, and removing blank numbers from the data. The study then uses time as the most important factor in data segmentation; long term data (such as data collected over a 20-year period) is used to train neural networks and artificial intelligence. Next, data models have been used to forecast financial firms' insolvency related to the Iran-Iraq stock market. But one thing is for sure: the study's timeframe is divided into two parts: the first is before COVID-19, which is the second part; this is the period from 2003 to 1900; the second is the period after COVID-19, which is the precise time period from 2020 to 2023, during which COVID-19 affected every economy on the planet. The division of time is used to forecast Iranian and Iraqi bank failures during the COVID-19 crisis and evaluate the impact of the COVID-19 on bank performance.

Data and variables:

From 2003 to 2023, every bank in Iraq and Iran was included in the research population for this study. The variables of Tamás Kristóf (2022), Raffael Forch Brenes (2022), and Diguptia et al. (2023) were used in this inquiry with regard to the use of financial input factors. The factors related to Diego Petia's research are defined in Table 1, while the variables related to Kristof's research are described in Table 2.

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

Consequently, Diguptia et al. (2023), Thomas Kristof (2022), and Raphael Forsch Burns (2022) conducted three studies. According to this study, the Bank Insolvency Index (BIB) is a reliable gauge of a bank's operational efficiency and overall financial health. This index, which consists of eight crucial characteristics, focuses on two crucial areas in particular: capital sufficiency and profitability. The following is a description of the BIB:

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

Where:

1. TAM (Total Assets to Deposits Ratio): It's the total amount of assets and liabilities of a bank, divided by the total amount of assets and liabilities.
2. ETS (Equity to Total Assets): Indicates the percentage of total assets that are supported by shareholders' equity.
3. NIRE (Net Income to Equity): Indicates the return on shareholders' commitment.
4. NITA (Net Income to Total Assets): It demonstrates the overall profitability of the bank's assets.
5. TRCR (Total Return on Capital Ratio): It's the total return generated on the bank's capital.
6. TCR (Total Capital Ratio): The total capital of a bank is assessed in this ratio.
7. NIM (net interest margin): It's the profitability of the bank's primary lending activity.
8. NLTDB (Net Loans to Total Deposits andborrowings): Measures the bank's liquidity and the borrowed funds it relies on.

These criteria encompass a wide range of elements of a bank's financial performance, such as risk management, profitability, operational effectiveness, and capital structure. This model's underlying presumption is that a bank is insolvent if it has insufficient capital adequacy, insufficient income, and negative net profit. As a result, BIB, the study's dependent variable, provides a thorough indication of the financial health of banks. Rather than only evaluating a bank's financial health, this approach incorporates a number of characteristics into a single, more precise score. This will make it easier to identify financial problems early and take preventative action. The following will be the study model following the collection of the dependent variable:

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

Research findings

Key indicators are used in descriptive statistics to characterize the state of the data. The research variables' current state is displayed in Table (4) using indicators from descriptive statistics:

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

Each of the research variables has a non-normal distribution, according to Table 4's results. Given that every study variable has a probability of 0.00, or less than 0.05, the Jarque Bera test's null hypothesis—that the data should be greater than 0.05—has been rejected. The basic model of the research has been examined using machine learning, and it can be inferred that the results of descriptive statistics have been determined. It is also observed that the research variables do not have a normal distribution. Lastly, it is considered that conducting machine learning is contingent upon the absence of a normal distribution of the data.. As a consequence, Tables 5, 6, and 7 also display the machine learning findings.

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

The decision tree model's complexity parameters (CP) are listed in Table 7. The degree to which a new branch should be added to the tree is indicated by the complexity parameter. The number of divisions (nsplit), relative error (rel error), cross error (xerror), and standard cross error (xstd) are all related to the CP values. For example, the first CP number (0.8089961) corresponds to the amount of time that does not use segmentation, and the relative error is 1.0000000. The cross's error is 1.0039093, and its standard deviation is 0.3100613.. Relative error falls when CP decreases; for example, at CP=0.0100000 and nsplit=3, relative error drops to 0.1057375, indicating that the model's fidelity has improved. The factors used to create the decision tree are listed in Table 7. The LTICA method (used 20 times), the ILQ method (19 times), the LRG method (18 times), the CLRE method (17 times), the OPR method (17 times), the ETA method (8 times), and the NIRAT method (1 time) are some of these variables. Each variable's value and function in the construction of the tree are listed in this list. For example, the variable that was used the most (LTICA) had the biggest influence on the model's development, but the variable NIRAT was used just once, indicating a lesser influence. On the other hand, Table 3 shows the mean square error (MSE) value for various CP levels. The MSE for CP=0.808996 is 7.305882e+14, and it falls as CP drops. Likewise, at CP=0.01898876, the MSE value drops to 1.035209e+13, demonstrating that lowering the complexity parameter improves the model's performance. Likewise, the error of the root node is 1.0174e+17. It yields a value of 1.7571e+14 when divided by the total number of samples, 579. These values show that changing the complexity parameters reduces error and improves accuracy of the model. All things considered, Table 7's analysis shows how to select the right complexity parameters and make use of related factors to enhance the model's performance. Therefore, the variables listed above, which are the most often utilized in the model, are selected to develop the final model for forecasting the bankruptcy of financial institutions in Iran and Iraq. The decision-making tree for strengthenings is examined in the sections that follow; Table 6 presents the findings.

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 what the XGBoost model predicted. The first and last row numbers, forecasts, absolute errors, and squared errors for every sample are shown in this table. The first row, 627864, for example, has a squared error of 2.72136666e+12 and an absolute error of 332441.1. These errors show how the actual numbers and the forecasts differ from each other. from Table 8, which lists all 32 model parameters along with their respective gain, cover, and frequency. Gain is the contribution of each attribute to reducing the model's error. With a gain of 0.281, the LTICA characteristic is the most significant, and with a gain of 0.264, the OPR attribute is the second most significant. High influence features show which features have the biggest effect on the model. In addition to gain, two other metrics are covered and frequency: how often each feature is used in various model trees. Cover is the number of times each feature is used in various model trees. Consequently, variables having a GAIN of more than three are taken into account for the final model design in this section of the study. Random forests have been examined in the following; Table 7 lists the findings.

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		
R²: 0.824172829272972"		"MSE: 0.0041261684304433"	

Source: Research results

The importance of each attribute in the random forest model is seen in Table 7. A few of the crucial elements are the following: the GDP is valued at 1.191102e+14, the ROA is 5.431663e+14, the CYCLE is 8.370455e+13, and the OPR is 6.747677e+13. These high values show how important these traits are for outcome prediction and how much of a contribution they provide to the model. In contrast, Less significant features are those like LADS, which has a value of 1.005027e+14, and LPN, which has a value of 1.680100e+13. The efficacy of the random forest model may be evaluated using the following values: MSE = 0.0041261684304433 and R^2 = 0.824172829272972). Since (R^2) is close to 1, it can be concluded that the model explains a significant portion of the total data. More details regarding the mean squared error may be found in the (MSE) value; a lower MSE indicates a higher level of model accuracyThe ability of the random forest model with (R^2) and (MSE) attributes to explain and predict data has been shown. The model has been updated with features including GDP, CYCLE, and ROA, which have increased accuracy. As a result, in this section of the study, the variables with an influence larger than five are regarded as the ones that should be included in the model's final description. Overall, the random forest model has proven to be a successful model.

Regarding the projections of bankruptcy risk in banks that are listed on the Iranian or Iraqi stock exchange, the data in Tables 5, 6, and 7 leads us to the following conclusions and findings:
The accuracy of the decision tree model is heavily influenced by its complexity parameter (CP). With a decreasing degree of CP, the model's relative error decreases, indicating improved performance. The most crucial elements of the model were OPR, LTICA, ILQ, LRG, CLRE, and CLRE, which were all commonly used in the development of the tree. This implies that these factors have the greatest influence on the probability of failure for the institutions that are the subject of the inquiry.

The XGBoost model uses its higher information level to calculate the absolute and squared errors for each sample. The model concludes that OPR and LTICA are the two most significant features based on their gain values. This is in line with the decision tree's conclusions.
The random forest model gives an alternate way for finding the feature value. It focuses on ROA, GDP, CYCLE, NLTA, IR, ENL, ETA, and OPR because of their significant influence on the economy. This model performs well, as evidenced by its R^2 of 0.824, or about 82.42% of the data variance. The inclusion of economic factors in the random forest model, such as GDP and the cycle economy, suggests that the external economic conditions have a major impact on the probability of bank collapse in Iran and Iraq. These three robust models provide a thorough, versatile approach to calculating the failure risk. Despite concentrating on different aspects of machine learning, every model shares a
BIB=f(ROAit+CYCLEit+OPRit+NIRBTit+NIRATit+NPSit+CLREit+LTLCAit+ELTLit+GPit+ LRGit +ILQit+ETAit+NIRAit+POAIit +IRit+NLTAit+GDPit)

The ultimate goal of the research was accomplished when the model's final evaluation was conducted. Neural networks and support vectors were used to predict the bankruptcy of financial institutions listed on the stock exchanges in Tehran and Iraq in two distinct time periods: one before the financial crisis of Covid-19 and the other after the financial crisis of 2020.

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

Table 8 presents a comparison of the average omission error rate for banks listed in the Islamic Republic of Iran and the Iraqi Republic for the past and current financial periods (2003-2019 and 2020-2023). It's clear that most factors were comparable between the two time periods, yet the average number of pupils who left school earlier during the financial crisis era (2020–2023) was marginally lower. This shows how stable banks were prior to the crisis and how they fared during it. One reason for this could be the banks' experience and lessons learned from previous financial crises. In the wake of the global financial crisis of 2008, banks reinforced their risk and financial management strategies and developed new emergency response capabilities. The government's efforts to encourage and correct for stability have also contributed significantly to this stability. Governments provided banks with assistance during the COVID-19 crisis by decreasing interest rates, providing cash infusions, and providing other packages to help them avoid the worst consequences of the crisis. Banks are now better equipped to handle emergencies thanks to these measures, and the average mistake rate associated with missing data has decreased.. Technology advancements and greater usage of the variety of loan and investment options available to banks have improved their ability to manage financial risks and mitigated their negative impacts. All things considered, the decrease in the average error rate of variable removal throughout the financial crisis suggests that banks were able to weather financial challenges by utilizing new strategies, technology, and government assistance. For the ELTL and POAI variables, there are differences in the average omission errors between the two periods. The mean error rate associated with omission in ELTL decreased to 0.978113838, from 1.044980531. which can point to modifications to the long-term financing arrangement. These modifications may be the consequence of bank policies altering their banking and lending procedures in response to the COVID-19 crisis. Variations in. All things considered, Table 9's results demonstrate that the prediction models' abilities differed before and after the crisis. The areas where these changes are most obvious are in the key variables and the RMSE results, which indicate an increase in pressure and noteworthy changes in the context of the COVID-19 issue. As a result, the Covid-19 problem has significantly impacted the models' average loss and root mean square error (RMSE), which has impacted the probability of bank collapse. Banks were obliged by the crisis to adapt to unpredictably changing conditions, which made model prediction more difficult. However, significant adjustments to variables like ELTL and POAI suggest that banks should reconsider and modify how they handle long-term debt and credit investments to be more.All in all, these analyses' findings point to the value of regular and comparative analysis as a means of understanding how banks' financial situation is changing. Changes in the RMSE and average error of omission show that forecasting model upgrades and regular analysis can have a big impact on banks' strategic planning and risk management. In the end, The findings show that interest rates and the gross domestic product (NIRBT) are two key national economic policies that influence bank failure. To lower the amount of failures during disasters, policymakers should take these aspects into consideration and offer workable solutions. Following the acquisition of the neural network findings, a support vector machine was used to carry out the last assessment of the study model; the results are shown 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 Table 9's data, the SVM model significantly contributed to the forecast of bankruptcy risk for banks listed in Iraq and Iran during the COVID-19 crisis. When comparing the pre-hardship period (2003-2019) with the financial hardship period (2020-2023), it can be shown that the model's accuracy rose during the crisis period (0.9321) in contrast to the pre-hardship period (0.9125). Additional performance indicators such as the kappa coefficient, sensitivity, and specificity also show this improvement.

The improved model performance during the COVID-19 pandemic could point to a number of important factors. First, banks might have improved their risk management by learning from the previous financial crises. Second, banks may have become more robust as a result of government backing for policies like interest rate reductions and liquidity assistance during the COVID-19 period. Third, the efficiency of forecasting models can have been impacted by the development of technology and the use of more precise data for risk assessment.

The results of the sensitivity and specificity tests for each of the three classes during the crisis phase show that the SVM model performed better at differentiating between positive and negative examples. The example of class 3, which had a sensitivity of 0.9732 and a specificity of 0.9221, makes this very clear. Furthermore, throughout the crisis, all classes' positive and negative forecasted values increased, demonstrating the model's excellent prediction performance.

Overall, the SVM model's findings are consistent with earlier neural network studies and show that Iranian and Iraqi banks were well-equipped to handle the danger of insolvency during the COVID-19 crisis. This indicates that the stability of banks and the precise forecasting of critical situations have been made possible by the use of historical information, improved risk management, government support, and technology advancements.

The results of Christoph (2022), Nobrega and Jesus (2023), and Bin Jaber and Sert (2023) are consistent with this study. These studies showed that neural networks and machine learning models are highly capable at forecasting bank failure. In particular, our findings concur with Christoph's about the importance of variables such as asset quality, managerial indicators, and capital adequacy. Additionally, the improved performance of the models during the COVID-19 crisis is consistent with findings by Parboli and Arab Nejad (20–21), who showed that large-scale policy decisions can benefit from machine learning-based decision support systems.

On the other hand, our results contradict the findings of Srivastava et al. (2020), who showed that logistic regression is a more accurate predictor of bank failures than other methods. Neural networks and machine-learning models performed better in our investigation. Furthermore, our research showed that SVM models and neural networks perform better than genetic algorithms, which is in opposition to the conclusions of Yuri Zelenkov and Nikita Volodarsky (2021), who claimed that genetic algorithms were the most successful in predicting bank collapse.

Our findings concur with those of Najari Ferosani et al. (2018), who examine the use of machine learning methods to sentiment analysis. (2024) over whether financial metrics are required to forecast bank failure. Our approach, on the other hand, is distinct and centers on the application of machine learning techniques. Furthermore, even though we took a more numerical simulationfocused approach, our work is consistent with Keshavarz Hadadha et al.'s (2024) investigation into the challenges and solutions facing the creation of a bankruptcy early warning system.

Concluding and Proposing

The goal of the current study was to use machine learning and neural network techniques to estimate the likelihood of bank failure for those listed on the Iraqi and Tehran stock exchanges during the COVID-19 pandemic. The results of various machine learning models, such as the random forest, XGBoost, and decision tree, indicated that LTICA, ILQ, LRG, CLRE, NIRBT, NIRAT, NPS,+ELTL, GP, ETA, NIRA, POAI, IR, NLTA, OPR, ROA, GDP, and CYCLE are the most important factors in determining the risk of bank failure.

A comparison of the preceding and succeeding eras using neural networks and support vector machines (SVMs) revealed that the models' quality increased throughout the crisis. This demonstrates how banks could more adeptly manage risk during times of crisis. The models' increased performance during the crisis may have been caused by government-sponsored programs, better risk management systems, and lessons from past financial crises. The findings of the SVM model demonstrated that prediction accuracy increased to 0.9321 during the Covid-19 crisis compared to 0.9125 before the crisis. The sensitivity and specificity indices increased in all three classes during the crisis, indicating that the model had greater capacity.. The study's findings demonstrate how crucial it is to employ a range of techniques when calculating the probability of bank failure. The combination of numerous machine learning algorithms and neural networks allows for a more accurate identification of the variables impacting bankruptcy risk as well as more accurate predictions. The investigation also demonstrated that economic factors like GDP and interest rates had a major impact on the probability of bank collapse. The study's conclusions emphasize the significance of government backing at this time from a political perspective. Policymakers should carefully evaluate how to develop and implement effective rescue plans for the banking sector during times of crisis. These actions can involve increasing liquidity, cutting interest rates, and extending support. Financially speaking, the data demonstrates that banks have done a better job of controlling the risk of insolvency during the COVID-19 era. Investor confidence and the stability of the financial system may both increase as a result. Moreover, the significance of macroeconomic variables in predicting the likelihood of bankruptcy implies that managing the risk of bankruptcy should take macroeconomic policies into account. The study's conclusions also emphasize how crucial it is for regulators, banks, and researchers to work closely together to create and enhance failure risk forecasting models. This partnership can assist in early threat identification and preventative

- Create an early detection system: The central banks of Iran and Iraq should employ state-of-the-art machine learning and neural network techniques to identify institutions that are susceptible to failure. This system must be flexible enough to adjust to changing market conditions and updated often with new data.

- Boost risk management: Banks need to focus on the key elements found in this research, including LTICA, ILQ, LRG, and OPR. This would mean creating internal risk prediction models, expediting regulatory processes, and increasing investment in risk management technologies.

- Training for development: Supervisors and banks should routinely teach employees on data analysis and state-of-the-art machine learning methods. This could facilitate a surge in

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