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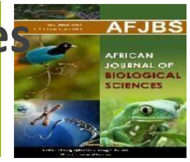

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The role of Bank Credits and Macroeconomic Variables in Predicting Financial Crises in Iran and Iraq: The approach of Machine learning and Neural Networks

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Abstract

This research has investigated the comparative role of bank credits and macroeconomic variables in predicting financial crises in Iran and Iraq by using machine learning approaches, neural networks and economic data of the two countries during the period 2000 to 2023. Various models for predicting financial crises (FC) using yield curve slope (YCS), debt service ratio (DSR), consumer price index (CPI), investment (INV), current account (CA), public debt (PD) variables. and bank credits (BC) were developed .The results indicate that in both countries, YCS and CA have the most influence in predicting financial crises. In Iran, the fuzzy system model showed the best performance with 79.18% accuracy and in Iraq, the cerebellar neural network with 67.89% accuracy. The optimal expectation algorithm showed that YCS is the most important predictive variable with a significance of 49.26% in Iran and 36.53% in Iraq. In contrast, BC was relatively less important in both countries (2.63% in Iran and 2.07% in Iraq). Therefore; The analysis showed that the average probability of financial crisis for Iran (0.9679) is slightly higher than Iraq (0.925), which can indicate a higher risk of financial crisis in Iran. This study reveals that despite the similarities in the factors affecting financial crises in the two countries, the relative importance of these factors is different. These findings emphasize the necessity of adopting distinct approaches and appropriate to the specific conditions of each country in economic policy-making and highlight the importance of paying attention to the unique economic characteristics of each country in the design of financial crisis prevention strategies.

Keywords: bank credits, financial crisis, neural network, learning algorithms, optimization

Introduction.

Financial crises are recurring phenomena in world economic history that have destructive effects on economic activity (Sufi & Taylor, 2022). These crises are generally associated with a sharp and unexpected decline in the value of assets. Research has shown that most of these crises originate from problems in the banking system and can cause a decrease in economic growth, deep recessions and a significant increase in unemployment (Danisman & Tarazi, 2024). Therefore, financial crises, as systematic disturbances in financial markets, have a significant potential to spread to other sectors of the economy. This can lead to fundamental changes in macroeconomic performance. The effects of these crises can be seen in the reduction of the GDP growth rate, the increase of inflation, the occurrence of stagnation and the increase of the balance of payments deficit (Cecchetti et al, 2009). In addition to their impact on macroeconomic variables, financial crises can also affect financial and banking indicators at the micro level, as the data related to these indicators serve as important decision criteria for borrowers, investors and policy makers. This information is very important for assessing economic risks and opportunities and is useful for formulating efficient strategies in the field of financial management and economic policy (Biljanovska et al, 2023).

Financial crises have been a common phenomenon throughout history, in which the value of financial assets in a market or economy falls sharply, creating widespread uncertainty and instability in the financial system, i.e. financial crises at different levels from banks and financial institutions to an entire national or even global economy (Gorton, 2018). Several factors can trigger a financial crisis, including over-indebtedness, mispricing of assets, lack of financial transparency, poor risk management and sudden market changes (Hellwig, 2008; Acharya and Richardson, 2009; Warwick et al, 2010) Therefore, the formation process of financial crises usually starts with the creation of a price bubble in the asset market, which eventually culminates in a sharp fall in prices and investor losses. This situation can lead to the bankruptcy of banks and other financial institutions (Aiginger, 2009). In order to deal with financial crises, governments and politicians usually take corrective and economic stimulus measures. These measures include providing financial assistance to banks, lowering interest rates and increasing government spending to restore confidence and stability in the economy (Pessoa, 2017). Therefore, given the broad and deep consequences of financial crises, timely identification of the warning signs of these crises is of strategic importance. Financial crises are generally associated with far-reaching economic and social consequences, whose effects can affect the economic and social structures of societies in the long run (Laborda and Olmo, 2021). The consequences of these crises include increased unemployment due to business closures, reduced household wealth and savings, and economic stagnation due to lack of credit and reduced consumption. The loss of confidence among consumers and businesses leads to a weakening of demand and investment, which in turn can lead to a crisis in banks and financial institutions and put severe financial pressure on governments, leading to budget deficits and an increase in public debt (Wang et al, 2023). In addition, social consequences such as rising inequality, declining quality of life, increased mental health problems and poverty can threaten social stability and weaken public confidence in financial systems and government institutions (Sheaffer et al, 1998). Considering the wide and varied consequences of financial crises, understanding these phenomena and how to manage them is essential and vital to maintaining a country's economic and social stability (Rewilak, 2018). Therefore, identifying the warning signs of financial crises is of great importance for policymakers, as timely diagnosis of these crises can help reduce the increasing risks (International Monetary Fund, 2008).

There are many challenges in accurately identifying the effective parameters for predicting financial crises. One of the main reasons for this is the relatively low frequency of financial crises in economic history, which limits the amount of data that can be analyzed and, as a result, makes it difficult to create valid forecasting models (Hennig et al., 2023; Tölö, 2020). In addition, the analysis of variables that influence the prediction of financial crises is complicated because these indicators are often visible and analyzed only after crises have occurred and reached critical points. As a result, using these post-crisis periods as historical data to build predictive models may not always be able to accurately predict future crises (Ramli et al, 2015; Hamdaoui et al, 2022). Therefore, the unpredictable nature of economic systems and the presence of unforeseen factors, such as the Covid-19 pandemic, which was largely unknown before 2020 and not included in previous economic models, can quickly plunge the global economy into crisis. This phenomenon illustrates how unpredictable factors can have profound and immediate effects on global economies, challenging economists and policy makers to understand and predict economic dynamics (Edison, 2003; Lepore et al, 2023).

In recent decades, the global economy has been continuously challenged by financial crises, which have had a profound impact on developing and emerging economies, including Iran and Iraq. In this regard, the growth of bank credit and changes in macroeconomic variables such as inflation, investment, balance of payments deficit and exchange rate are useful indicators for examining financial crises at national and international levels (Joseph, 2020; Buckmann and Joseph, 2023). In other words, the growth of bank credit and changes in macroeconomic variables increase the probability of accurately predicting financial crises, which is also confirmed by the studies of Allen (2009) and Kristina et al. (2023). Therefore, one of the important and predictive factors in the occurrence of financial crises is the disproportionate development of bank loans and the increase in the volume of liquidity, which leads to an imbalance in the financial and economic markets (Bluwstein et al., 2023). By analyzing the available data and examining the main macroeconomic variables, this research seeks to identify patterns that will provide the possibility of predicting financial crises in Iran and Iraq and help policymakers to take more effective measures. Therefore, the economic structure dependent on oil resources and the lack of sufficient diversity in income sources generally exposes Iran and Iraq to economic fluctuations caused by changes in global oil prices. In this situation, banks and financial institutions play a central role as an important tool for financing different sectors of the economy (Mishra and Burns, 2017).

In addition, the existing financial regulatory and legal systems in these two countries may not be able to fully apply the necessary restrictions to prevent excessive and unbalanced growth in bank lending. This may lead to the emergence of credit bubbles and increased risk-taking in the financial sector, resulting in credit and liquidity crises. Thus, another important aspect in predicting financial crises is the ability of the macroeconomy to manage public and private sector debt. Excessive and unplanned borrowing can exacerbate financial instability and, ultimately, financial crises. Historical evidence shows that periods of rapid expansion of bank credit and financial innovation can lead to situations where financial risks are not properly identified and managed, leading to severe financial crises (Bordo and Meissner, 2016; Schularick, 2014; Koh et al., 2020; Stockhammer, 2022; Lewis and Dangerfield, 2021). As a result, attention to external factors such as economic sanctions, political tensions and the impact of the international financial system can play an important role in better understanding how financial crises occur and preparing for timely responses. Access to accurate, timely and transparent data, especially in the financial and banking sectors, is also crucial to enable analysts to identify emerging patterns before they develop into financial crises. Quantitative modelling and forecasting based on this data can provide policymakers with powerful tools for taking preventive measures and effective interventions at the right time. In light of the above, the current research examines the dynamics of public and private debt, as well as their relationship with macroeconomic variables such as gross domestic product, inflation rate, and the value of the national currency, in order to provide a comprehensive understanding of how these factors function as early indicators of financial crisis. brought Therefore, the main objective of this research is to investigate the role of bank credit and macroeconomic variables in predicting financial crisis for Iran and Iraq.

Literature Review

Some analysts believe that the deeper roots of the recent financial crisis lie in developments after 1970 and the abandonment by the United States of the unilateral monetary system based on the gold standard (the Bretton Woods monetary system). These developments led to the emergence of a new era in the international monetary system. Based on this new system, the US dollar replaced gold in the national reserves and created an extraordinary opportunity for America to earn more credit by issuing new dollars and obtaining new sources of investment (Shafi'i et al., 2018). Until recently, perspectives on financial crises in the academic literature were sharply divided into two opposing schools of thought, one associated with monetarists and the other offering a more diverse perspective supported by scholars such as Charles Kindleberger and Hyman Minsky. Led by influential figures such as Friedman and Schwartz in their seminal 1963 paper, the monetarists have established a link between financial crises and banking panics. They emphasise the importance of banking panics and see them as the main cause of the contraction of the money supply, which subsequently leads to a significant slowdown in overall economic activity in the United States. Monetarists would not classify events in which there is a significant decline in asset values and an increase in business closures as true financial crises if there were not the potential for a banking panic and a consequent sharp contraction in the money supply. Indeed, Schwartz (1986) refers to these scenarios as "pseudo-financial crises". Intervention in a pseudo-financial crisis is seen by monetarists as unnecessary and potentially harmful, as it can reduce economic efficiency by bailing out failing firms or by causing excessive growth in the money supply that leads to inflation. such intervention can disrupt natural market mechanisms and lead to distortions in the allocation of resources, ultimately hindering long-term economic stability and growth. Kindleberger (1978) and Minsky (1972) provide an alternative perspective on financial crises that differs from that of the poltergeist. They provide a broader definition of what constitutes a true financial crisis. According to their analysis, financial crises include significant declines in asset values, the collapse of large financial institutions and non-financial corporations, inflationary or deflationary scenarios, disruptions in foreign exchange markets, or a combination of these factors. They argue that any of these potential disruptions would have serious consequences for the wider economy. Consequently, they propose a broad role for government intervention in times of financial crisis, as broadly defined by their criteria. A problem associated with the Kindleberger-Minsky view of financial crises is the lack of a comprehensive theoretical framework that defines the key features of a financial crisis. This deficiency in the theory makes it susceptible to widespread application and potentially leads to unwarranted government intervention that may not necessarily benefit the economy as a whole. This criticism forms the basis of Schwartz's (1986) critique of the Kindleberger-Minsky perspective and highlights the need for a more nuanced and differentiated understanding of financial crises. Conversely, the political economy approach to financial crises is severely limited because it focuses mainly on the impact of banking panics on the money supply and does not take into account other important factors that may contribute to the emergence and propagation of financial crises. This narrow focus limits the explanatory power of the poltarist perspective and emphasises the importance of incorporating a broader perspective when analyzing and dealing with financial instability (Mishkin, 1992). Economic systems are inherently unpredictable, but understanding vulnerabilities can help prepare for a crisis.

Previous research has emphasised the importance of focusing on explanatory factors such as the spread of credit, as shown in studies by Burio and Derman (2009), Jorda et al. (2015), Krishnamoorthy and Muir (2020), Aldasoro et al. (2018) and Greenwood et al. (2022) (Bluestein et al., 2023). Banks play an important role as the main providers of capital in most economies around the world. It is therefore important to understand the rationale behind their decisions to lend to individuals and firms. Similarly, it can be argued that credit statistics play a vital role in banking operations and are a fundamental aspect of overall economic activity, particularly in the context of the operation of businesses, which are largely dependent on access to bank credit. Anastasio et al., 2021). The health of an economic enterprise in a highly competitive business environment is affected by factors such as (1) the amount of financing at the beginning of its establishment, (2) its ability, relative flexibility and efficiency in generating cash from ongoing business operations, (3) access to capital markets, and (4) financial capacity and ability to continue life in the face of unexpected and far-fetched shortages of money (J. Lo et al., 2018; Moradi et al., 1402). Some researchers have concluded that the slope of the yield curve and credit growth are known to be important predictors of financial crises in both domestic and global contexts (Bluestein et al, 2023).
At present, credit institutions use predetermined procedures to measure the creditworthiness of customers, but since today's world is constantly changing, relying on fixed criteria does not have the necessary scientific validity and stability, and for this reason it is necessary to conduct audits. Taking into account the conditions of the society, different crises should be taken into account. (Smalls, 2021; Hao and Lee, 2021). This is because a financial crisis can affect many macroeconomic indicators (Shafiei et al., 2018). For an economy as a whole to be healthy, it is necessary for all sectors to be healthy in turn. A good financial position at the micro level contributes to a good financial position at the macro level, but the favorable development of macroeconomic variables also contributes to the proper performance of a company. Therefore, it is absolutely necessary to maintain the financial equilibrium of firms (Giotio and Hemgaran, 2015). In the supervisory framework following the 2008-2007 financial crisis, credit growth has been recognized as a key indicator to detect risks and potential crises, which will influence macroprudential policies. Other variables such as stock prices, house prices and current account deficits also play an important role in predicting financial crises and probably deserve more attention in policy discussions (Kiely, 2021). Recent studies on the prediction of corporate bankruptcy have considered many factors, mostly related to financial ratios derived from corporate financial statements. However, the current crisis and the subsequent exponential increase in the bankruptcy rate have clearly shown that the bankruptcy phenomenon cannot be explained without reference to macroeconomic variables. Therefore, the general state of the economy should be taken into account, and not only the internal financial ratios of companies (Acosta-González et al., 2019).
As a result, there are many empirical studies on the prediction of financial crises, some of which are examined in Table 1.

Table 1. Background of empirical research

Author(s)	Research Title	Research Objective	Method/Approach	Conclusions and Findings
Ashtab et al. (2017)	Predicting Financial Crises Using Earnings Management	To evaluate the accuracy of financial crisis prediction models and examine earnings	Comparison of machine learning models with statistical models and multiple linear regression analysis	Machine learning models have higher accuracy in predicting financial crises, and predicted financial crises have an inverse relationship with operating cash flow earnings

		management methods		management and a direct relationship with earnings management in production costs and accruals
Khajavi & Ghadirian Arani (2017)	Examining and Improving Financial Crisis Prediction Using Management Ability	Investigating the effect of management ability on financial crisis prediction	Data from 402 company-years, comparison of models based on financial ratios and management ability, using boosting, bagging, and rotational forests	Management ability significantly increases the accuracy of financial crisis predictions
Wang & Wu (2017)	Financial Crisis Prediction: Integrating Probabilistic Neural Network with Backpropagation Based on Adaptive Boosting	To enhance the accuracy of financial crisis prediction (FCP)	Combining Probabilistic Neural Network (PNN) with Backpropagation (BP) algorithm and Adaptive Boosting (AdaBoost)	The new combined model showed the highest prediction accuracy, proving to be an excellent method for financial crisis prediction
Khajavi & Ghadirian Arani (2018)	Financial Crisis Prediction Using Intellectual Capital	Assessing the impact of intellectual capital and its components on financial crisis prediction	Data from 400 company-years, comparison of models based on financial ratios and intellectual capital, with emphasis on boosting and bagging	Intellectual capital significantly enhances the accuracy of financial crisis predictions
Yousef & Aldeen (2018)	Predicting Financial Crises in Iraqi Banks Using Neural Networks	Using neural networks to predict financial crises in Iraqi banks	Analyzing financial ratios of banks over the period 2007 to 2015	Neural networks have high accuracy in predicting financial crises with an AUC of 0.975
Taheri Bazkhaneh et al. (2019)	Design of an Early Warning System for Financial Crises	Developing a new financial index to predict various financial sector states	Principal component analysis in the period 1990 to 2016 using a Markov switching approach	Crisis states have low stability and often transition to stability; direct transitions from crisis to boom are unlikely
Emamverdi & Jafari (2019)	Effect of Financial Crises on Shock Transmission and Volatility Spillover	Examining the impact of financial crises on shock transmission and volatility spillover among stock markets	Modified cumulative sum of squares algorithm and multivariate GARCH model in the period 2003 to 2017	Shock and volatility transmission is unidirectional from developed and emerging markets to Iran's capital market
Beutel et al. (2019)	Predicting Bank Crises with Machine Learning	To evaluate and compare the predictive performance of various early warning models for systemic banking crises	Comparison of logit approach with machine learning methods	Traditional logit models outperformed machine learning methods in out-of-sample evaluations
Samtani et al. (2020)	An Early Warning System for Predicting Financial Crises Using Machine Learning	To improve standard crisis prediction patterns using early warning indicators	Network analysis and machine learning algorithms	The effectiveness of using machine learning reached 98.8%, demonstrating very high prediction accuracy

Nora Metawa et al. (2021)	Computational Intelligence-Based Financial Crisis Prediction Using Optimal Feature Subset Selection with Deep Belief Network	To design an accurate financial crisis prediction (FCP) approach	Using Elephant Herd Optimization (EHO) and Modified Water Wave Optimization (MWWO) algorithms with Deep Belief Network (DBN)	The proposed model achieved maximum classification performance, outperforming recent approaches
Ahmad et al. (2021)	The Impact of Financial Crisis on Macroeconomic Variables in Iraq, Iran, and Turkey	Examining the impact of financial crises on macroeconomic variables such as GDP, exports, inflation, and exchange rates	Analyzing data over the period 1980 to 2017	Financial crises have different impacts on macroeconomic variables, with the Asian financial crisis significantly negatively affecting GDP in Iran and Iraq
Salman et al. (2021)	Safety Indicators in Financial Crises and Their Impact on Banking Finance: A Case Study of Iraqi Banks	Reviewing and assessing financial safety indicators implemented by the Central Bank of Iraq	Analyzing specific safety indicators on the Iraqi banking system	The Central Bank of Iraq adheres to international standards like Basel II, with the banking system showing satisfactory capital adequacy ratios
Laborda & Olmo (2021)	Volatility Spillovers Between Economic Sectors in Predicting Financial Crises: Evidence from the Great Financial Crisis and the COVID-19 Pandemic	To measure volatility spillovers among different economic sectors using network connectivity measures	Using the methodology presented by Diebold and Yilmaz (2012)	Banking and insurance, energy, technology, and biotechnology sectors play crucial roles in transmitting shocks to the broader economy
Liu et al. (2022)	Predicting Financial Crises with Machine Learning Methods	To create an effective early warning system for predicting financial crises	Comparison of logistic model and seven machine learning methods, using Shapley value analysis	Machine learning models, especially random forest, gradient boosting decision tree, and ensemble models, performed better than the logistic model in providing early predictions of financial crises
Sufi & Taylor (2022)	Financial Crises: A Survey	To explore how crises are measured, their predictability, and reasons for their association with economic contractions	Literature review	Historical narrative techniques remain the backbone of crisis measurement, but exciting developments have occurred in the use of quantitative data
Muthukumaran & Harihaaranath (2022)	Financial Crisis Prediction with Deep Learning for Small and Medium Industries	To design an optimized deep learning-based financial crisis prediction model for SMEs	Using Archimedes Optimization Algorithm (AOA) for feature selection and Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) for data classification	The proposed ODL-FCP technique outperformed other techniques
Venkateswarlu et al. (2022)	Deep Learning-Based Financial Crisis	To develop a model for financial crisis	Using Hadoop MapReduce for big	The OALOFS-MLC algorithm outperformed recent

	Prediction in Big Data Environment	prediction in a big data environment	data management and Oppositional Ant Lion Optimization (OALO) for feature selection	approaches
Jafarimanesh & Gholami (2022)	Predicting Financial Crisis of Companies in Tehran Stock Exchange Based on Company-Level and Macroeconomic Factors	Examining the impact of company-level and macroeconomic factors on corporate crises and validating the company life cycle theory	Panel regression modeling on data of 122 companies over a 10-year period	Company life cycle stages have an inverse relationship with financial crises, and this relationship is stronger in the post-sanctions period
Bluwstein et al. (2023)	Predicting Financial Crises Using Credit Growth and the Yield Curve: A Machine Learning Approach	To create early warning models for predicting financial crises using machine learning techniques	Using various nonlinear machine learning models to analyze macro financial data	Most nonlinear machine learning models outperform logistic regression when predicting financial crises
Papik & Papikova (2023)	The Effects of Crisis on the Performance of SME Bankruptcy Prediction Models	To analyze the impact of crisis on the performance of bankruptcy prediction models	Developing prediction models for three periods using Cat Boost, LightGBM, and XGBoost methods	The performance of prediction models in crisis periods was significantly weaker than in non-crisis periods
Temrinia et al. (2023)	A Hybrid Model for Predicting Financial Crises Based on Free Cash Flows	Developing a hybrid prediction model for financial crises based on free and operational cash flows	Data from 260 companies in Tehran Stock Exchange (2008 to 2017), logistic regression model and ROC curve	The hybrid model based on free cash flows has higher accuracy compared to Zmijewski and Altman models
Shehata et al. (2023)	Predicting Contemporary Economic Crises in the Arab Region - Causes and Consequences	Analyzing the impact of economic crises due to COVID-19 pandemic and Russia-Ukraine war	Descriptive approach, secondary data from IMF, World Bank, and Arab Monetary Fund	These crises impacted economic growth rates, trade balances, and international reserves, leading to increased poverty and social inequality
Rouhisera et al. (2023)	Financial Crisis Prediction Model for Iran's Capital Market Using Hybrid Algorithms	Developing a dynamic model for predicting financial crises in companies	Thematic analysis, data from 173 companies (2009 to 2019), and algorithms including multivariate regression, ant colony, and particle swarm optimization	The model can predict financial crises with relatively high accuracy up to five years before the crisis, but accuracy decreases closer to the crisis
Ristolainen et al. (2024)	Financial Crises and Historical Headlines	To investigate if changes in specific types of narrative information in newspaper article headlines predict financial crises	Integration of information from economic news articles with traditional macroeconomic and financial indicators	The predictive information in newspaper article headlines indicating upcoming crises is significant beyond macroeconomic and financial indicators
Khadr & Khoshnaw (2024)	The Role of Financial Crisis Management in Implementing Investment Development in Iraqi Kurdistan	Assessing the role of crisis management in handling financial crises and their impact on	Mitroff's five-stage model, decision analysis, using SPSS 28.0 for financial analysis	The COVID-19 pandemic had a more limited impact on investment projects compared to the ISIS conflict, with more effective crisis management during the pandemic

	investment growth in Kurdistan region	

The destructive impact of the financial crisis on countries' economies and citizens' lives is significant. A financial crisis can lead to a sharp decline in the value of assets, a reduction in investment, and a loss of jobs and household income. Crisis-induced instability also increases unemployment and public deficits, and can undermine confidence in financial and governance systems. Therefore, the ability to anticipate and take corrective action before, or in the early stages of, financial crises is important to prevent the negative and long-term consequences of these crises on society and the economy. Understanding the challenges involved in predicting and dealing with financial crises requires extensive research into the relationships between macroeconomic variables and financial indicators. This research seeks to find patterns that can help identify and predict financial crises by examining historical data and analyzing variables such as bank credit growth, inflation, investment and balance of payments deficits. In this regard, the use of modern tools such as neural networks and economic simulation methods can provide new perspectives in this study, especially for countries such as Iran and Iraq whose economies are affected by factors such as global oil price fluctuations. In addition, it is important to review financial regulatory and supervisory systems and to use quantitative patterns to predict how future crises will occur in order to stabilize financial markets. This study, based on deep data analysis and advanced modelling, will allow policymakers to adopt effective strategies to prevent and manage financial crises, thereby helping to improve the resilience and stability of the financial sector and the macroeconomy against potential shocks. did Therefore; According to the studies conducted on the existing literature in the field of predicting financial crises in Iran and Iraq. It can be seen that the researches conducted in this field have generally paid attention to other countries and the countries of Iran and Iraq have received much less attention. In addition, the amount of research on predicting financial crises in Iran and Iraq in terms of bank credit and macroeconomic parameters is not of good quality and an increase in research in this area is much needed. Also, paying attention to issues such as the subject of the current research using new approaches that have certain complexities and as a result include larger dimensions of the discussion, there is a research gap in the existing literature that this research aims to fill. the research gap for both Iran and Iraq. According to the studies conducted in the research literature on the role of bank credit and macroeconomic variables in predicting financial crises in Iran and Iraq, it can be seen that international studies have been conducted from the perspective of predicting crises. financial is complete, but the internal studies of Iran and Iraq regarding the role of bank credit and macroeconomic variables are very few. They do not have Iraq, which shows the gap between the studies conducted in both countries, therefore, in this research, the aim is to use bank credit and macroeconomic variables to develop a model using machine learning algorithms and neural networks to predict financial crises in Iran and Iraq should be explained that this indicates the need to conduct research.

Methodology

In recent decades, financial crises have emerged as one of the most challenging economic issues at the global level. These crises not only affect the economies of the countries involved, but due to the extensive economic linkages in the era of globalization, their effects quickly spread to other countries. Meanwhile, developing countries such as Iran and Iraq are more vulnerable to these crises due to their specific economic structures and dependence on oil revenues. Therefore, predicting and identifying the effective factors in the occurrence of financial crises in these countries is of particular importance. With the aim of providing a comprehensive and multidimensional approach to the problem of predicting financial crises, this research has used a combination of advanced data analysis and machine learning methods. These methods include nearest neighbour, random forest, demand-based forecasting models, adversarial learning, principal component analysis, functional neural networks, cerebellum, autoencoder and neuro-fuzzy systems. Each of these methods has unique capabilities to identify patterns and complex and non-linear relationships between variables. Using this combined approach, this study seeks to examine the role of bank credit and macroeconomic variables in predicting financial crises in Iran and Iraq, in order to gain a deeper understanding of the economic dynamics of these two countries and to provide effective solutions for crisis prevention and management. The possibility of achieving the future. Below is a brief description of each of the methods mentioned.

- k-Nearest Neighbors

The k-nearest neighbor algorithm is a simple but powerful classification and forecasting method that can be very useful in analyzing the role of bank credit and macroeconomic variables in predicting financial crises in Iran and Iraq. In this method, to predict the economic situation of a certain period (for example, the occurrence or non-occurrence of a financial crisis), the k-algorithm finds the nearest data point in the multidimensional space of economic variables and makes a prediction based on the situation of these neighbouring points. Anvari et al., 2023). The basic formula for calculating the distance between data points (usually the Euclidean distance) is as follows

$$d(x,y) = \sqrt{(\Sigma(i=1 \text{ to } n)\ (xi - yi)^2)}$$

where x and y are two data points in n-dimensional space and xi and yi are the i-th variable values for these two points. In order to use this method in the field of financial crisis prediction, a set of historical data including macroeconomic variables (such as inflation rate, GDP growth, unemployment rate) and bank credit indicators (such as loan-to-deposit ratio, credit growth rate) is first collected for the two countries Iran and Iraq. Each data point in this set represents the economic situation in a given period and is characterized by a label (occurrence of crisis or non-occurrence of crisis). Then, to predict the economic situation in a new period, the k-NN algorithm calculates the distance of this point with all available data points and finds k nearest neighbors. The final prediction is based on the majority of the labels of these k neighbors. For example, if 3 of the 5 nearest neighbors are labelled 'crisis', the algorithm predicts that a financial crisis will also occur in the new period. This method can help to identify similar patterns in historical data and offers the possibility of predicting future crises based on the similarity of economic conditions (Göbel & Araújo, 2020).

- Random Forest

Random forest is a powerful machine learning technique that can be very useful for predicting financial crises in Iran and Iraq using bank lending and macroeconomic variables. This algorithm creates a series of decision trees, each based on a random sample of the training data. In this particular case, the input data includes variables such as the volume of bank credit, inflation rate, economic growth, exchange rate and other macroeconomic indicators. Each tree in the random forest makes a prediction about the probability of a financial crisis, and the final result is obtained by majority voting or by averaging the predictions of all the trees (Chehreh & Sarabadani, 2024). The main formula for the Random Forest prediction is as follows:

$$f(x) = 1/B * \Sigma\ (i=1 \text{ to } B)\ f_i(x)$$

where B is the number of trees, fi(x) is the prediction of the ith tree, and f(x) is the final prediction of the model. In order to use Random Forest in this research, historical data related to economic and credit variables of Iran and Iraq, as well as information related to past financial crises, are first collected. Then, these data are divided into two parts, training and testing. The Random Forest model is run on the training data to learn patterns related to the occurrence of financial crises. After training, the model can be used to predict the probability of a future financial crisis using new economic and credit data. One of the key advantages of Random Forest is its ability to assess the relative importance of each variable in the prediction. This feature allows researchers to determine which economic and credit factors have the greatest impact in predicting financial crises in Iran and Iraq (Ebrahimi-Khusfi, 2021). The importance of variable i can be calculated using the following formula:

$$VI_i = 1/B * \Sigma\ (j=1 \text{ to } B)\ (MSEOOB^j - MSEOOB^{ij})$$

where VI_i is the importance of variable i, MSEOOBj is the out-of-bag error for tree j, and MSEOOBij is the out-of-bag error for tree j after permuting variable i.

- Demand-based forecasting models

Demand-based forecasting models are an innovative approach to forecasting financial crises, taking into account the role of bank credit and macroeconomic variables in Iran and Iraq. These models are based on the assumption that demand for credit and macroeconomic conditions can be an important indicator of the likelihood of financial crises. In this method, a dynamic model is developed that takes into account the changes in credit demand and macroeconomic indicators over time (Sheikhli et al., 2023). The main formula of this model may be as follows:

$$P(Crisi_t) = f\ (\text{Credit Demand}_t, \text{Macro Variables}_t, \varepsilon_t)$$

In this formula, $P(Crisis_t)$ is the probability of a financial crisis at time t, Credit Demand is an index of credit demand at time t, Macro Variablest is the vector of macroeconomic variables at time t, and ε_t is the error component. The function f can be a logistic or a probit function, defined as follows

$$f(z) = 1 / (1 + e^{(-z)}) \text{ for the logistic function}$$

$f(z) = \Phi(z)$ for the probit function, where Φ is the standard normal cumulative distribution function.

To use this model to study the financial crises in Iran and Iraq, we first need to collect appropriate indicators of credit demand (such as the volume of loan applications, credit growth rate) and macroeconomic variables (such as inflation rate, GDP growth, exchange rate). Then, using historical data, we train the model to learn the relationship between these variables and the likelihood of a financial crisis. One of the advantages of this method is its ability to account for dynamic changes in credit demand and economic conditions; to improve the accuracy of the model, we can use more advanced techniques, such as vector autoregression (VAR) models, which allow time dependencies between variables to be taken into account (Rezaee, 2022). The general formula of VAR model is as follows:

$$Y_t = c + A_1\, Y\{t-1\} + A_2\, Y\{t-2\} + ... + A_p\, Y\{t-p\} + \varepsilon_t$$

In this formula, Y_t is a vector of model variables at time t, c is a vector of constants, Ai is a matrix of coefficients, and ε_t is a vector of errors. Using these models, we can not only predict the probability of financial crises, but also assess the impact of changes in credit policies and macroeconomic conditions on financial stability in Iran and Iraq.

- Adversarial learning

Adversarial learning is an advanced technique in the field of machine learning that can be used to predict financial crises according to the role of bank credit and macroeconomic variables in Iran and Iraq. This method involves two models: a generator that produces artificial data and a discriminator that tries to distinguish between real and artificial data. In the context of predicting financial crises, the generator can simulate different economic and financial scenarios, while the discriminator tries to identify the situations that lead to the crisis (Puli et al, 2024). The general formula for the objective function in adversarial learning is as follows

$$\min_G \max_D V(D, G) = E[\log(D(x))] + E[\log(1 - D(G(z)))]$$

In this formula, G is the generator, D is the detector, x is the real data, and z is the random noise. The goal is to optimize this function through simultaneous training of G and D. To use this method in the study of financial crises in Iran and Iraq, we first collect historical data related to bank credits (such as volume of loans, interest rates) and macroeconomic variables (such as inflation rate, GDP growth, exchange rate). We train the generator to generate different economic scenarios, while we train the detector to identify patterns that lead to crises. After training, we can use the model to simulate different scenarios and predict the probability of financial crises. One of the main advantages of this method is its ability to generate synthetic data that can help overcome the limitations of historical data. To improve the performance of the model, we can use more advanced techniques such as Conditional GAN, which allows more control over the generated data (Sharma, p. et al, 2024). Conditional GAN formula is as follows:

$$\min_G \max_D V(D, G) = E[\log(D(x|y))] + E[\log(1 - D(G(z|y)))]$$

In this formula, y is an additional condition (such as a particular economic situation) given to the generator and the detector. Using this method, we can create a model that is not only able to predict financial crises, but can also simulate different scenarios based on the specific economic and credit conditions of Iran and Iraq.

- Principal Component Analysis

Principal component analysis (PCA) is a powerful statistical technique that can be very useful in investigating the role of bank credit and macroeconomic variables in predicting financial crises in Iran and Iraq. This technique helps to reduce the dimensionality of the data and to identify the main variables that have the most influence in explaining the variance of the data. In the context of financial crises, PCA can help us identify the main economic and credit factors associated with financial crises (Sharma, H. et al, 2024). The basic formula of PCA is as follows

$$PC_i = a_{i1}X_1 + a_{i2}X_2 + ... + a_{in}X_n$$

In this formula, PC_i represents the ith principal component, X_j is the jth variable, and a_{ij} are the coefficients chosen to maximize the variance of PC_i, provided that the sum of squares of the coefficients is equal to 1:

$$a_{i1}^2 + a_{i2}^2 + \cdots + a_{in}^2 = 1$$

To use PCA in the study of financial crises in Iran and Iraq, we first identify a set of variables related to bank lending (such as the volume of loans, loan-to-deposit ratio, interest rates) and macroeconomic indicators (such as the inflation rate, GDP growth, unemployment rate, currency). We then use PCA to reduce these variables to a few principal components that explain most of the variance in the data. These principal components can be viewed as composite indicators of economic and credit status. We can then examine the relationship between these principal components and the occurrence of financial crises. To determine the optimal number of principal components, we can use the Kaiser criterion, which selects components with eigenvalues greater than 1, or the scree chart, which breaks at the plot shows the eigenvalues (Haerinasab et al, 2022). We can also use the percentage of variance explained:

$$\text{Cumulative Variance Explained} = \Sigma(\lambda_i) / \Sigma(\lambda_j)$$

where λ_i are the eigenvalues of the selected components and λj are all the eigenvalues. Typically, the goal is to explain 80-90% of the variance. Using this method, we can create a simpler and more interpretable model for predicting financial crises in Iran and Iraq, focusing on the most important economic and credit factors.

- Functional Neural Networks

Functional Neural Networks (FNN) are an advanced method in machine learning that can be used to investigate the role of bank lending and macroeconomic variables in predicting financial crises in Iran and Iraq. These types of networks are capable of modelling high-dimensional data and complex relationships, and are particularly suited to working with time-series data and dynamic patterns. In the context of financial crisis prediction, FNNs can account for non-linear relationships and time dependencies between economic and credit variables (Sobhanifard & Shahraki, 2021). The general structure of an FNN can be illustrated as follows:

$$y(t) = \Sigma \text{ (i=1 to N) } w_i * \varphi_i(x(t)) + \varepsilon(t)$$

In this formula, y(t) is the output of the model (probability of financial crisis) at time t, x(t) is the vector of inputs (economic and credit variables) at time t, φ_i is the basic functions (such as sigmoid or ReLU functions), wi is the weights of the network; N is the number of neurons in the hidden layer, and ε(t) is the error component. To use FNN in the study of financial crises in Iran and Iraq, first, time series data related to bank credit variables (such as volume of loans, interest rates, loan-to-deposit ratio) and macroeconomic indicators (such as inflation rate, GDP growth, unemployment rate, we collect the exchange rate. Then, we give this data as input to the FNN network. We train the network using optimization algorithms such as gradient descent to learn the relationship between these variables and the probability of a financial crisis. The cost function for network training can be as follows:

$$L = \Sigma \text{ (t=1 to T) } (y(t) - \hat{y}(t))^2 + \lambda * \Sigma \text{ (i=1 to N) } ||w_i||^2$$

In this formula, L is the cost function, y(t) is the actual value, ŷ(t) is the predicted value, λ is the tuning parameter to avoid overfitting, and ||wi|| are the soft weights. One of the main advantages of FNN is its ability to learn complex and non-linear functions that can discover hidden relationships between economic and credit variables. To improve model performance, we can use more advanced techniques such as Recurrent Neural Networks (RNN) or Long-Short-Term Memory (LSTM) networks, which are specifically designed to work with time series data. The LSTM formula is as follows:

$$f_t = \sigma\, (W_f \cdot [h\_\{t-1\}, x_t] + b_f)$$
$$i_t = \sigma\, (W_i \cdot [h\_\{t-1\}, x_t] + b_i)$$
$$o_t = \sigma\, (W_o \cdot [h\_\{t-1\}, x_t] + b_o)$$
$$\tilde{c}_t = \tanh\, (W_c \cdot [h\_\{t-1\}, x_t] + b_c)$$
$$c_t = f_t * c\{t-1\} + i_t * \tilde{c}_t$$
$$h_t = o_t * \tanh(c_t)$$

In these formulas, f_t, i_t, and o_t are the forgetting, input, and output gates, respectively, c_t is the cell state, and h_t is the final output. Using these advanced models, we can develop a more accurate prediction system for the financial crises in Iran and Iraq, which is able to take into account long-term time dependencies in economic and credit data.

- Cerebellar Network

Cerebellar Model Articulation Controller (CMAC) is a special type of artificial neural network that can be used to predict financial crises according to the role of bank loans and macroeconomic variables in Iran and Iraq. This model, inspired by the structure of the cerebellum of the human brain, is very good at learning complex and non-linear functions and can discover hidden patterns in economic and financial data. The basic structure of CMAC consists of an input layer, a concept mapping layer and an output layer (Achmad et al, 2024). The general formula of CMAC output is as follows:

$$y = \Sigma \text{ (i=1 to N) } w_i * a_i(x)$$

In this formula, y is the output of the model (probability of financial crisis), x is the input vector (economic and credit variables), w_i is the network weights, $a_i(x)$ is the activation function for the i-th unit in the conceptual mapping layer, and N is the number of active units in the mapping layer. It is conceptual. The function $a_i(x)$ is usually a binary function that determines whether the input x is in the coverage area of the ith unit or not. To use CMAC in the study of financial crises in Iran and Iraq, first a set of variables related to bank credits (such as volume of loans, loan-to-deposit ratio, interest rates) and macroeconomic indicators (such as inflation rate, GDP growth, unemployment rate, we collect currency). These variables are given as input to the CMAC network. Then, we train the network using historical data to learn the relationship between these variables and the probability of a financial crisis (Levay & Mjörnell, 2019). The learning algorithm for updating the weights is as follows:

$$w_i(t+1) = w_i(t) + \eta * (y_d - y) * a_i(x)$$

In this formula, $w_i(t)$ is the ith weight at time t, η is the learning rate, y_d is the desired (actual) value, and y is the value predicted by the model. One of the main advantages of CMAC is its high learning speed and good generalization ability. These features are particularly useful in the context of predicting financial crises, as economic conditions can change rapidly and the model must be able to adapt quickly to new conditions. To improve the performance of the model, we can use more advanced techniques such as multi-layer CMAC, or combine CMAC with other machine learning algorithms. For example, we can use a hybrid CMAC-LSTM model, where CMAC is used to extract non-linear features from the input data and LSTM is used to model temporal dependencies. This combination can improve the accuracy of predicting financial crises by both accounting for complex patterns in economic and credit data and modelling time trends. Using this approach, we can create a powerful forecasting system for financial crises in Iran and Iraq that is able to identify early signs of crisis based on changes in credit and economic variables. This model can help policymakers and financial authorities to take preventive measures to prevent or reduce the impact of financial crises (Doumpos et al, 2023).

- Self-Encoding Neural Network

Autoencoder Neural Network is a special type of artificial neural network that can be very useful for analyzing and predicting financial crises according to the role of bank loans and macroeconomic variables in Iran and Iraq. These networks are specifically designed to reduce the dimensionality of data and extract important features, which is very valuable in the field of analyzing complex economic and financial data. The basic structure of an autoencoder consists of two main parts: Encoder and Decoder. The encoder maps the input data into a lower dimensional space, while the decoder attempts to reconstruct the original data from this compressed representation (Khosroyani et al, 2023). The main formulas for these two parts are as follows

$$\text{Encoder: } h = f\,(Wx + b)$$

$$\text{Decoder: } x' = g\,(W'h + b')$$

In these formulae, x is the input data, h is the compressed representation (code), x' is the reconstruction of the input data, W and W' are the weight matrices, b and b' are the biases, and f and g are the activation functions (such as sigmoid or ReLU). Auto coders can play an important role in studying the financial crises of Iran and Iraq. By receiving a set of variables related to bank loans and macroeconomic indicators, these systems are able to extract important features and reduce data dimensions. After collecting and normalizing the data, a self-encoding network is designed and trained. This network is trained using the error mean square cost function as follows to reconstruct the input data with high accuracy (Abbasi Nejad et al, 2023).

$$(L = 1/n * \Sigma\ (i=1\ \text{to}_n)\ ||x_i - x'_i||^2)$$

The network encoder part is then used to extract compact features that are used to train a financial crisis prediction model. To improve the performance of the model, more advanced types of autoencoders such as variable, noisy or recursive autoencoders can be used. These approaches can help to identify more complex patterns in economic and credit data. The variable autoencoder can be used for uncertainty analysis, the noisy autoencoder is more robust to data fluctuations, and the recursive autoencoder is suitable for modelling temporal dependencies. Using these techniques, it is possible to build a robust forecasting system for financial crises in Iran and Iraq, which helps policymakers to identify possible risks early and take preventive measures (Franco et al, 2021).

- Neural Fuzzy Systems

Neural-fuzzy systems are a powerful way of combining the learning capabilities of neural networks with the reasoning capabilities of fuzzy logic. In the context of predicting financial crises in Iran and Iraq, these systems can take macroeconomic variables (such as inflation rate, economic growth, exchange rate) and bank credit indicators (such as non-performing loan ratio, capital adequacy ratio) as inputs. Then, using fuzzy rules such as "if the inflation rate is high and economic growth is low, then the probability of a financial crisis is high", these variables are converted into fuzzy sets. The neural network determines the appropriate weights for these rules by learning from historical data. In the next step, the neuro-fuzzy system calculates the degree of membership of each variable in the fuzzy sets using fuzzy membership functions. For example, the Gaussian membership function for the inflation rate can be defined as $\mu(x) = \exp((xc)2 / (2\sigma2))$, where c is the center and σ is the standard deviation. Then fuzzy rules are applied using fuzzy operators such as min or multiply. Finally, the fuzzy output is transformed into a deterministic value for the probability of a financial crisis using methods such as Centre of Gravity ($COG = \int x\mu(x)dx / \int\mu(x)dx$). This process is constantly updated with new data to increase the accuracy of the predictions. After determining the information related to the research methodology, the specification of the model was discussed, which is as follows (Javadi et al., 2020).

- Dependent variable: Financial crisis

Financial crises are rare events. While there are a few truly global financial crises, such as the Great Depression and the 2007-2008 global financial crisis, most crises occur primarily in a single country or small group of countries. A financial crisis is an event in which a country's banking sector faces a bank run, a sharp increase in default rates accompanied by large capital losses, leading to public intervention, bankruptcy or forced mergers of financial institutions (Bordo et al., 2001; Laeven and Valencia, 2008; Reinhart and Rogoff, 2009; Cecchetti et al., 2009). Since the aim of this study is to predict financial crises for Iran and Iraq using bank credit and macroeconomic variables, we use economic data for Iran and Iraq between 2000 and 2023, following the approach of Christina Blustein et al. (2023). Our goal is to predict crises before they occur, so we consider one and two years before the onset of a crisis as the "crisis period". For greater accuracy, we exclude the actual year of the crisis and four years after the crisis from our analysis. This helps us to distinguish between normal economic conditions and post-crisis recovery periods. Finally, we use a simple yes/no variable to indicate the presence or absence of a crisis. This method allows us to better identify the actual signals that lead to a crisis and to make more accurate predictions. Therefore, based on the definition of financial crisis in Christina Blustein et al. (2023), the financial crisis index for Iran and Iraq is constructed as follows

Financial crisis = bank run + sharp increase in default rates with large capital losses + government intervention + bankruptcy of financial institutions + forced mergers of financial institutions.

In order to predict financial crises in Iran and Iraq based on Christina Blustein et al. (2023), two conditions must be met:

I. Crisis prediction: The target variable (crisis occurrence) is considered positive for 1 and 2 years prior to the onset of the crisis to enable crisis prediction.

II. Exclusion of the post-crisis period: The year of crisis occurrence and 4 years after are excluded from the analysis to avoid post-crisis bias.

This measurement method considers the financial crisis as a discrete event (occurrence or non-occurrence) and focuses on identifying the pre-crisis period as a warning signal.

- Explanatory variables

According to Christina Bluestein et al. (2023), we use the following explanatory variables

1. The slope of the yield curve, which is equal to the difference between short-term and long-term interest rates;
2. The debt service ratio, which is the ratio of the long-term interest rate on bank loans to GDP;
3. Consumer price index;
4. Investment is the sum of public and private investment;
5. Current account: net exports and imports of goods and services between a country and other countries;
6. Public debt: the total debt owed by the government to domestic and foreign lenders.
7. Bank credit: Bank loans to the private sector.

The time frame of the current research is from 2000 to 2023, which covers 24 years. The statistical population of this research includes Iran and Iraq, whose financial data are extracted from the following websites:

i. https://data.worldbank.org/
ii. https://tsd.cbi.ir/
iii. http://www.ifdc.ir/
iv. https://databank.mefa.ir /
v. https://stats.oecd.org /
vi. https://codal.ir /
vii. https://mabnadp.com/products/rahavard-novin
viii. https://www.tse.ir /
ix. http://www.isx-iq.net/isxportal/portal/homePage.html
x. https://globaledge.msu.edu/globalresources/resourcesbytag/iraq
xi. https://response.reliefweb.int/iraq/data?page=2&q=/iraq/data
xii. https://www.iraqidata.com/en/Banking-Sector

Finally, the mathematical model of the research will be as follows:

$$FC_{it}= f(YCS_{it}+DSR_{it}+CPI_{it}+INV_{it}+CA_{it}+PD_{it}+BC_{it})$$

Where: FC (financial crisis) = f ((YCS (yield curve slope), DSR (debt service ratio), CPI (consumer price index), INV (investment), CA (current account), PD (public debt), BC (bank credit)).

The above equation specifies the financial crisis as a function of macroeconomic and banking variables.

1. Data and information analysis

In any economic research, examining the descriptive statistics of variables is the first and necessary step in the data analysis process. This step allows researchers to get a general picture of the main characteristics of the collected data. Descriptive statistics include central indicators such as mean and median, dispersion measures such as standard deviation and range of changes, as well as frequency distribution of variables. This information not only provides a basic understanding of the nature of the data, but also prepares the ground for choosing the appropriate methods of statistical analysis in the next stages of the research. Therefore; Before starting the analysis of research data and information, the descriptive statistics of the research variables have been investigated, and the results are as described in Table (2).

Table 2. Descriptive statistics

Variable	Symbol	Q1	Q3	Jarque- Bera	
				Statistic	Probability
Financial Crisis	FC	12.67	32.55	25.1	0.00004
Interest Rate Spread	YCS	78.93	221.09	36.358	0.00000
Demand for Semi-Imports	DSR	88.95	250.28	29.975	0.00000
Consumer Price Index	CPI	17.31	42.45	1.4796	0.00628
Investment	INV	13.23	50.01	0.0897	0.78541
Current Account	CA	11.4	38	1.201	0.0058
Visual Deficit	PD	14.82	45.41	2.3621	0.0132
Banking Credits	BC	13.85	47.81	1.2201	0.1153

Source: Research calculations

Based on Table 2, the results of the Jarek-Bera test for different variables show that Financial Crisis (FC), Yield Curve Slope (YCS), Debt Service Ratio (DSR), Consumer Price Index (CPI), Current Account (CA) and Public Debt (PD) have non-normal distributions with very low probabilities, while Investment (INV) and Bank Credit (BC) have higher probabilities with coefficients of 0.0897 and 1.2201, respectively, indicating that their distributions are close to normal. 0897 and 1.2201 respectively, indicating that their distributions are close to normal. is In general, most variables are far from a normal distribution, which can affect statistical and economic analyses. According to the results of the descriptive statistics of the research variables, the prediction of financial crises in terms of bank loans and macroeconomic variables has been studied using machine learning, so the main advantages of this type of non-parametric statistical methods can be He also used data that do not have a normal distribution, so the results of research for machine learning, which includes nearest neighbour and random forest, can be seen in Table 3. Therefore, in this study, two machine learning methods, namely Random Forest and K-Nearest Neighbors (KNN), were used to analyses and predict the financial crises in Iran and Iraq. Sum of Random Forest, as a non-linear and complex method, is able to identify non-linear relationships between macroeconomic variables and financial crises, and it performs well especially in situations where the data are more complex and nuanced. On the other hand, KNN, as a simple and practical method, performs classification and prediction using the distance between data points, and is suitable for basic analysis and better understanding of the data structure. Finally, to improve the quality and accuracy of the results, two main methods were used to identify and remove outlier data: The spike method and the standard deviation method. The spike method detects sudden and unusual changes in the data, while the standard deviation method considers data that are more than a certain distance (usually 2 or 3 times the standard deviation) from the mean to be outliers. This data sorting process removes outliers and thus reduces unwanted effects on model outputs. By using these two methods, the accuracy and validity of the predictions made for the financial crises in Iran and Iraq have increased. The results of these two methods are shown in Table 3 below.

Table 3. Prediction of financial crises using KNN and Random Forest

variable	Importance (Iran)		Importance (Iraq)				
YCS	68.582		104.602				
DSR	45.006		46.212				
CPI	37.906		28.436				
INV	42.067		33.265				
CA	87.037		100.137				
PD	63.163		45.084				
BC	55.428		41.417				
Country	**Algorithm**	**mtry**	**Accuracy**	**Sensitivity**	**Feature**	**RMSE**	**R-squared**
Iran	Random Forest	2	0.920	0.914	0.946	0.271	0.595
		3	0.890	0.890	0.892	0.276	0.572
		4	0.890	0.890	0.892	0.277	0.564
		5	0.885	0.890	0.865	0.274	0.573
		6	0.890	0.890	0.892	0.275	0.574
		7	0.895	0.896	0.892	0.277	0.566
	KNN	3	0.855	0.908	0.622	0.327	0.362
		5	0.890	0.926	0.730	0.293	0.467
		7	0.855	0.896	0.676	0.301	0.438
		9	0.890	0.926	0.730	0.296	0.458
		11	0.895	0.939	0.703	0.288	0.483
Iraq	Random Forest	2	0.900	0.898	0.907	0.282	0.591
		3	0.895	0.892	0.907	0.278	0.590
		4	0.905	0.904	0.907	0.276	0.591
		5	0.900	0.898	0.907	0.275	0.590
		6	0.905	0.898	0.930	0.276	0.587
		7	0.905	0.898	0.930	0.281	0.572
	KNN	3	0.885	0.911	0.791	0.310	0.449
		5	0.895	0.936	0.744	0.298	0.479
		7	0.885	0.917	0.767	0.306	0.462
		9	0.895	0.917	0.814	0.299	0.494
		11	0.890	0.904	0.837	0.293	0.520

Source: Research calculations

Based on the data presented, macroeconomic variables play an important role in predicting financial crises in Iran and Iraq. In both countries, YCS (yield curve slope) and CA (current account balance) are the most important in predicting financial crises. For Iran, CA with an importance of 87.037 and YCS with 68.582 are at the top, while for Iraq, YCS with 104.602 and CA with 100.137 are the most important variables. This shows that the state of the yield curve and the current account balance play a key role in predicting financial crises in both countries. PD (public debt) also plays a significant role in these predictions, with an importance of 63.163 in Iran and 45.084 in Iraq. On the other hand, regarding the role of bank credit (BC), this variable is significant in both countries, but not as much as YCS and CA. In Iran, BC ranks fifth with a significance of 55.428, while in Iraq it ranks sixth with a significance of 41.417. This shows that although bank credit plays an important role in predicting financial crises, other variables such as the slope of the yield curve, the current account balance and public debt are more influential. Other variables such as DSR (debt service ratio), CPI (consumer price index) and INV (investment) also play a role in these forecasts, but to a lesser extent. This analysis shows that in order to accurately predict the financial crises in Iran and Iraq, one should pay attention to a wide range of macroeconomic variables, with special emphasis on the slope of the yield curve, the current account situation and the level of public debt. According to the results of learning machine learning to predict financial crises in Iran and Iraq using bank loans and macroeconomic variables using the algorithm of forecasting models based on demand, adversarial learning and component analysis The original has been paid. Therefore; In this study, financial crisis forecasting has been carried out using three different methods, including demand-based forecasting, contrast learning and principal component analysis. Demand-based forecasting examines consumption and demand patterns in the economy to anticipate fluctuations and crises, while adversarial learning models complex relationships between economic variables and can identify their mutual effects. Principal component analysis also helps to reduce the dimensions of the data and identifies the important relationships by identifying the principal components. To ensure the quality of the data and the accuracy of the results, outliers were identified and removed. This process involved the use of statistical measures such as standard deviation and interquartile range (IQR) to remove outliers from the dataset that could negatively affect the results. In this way, the combination of these three methods and careful data processing not only helped to increase the accuracy of the forecasts, but also led to a better analysis of financial crises; the related results are described in Table 4 below.

Table 4. Prediction of financial crises using demand-based forecasting, contrast learning and principal component analysis

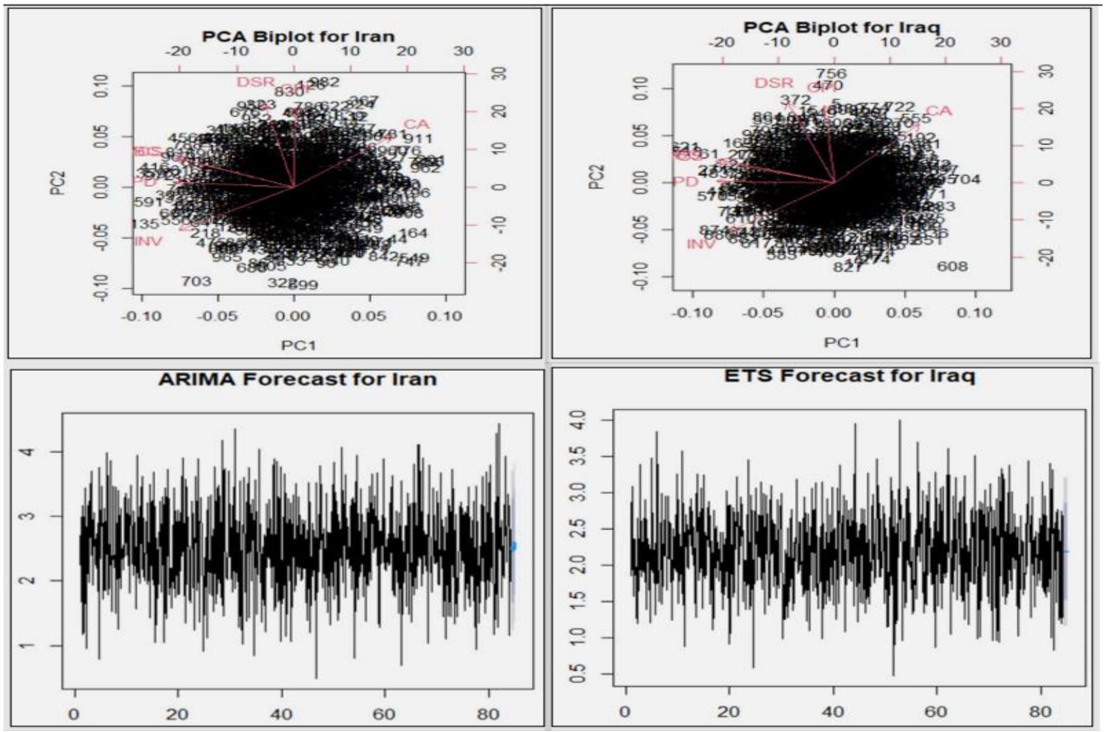
Country	Model	Metric	Value
Iran	Demand-Based	ARIMA RMSE	0.628
	Demand-Based	ARIMA MAE	0.5
	Demand-Based	ETS RMSE	0.63
	Demand-Based	ETS MAE	0.502
	PCA	PC1 Variance Explained	0.453
	PCA	PC2 Variance Explained	0.308
	PCA	PC3 Variance Explained	0.131
	PCA	PC4 Variance Explained	0.059
	PCA	PC5 Variance Explained	0.049
	PCA	PC6 Variance Explained	0
	PCA	PC7 Variance Explained	0
	Adversarial Learning	Original Accuracy	0.835
	Adversarial Learning	Adversarial Accuracy	0.77
Iraq	Demand-Based	ARIMA RMSE	0.518
	Demand-Based	ARIMA MAE	0.412
	Demand-Based	ETS RMSE	0.523
	Demand-Based	ETS MAE	0.415
	PCA	PC1 Variance Explained	0.445
	PCA	PC2 Variance Explained	0.309
	PCA	PC3 Variance Explained	0.129
	PCA	PC4 Variance Explained	0.065

PCA	PC5 Variance Explained	0.052
PCA	PC6 Variance Explained	0
PCA	PC7 Variance Explained	0
Adversarial Learning	Original Accuracy	0.845
Adversarial Learning	Adversarial Accuracy	0.755

Source: Research findings

According to the results presented in Table 4, macroeconomic variables play an important role in predicting financial crises in Iran and Iraq. Principal component analysis (PCA) shows that in both countries the first three principal components explain more than 89% of the data variance. This indicates a strong correlation between the macroeconomic variables (YCS, DSR, CPI, INV, CA, PD and BC). Considering that PC1 explains about 45% of the variance in both countries, it can be concluded that a combination of important variables such as the slope of the yield curve (YCS), the current account (CA) and public debt (PD) probably play the main role in this component. perform Regarding the role of bank credit (BC), although this variable is not directly visible in the PCA results, it is likely to be present in the principal components in combination with other variables. The results of the demand-based forecasting models (ARIMA and ETS) show that these models performed better in Iraq than in Iran (lower RMSE and MAE). This indicates the greater complexity of the relationships between variables in the Iranian economy. The adversarial learning results also show that the forecasting models are relatively robust in both countries, but their accuracy decreases when faced with conflicting data (from 0.835 to 0.77 in Iran and from 0.845 to 0.755 in Iraq). This shows the importance of taking into account unexpected conditions and sudden changes in economic variables, including bank credit, when forecasting financial crises. The following is a graphical examination of financial crisis prediction using demand-based forecasting, contrast learning and principal component analysis, the results of which are shown in Chart 1.

Figure 1. Predicting financial crises using demand-side forecasting, contrast learning and principal component analysis



Source: Research findings

Based on Chart 1, the results of Principal Component Analysis (PCA) show that macroeconomic variables in both countries of Iran and Iraq are similar and have a higher density in the center of the chart. Variables such as (DSR), (CA), (PD) and (INV) are of great importance and the density of data in the center indicates the correlation between these variables. This indicates the similar impact of bank credit and macroeconomic variables on the financial situation of these two countries. On the other hand, time series forecasts using ARIMA models for Iran and ETS for Iraq show significant fluctuations in the data. In Iran, the ARIMA model shows that the fluctuations are confined to a small fluctuation band, which may reflect the complexity and timing changes of the economic variables. In Iraq, the ETS model shows similar fluctuations, indicating non-linear behavior in the data. These results can help policy makers to identify and manage these fluctuations and adopt more appropriate strategies to prevent financial crises in the future. Therefore; After determining the results related to demand-based prediction models, contrast learning and principal component analysis to predict financial crises using four neural network methods, including functional neural network, cerebellar model articulation controller, self-encoders. Autoencoder) and Fuzzy Logic.

The Functional Neural Network, which has the ability to model complex and non-linear relationships, uses neurons with complex activation functions. The Cerebellar Neural Network, designed to mimic the function of the brain, uses a special neural structure with multiple layers and complex connections. Autoencoders, used for data compression, consist of a symmetrical structure with encoder and decoder layers. Although the fuzzy system is not a traditional neural network, it is implemented with fuzzy neurons that use membership functions to process information. It also uses a standard neural network and a support vector machine (SVM), the former consisting of neurons with standard ReLU and sigmoid activation functions, and the latter using a non-neural structure for classification. In general, functional neural networks help to model complex and non-linear relationships between variables and are effective in predicting critical situations due to their ability to learn from large and complex data. The cerebellum is used to mimic brain function and learn dynamic patterns, and can process input information more effectively. For data compression, self-encryptors create online structures to identify the main features of the data, thus improving data quality. Fuzzy is also used to analyses fluctuations and uncertain behavior in the economy due to its ability to adapt and make decisions under conditions of uncertainty. To protect the accuracy of the model, outliers were identified and removed, using measures such as standard deviation and interquartile range (IQR) to identify outliers. In this way, the use of these four methods and accurate data processing led to a significant improvement in the accuracy of predicting financial crises.

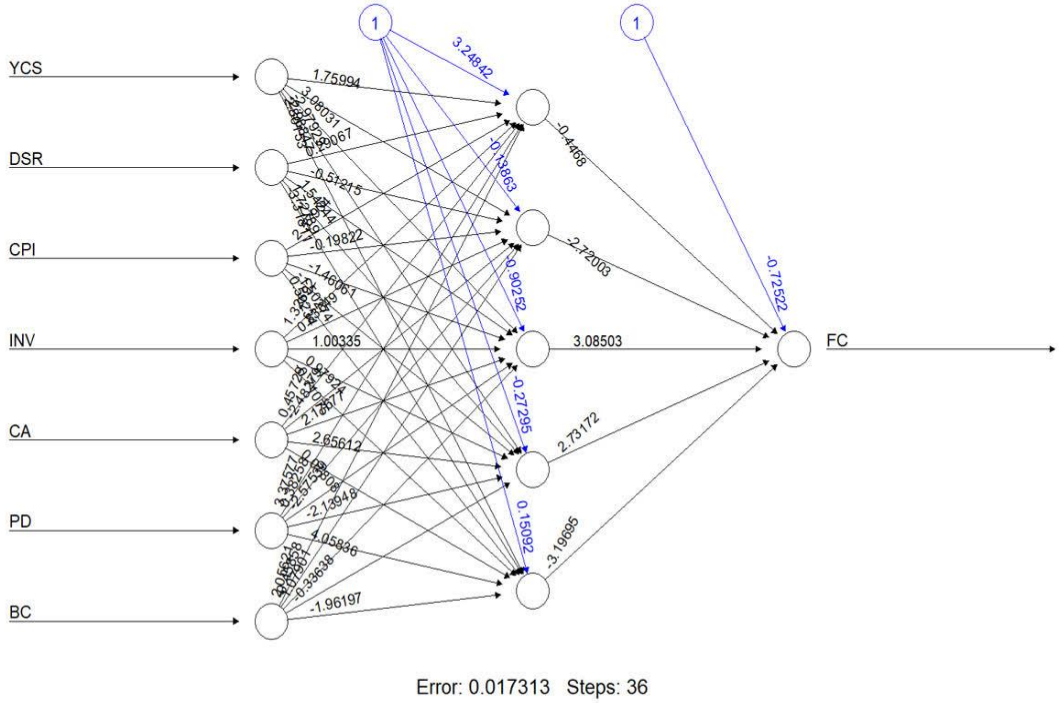
Table 5. Prediction of financial crises using functional, cerebellar, autoencoder and fuzzy neural networks.

Importance of variables			**Examining research models**		
Variable	**Iran**	**Iraq**	**Metric**	**Iran**	**Iraq**
DSR	1983	2112	Functional Neural Network (Accuracy)	0.4820	0.4944
INV	7.1551	13.4483	Functional Neural Network (MSE)	0.5180	0.5056
CA	7.1679	5.8238	Cerebellar Neural Network (Accuracy)	0.7603	0.6789
BC	5.2499	1.5291	Cerebellar Neural Network (MSE)	0.2397	0.3211
PD	0.3003	3.7240	Support Vector Machine (SVM) (Accuracy)	0.7498	0.6201
CPI	0.7919	0.9497	Support Vector Machine (SVM) (MSE)	0.2502	0.3799
YCS	0.0097	0.0096	Neural Network (Accuracy)	0.7624	0.5463
			Neural Network (MSE)	0.2376	0.4537
			Fuzzy System (Accuracy)	0.7918	0.6092
			Fuzzy System (MSE)	0.2082	0.3908
			Best Model	Fuzzy System	Cerebellar Neural Network

Source: Research findings

Based on the results of Table 5. Importance of variables in both Iran and Iraq, current account (CA) and investment (INV) variables are the most important in predicting financial crises. This shows that the state of foreign trade and the amount of investment in the economy play a key role in the financial stability of these countries. In Iran, bank credit (BC) is more important than in Iraq, which may indicate a stronger role of the banking system in the Iranian economy. Therefore, in the comparison of forecasting models, the fuzzy system for Iran and the cerebellar neural network for Iraq performed best. This difference is the result of the different complexity of the economic structures of the two countries. Fuzzy system with 79.18% accuracy for Iran and cerebellar neural network with 67.89% accuracy for Iraq has provided the best results. Thus, the differences between the two countries, when comparing the results, show that the forecasting models for Iran are generally more accurate than for Iraq. This is because there is more relative stability in Iran's economic data or less complexity in the relationships between economic variables. Also, the different importance of variables in two countries (e.g. greater importance of DSR and PD in Iraq) indicates the structural differences in the economies of these two countries. Finally, these results show the importance of considering different macroeconomic variables and bank loans in predicting financial crises. In order to improve financial stability, policymakers in both countries should pay special attention to the current account, investment and, in the case of Iran, bank credit. In addition, the use of appropriate forecasting models for each country (fuzzy system for Iran and cerebellar neural network for Iraq) can help predict financial crises more accurately and take appropriate preventive measures. Below is a graphical analysis of financial crisis prediction using neural networks for Iran and Iraq, the results of which are shown in Figures 2 and 3.

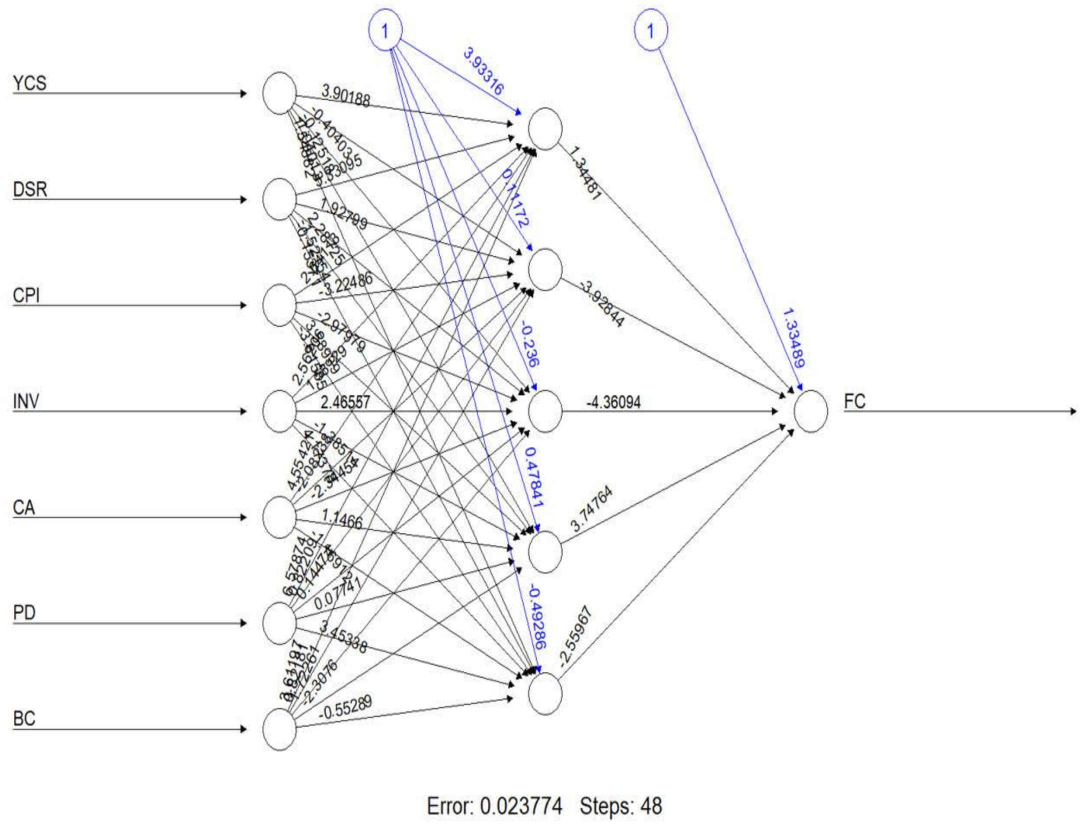
Chart 2. Financial crisis prediction using neural networks for Iran



Source: Research calculations

Figure 2 shows the artificial neural network for predicting financial crises in Iran using macroeconomic variables and bank loans. Variables such as YCS, DSR, CPI, INV, CA, PD and BC were used as network inputs. These variables are linked to the output variable FC (financial crisis function) through the hidden layer neural network. The weights of the communication lines between the nodes determine the impact of each input variable on the final prediction; higher weights indicate more importance of that particular variable for the model. The low network error indicates the high accuracy of the model during training and its ability to predict (0.017313) .financial crises according to economic variables and bank loans

Figure 3. Financial crisis prediction using neural networks for Iraq



Source: Research results

The artificial neural network diagram for Iraq shows the role of bank credit and macroeconomic variables in predicting financial crises. The network inputs include YCS, DSR, CPI, INV, CA, PD and BC. These inputs are connected through hidden layers to the output variable Financial Crisis (FC). The weights of the connecting lines between the nodes show the influence of each input variable on the final prediction; higher weights represent the greater importance of that particular variable. The grid error (0.023774) indicates acceptable accuracy, although it generally has more error than the Iranian grid, which may indicate greater complexity in Iraq's economic variables. This analysis helps Iraqi policymakers to better understand the impact of changes in bank credit and macroeconomic variables, and to take more effective steps to predict and manage future financial crises. Finally, the forecasting of financial crises in Iran and Iraq was done using the optimal expectation algorithm. The optimal expectation algorithm in forecasting financial crises uses a network structure in which each element or "neuron" represents one of the macroeconomic variables. This algorithm adjusts the weights and relationships between variables using input data such as coefficients, P-values, odds ratios and the importance of each variable. This structure takes into account various macroeconomic variables such as YCS, DSR, CPI, INV, CA, PD and BC. By iterating and continuously updating the weights based on these parameters, the algorithm gradually creates an optimal model for predicting financial crises in each country. This approach allows the differences in the importance and impact of each variable between two countries to be taken into account, thus providing a dynamic and flexible framework for analyzing and predicting financial crises. Therefore, the results in terms of the expected optimization algorithm, as described in Table 5, are as follows.

Table 5. Prediction of financial crises using optimal expectation algorithm

Variable	Iran Coefficient	Iran P-Value	Iran Odds Ratio	Iran Importance	Iraq Coefficient	Iraq P-Value	Iraq Odds Ratio	Iraq Importance	Iran Mean FC	Iraq Mean FC
YCS	14.6409	0.2024	2282687	49.2555	2.5827	0.0711	13.233	36.5325	0.9679	0.925
DSR	-7.1654	0.1658	0.0008	24.106	-1.5723	0.0017	0.2076	22.2405	0.9679	0.925
CPI	0.2228	0.3238	1.2496	0.7496	0.1405	0.0591	1.1509	1.9878	0.9679	0.925
INV	2.7442	0.1675	15.5524	9.2322	1.0573	0.0007	2.8785	14.9551	0.9679	0.925
CA	-3.2169	0.1728	0.0401	10.8225	-1.0626	0.0088	0.3456	15.0299	0.9679	0.925
PD	0.9525	0.1361	2.5921	3.2043	0.5077	0.0013	1.6614	7.1812	0.9679	0.925
BC	-0.7817	0.1664	0.4576	2.63	-0.1466	0.0135	0.8637	2.0731	0.9679	0.925

Source: Research results

Based on the results presented in Table 5, it can be seen that the optimal expectation algorithm has been used to predict financial crises in Iran and Iraq. In both countries, the slope of the yield curve (YCS) is the most important variable in predicting financial crises, but its effect is much larger in Iran (with a coefficient of 14.6409 and a significance of 49.2555) than in Iraq (with a coefficient of 2.5827 and a significance of 36.5325). The debt service ratio (DSR) is the second most important variable in both countries, with a negative effect on the probability of a financial crisis. Investment (INV) and current account (CA) are more important in Iraq than in Iran, while public debt (PD) is more influential in Iraq. Consumer price index (CPI) and bank credit (BC) are the least important in both countries. Therefore, it can be seen that the mean probability of financial crisis (Mean FC) for Iran (0.9679) is slightly higher than that for Iraq (0.925), indicating that the risk of financial crisis is slightly higher in Iran. This analysis shows that the factors affecting financial crises in these two countries are similar, but of different importance. According to the significant differences in the P-value of the variables between the two countries, it can be seen that for Iraq most of the variables have a P-value less than 0.05, indicating the high statistical significance of these variables in predicting financial crises. On the contrary, for Iran, the P-values are generally higher, indicating more uncertainty in the predictive model for Iran. This is because there are more complications in the Iranian economy or the influence of external factors such as sanctions. Also, the odds ratio for the YCS variable is much higher in Iran than in Iraq, showing that small changes in the slope of the yield curve can have a much larger effect on the probability of a financial crisis in Iran. Finally, comparing the coefficients and importance of the variables between the two countries shows that policymakers in Iran and Iraq should take different approaches to preventing financial crises. In Iran, focusing more on managing the yield curve and the debt service ratio may be more effective, while in Iraq it is more important to pay attention to a wider range of variables, especially investment and the current account. In addition, the lower role of bank credit (BC) in both countries compared to other variables may indicate the need to revise credit and banking policies to increase the impact of this sector on financial stability. These findings can be a valuable guide for economic policy makers in both countries to predict and prevent future financial crises. Therefore, the present study is in line with many recent researches on predicting financial crises using machine learning methods, especially Random Forest and KNN. Researchers such as Ashtab et al. (2017), Wang & Wu (2017), Liu et al. (2022), and Blustein et al. (2023) have also highlighted the superiority of these methods, indicating a strong trend in the use of artificial intelligence in this area. The focus on macroeconomic variables such as YCS and CA is consistent with the findings of Ahmad et al. (2021) and Laborda & Olmo (2021). Ristolainen et al. (2024) have also emphasised the importance of information in news headlines, which may complement these findings.

In the case of Iran, the findings of greater uncertainty and ambiguity in the economy are consistent with the studies of Taheri Bazkhaneh et al. (2019), Emamverdi & Jafari (2019) and Jafarimanesh & Gholami (2022). For Iraq, the better performance of the cerebellar neural network is consistent with the findings of Yousef & Aldeen (2018) and Salman et al. (2021).

Other studies such as Samtani et al. (2020), Nora Metawa et al. (2021), Muthukumaran & Harihaaranath (2022) and Venkateswarlu et al. (2022) have also highlighted the importance of advanced methods in predicting financial crises. In sum, this study is in line with the general trend of recent research by emphasising the use of advanced machine learning methods, paying attention to macroeconomic variables and taking into account the specific conditions of each country, which can help to improve the accuracy of predictions and deepen the understanding of the factors influencing financial crises.In sum, this study is in line with the general trend of recent research in this field by emphasising the use of advanced machine learning methods, paying attention to macroeconomic variables and taking into account the specific conditions of each country in predicting financial crises. This comprehensive approach can help to improve the accuracy of forecasts and provide a deeper understanding of the factors that influence financial crises.

Research conclusions and proposals

Financial crisis forecasting at the national level is recognized as a key tool for economic management and policy making. These forecasts allow economic authorities to respond appropriately to sudden changes in the financial and economic situation and to prevent crises. By identifying warning signs early, governments can design and implement preventive and corrective policies that can strengthen economic fundamentals and protect national wealth. In addition, this type of forecasting helps in optimal planning of investments and allocation of financial resources and can increase the confidence of investors and citizens in the country's financial system. Therefore, attention and emphasis on systematic forecasting of financial crises in economic policy not only helps to improve the financial situation of countries, but also provides economic stability. Therefore, the present study investigates and analyses the financial crises in Iran and Iraq using economic data and macro variables, including bank loans, between the years 2000 and 2023. In this research, key variables including yield curve slope (YCS), debt service ratio (DSR), consumer price index (CPI), investment (INV), current account (CA), public debt (PD) and bank credit (BC) have been measured. The obtained results show that these variables have a direct impact on the occurrence and severity of financial crises in both countries, and the accuracy of their prediction can help policy makers to make appropriate and timely decisions. Firstly, based on the descriptive statistics and the information obtained from the Jarque-Bera test, it was found that the majority of the variables studied are far from normal distribution. This highlights the need to use non-parametric statistical methods and machine learning models. The use of advanced algorithms such as Random Forest and K-Nearest Neighbors (KNN), especially in discovering the non-linear and complex relationships between economic variables and financial crises, showed that these methods can identify more information and make more accurate predictions. find Also, the prediction results using these methods indicated the great importance of macroeconomic variables in determining financial crises; in particular, YCS and CA variables were identified as the most important predictors. Therefore; Machine learning methods (Random Forest and KNN) in this study showed that Yield Curve Slope (YCS) and Current Account (CA) are the most important variables in predicting financial crises in both Iran and Iraq. This result is important in several respects. The YCS has a stronger effect in Iran, indicating the importance of monetary policy and interest rates for financial stability, while it has a smaller effect in Iraq. Changes in the current account balance are important in both countries, but have a greater impact in Iran due to its dependence on oil exports. The use of these methods is due to their ability to identify complex patterns and deal with non-linear data. Changes in the YCS can indicate changes in inflation expectations and economic growth, while current account deficits can lead to currency depreciation and increase the risk of financial crisis. These findings have important implications for policymaking in both countries, indicating the need to pay special attention to the management of interest rates and the trade balance. Finally, these results emphasise the importance of using advanced data analysis methods in economic policy-making and show that a comprehensive approach, tailored to the specific conditions of each country, is needed to predict and prevent financial crises.

Principal component analysis (PCA) showed that the first three principal components explained more than 89% of the variance in the data in both countries, indicating a strong relationship between macroeconomic variables. These three components are the most probable: Yield Curve Slope (YCS) and Current Account (CA): This component indicates the relationship between monetary policy and the state of foreign trade. The impact of this component on the economy is that an increase in the slope of the yield curve is usually a sign of higher inflation expectations and economic growth in the future, while an improvement in the current account may indicate an increase in exports or a decrease in imports. Debt service ratio (DSR) and public debt (PD): This component shows the debt situation of the country. Its impact on the economy is that an increase in these ratios can indicate more financial pressure on the government and the private sector, which can lead to a decrease in investment and economic growth. Investment (INV) and Bank Credit (BC): This component represents domestic economic activity. Its impact on the economy is that an increase in investment and bank credit usually indicates economic growth and an increase in production activities. The importance of this finding is that it shows that these three main components can explain a large part of the changes in the economic situation and the possibility of a financial crisis. This helps policymakers to manage the economy more efficiently and prevent financial crises by focusing on these components. Caution is needed because this strong relationship between variables shows that a change in one of them can have a significant impact on other variables and thus on the economy as a whole. For example, a change in monetary policy that affects the slope of the yield curve may also indirectly affect investment and bank lending. These results also show the importance of using multivariate approaches in analyzing and predicting financial crises, because focusing on one variable alone may not provide a complete picture of the economic situation.

Accurate forecasting of economic trends is essential for effective policy-making and risk management in national economies. In other words, the forecasting and management of economic and financial risks is crucial for policy-making and economic development. In this regard, the use of advanced data analysis and modelling techniques can provide valuable information on the economic structure and dynamics of countries. Using a wide range of methods, from traditional time series models to advanced machine learning techniques, this study examines and compares the economic situation of Iran and Iraq. Demand-based forecasting models (ARIMA and ETS) performed better in Iraq than in Iran, which could indicate the greater complexity of economic relationships in Iran. In Iran, the weaker performance of these models is due to the presence of multiple and more complex factors in the economy, such as economic sanctions, extreme fluctuations in exchange rates and rapid changes in economic policies. On the contrary, the better performance of these models in Iraq indicates simpler and more linear relationships in the country's economy.

In the field of neural networks, significant results were obtained when comparing the economies of Iran and Iraq. A fuzzy system showed the best performance for Iran, while a cerebellar neural network showed superior results for Iraq, providing deep insights into the different economic structures of the two countries. For Iran, the better performance of the fuzzy system indicates a considerable degree of uncertainty and ambiguity in the economy. This characteristic is consistent with Iran's economic conditions, which include fluctuating economic sanctions, high exchange rate volatility, rapid changes in economic policy and a diverse economy. These conditions often make the relationships between economic variables in Iran non-linear and ambiguous, which the fuzzy system is particularly adept at modelling. In contrast, the superior performance of the cerebellar neural network for Iraq suggests identifiable and learnable patterns in that country's economy. This can be attributed to a heavy reliance on oil, more regular economic cycles, more stable economic policies and limited trade relations. This difference in model performance has important implications for policymaking in both countries. In Iran, policymakers must be prepared to navigate uncertain and fluctuating conditions and adopt flexible decision-making methods, while in Iraq they can use identified patterns for more precise planning, but must also be wary of over-reliance on these patterns. Ultimately, these findings emphasise that the use of diverse and advanced data analysis methods is essential for understanding and effectively managing the economy, with each country requiring an approach tailored to its unique economic characteristics. Additionally, the optimal expected algorithm demonstrated that the slope of the yield curve (YCS) is the most crucial factor in both countries; however, its impact is significantly greater in Iran than in Iraq. In Iran, the greater importance of YCS may indicate increased sensitivity of the economy to changes in interest rates and inflation expectations. Conversely, the lesser importance of YCS in Iraq may reflect the minor impact of monetary policies on that country's economy. Therefore, bank credit (BC) was found to be less significant than other variables in both countries, suggesting that credit and banking policies may require reevaluation. This finding could indicate the inefficiency of the banking system in influencing financial stability in both countries. In Iran, this may stem from structural issues within the banking system, while in Iraq, it may be due to the underdeveloped banking system and the economy's heavy dependence on oil revenues. Consequently, the average probability of a financial crisis was slightly higher in Iran compared to Iraq, indicating a greater risk of financial crises in Iran. This difference may be attributed to greater economic complexities, international sanctions, more severe fluctuations in economic variables, and structural challenges in Iran's banking and financial system. In Iraq, the lower probability of a financial crisis may be linked to a simpler economic structure and lesser dependence on non-oil sectors. Thus, these findings carry significant implications for economic policy in both countries. In Iran, policymakers should employ more complex models for economic forecasting and management, prioritize the management of interest rates and inflation expectations, and implement additional preventative measures to reduce the probability of financial crises. In Iraq, while simpler models may be sufficient, policymakers should focus on maintaining current stability and gradually diversifying the economy. Ultimately, this study suggests that a comprehensive approach tailored to each country's specific conditions is necessary for predicting and preventing financial crises. Utilizing advanced data analysis methods in economic policymaking can enhance decision-making and improve financial stability in both countries. Overall, the practical recommendations from the research are as follows:

i. For Iran, given the greater complexity and high uncertainty in the economy, it is suggested that policymakers utilize more advanced and flexible predictive models such as fuzzy systems.

Additionally, given the high significance of the slope of the yield curve (YCS), it is recommended that monetary policies be adjusted with greater care, prioritizing the management of interest rates and inflation expectations. To reduce the economy's vulnerability to external shocks, diversifying income sources and reducing reliance on oil exports are essential. Reforming the banking system and enhancing its efficiency should also be prioritized, as bank credit has had less impact on financial stability. Furthermore, due to the higher probability of financial crises, the establishment of early warning systems and strengthening oversight of financial markets is advised.

ii. For Iraq, given the simpler economic structure and identifiable patterns, using time series-based predictive models like ARIMA and ETS could be beneficial. Additionally, considering the good performance of cerebellar neural networks, employing this method to identify economic patterns is recommended. Although the impact of YCS is less significant in Iraq, it remains important and should be considered in economic policymaking. Due to the heavy reliance on oil revenues, diversifying the economy and developing non-oil sectors should be prioritized. Modernizing and developing the banking system could also enhance the impact of bank credit on financial stability. Additionally, despite a lower probability of financial crises compared to Iran, establishing preventive mechanisms and strong regulatory systems is essential to maintain economic stability.

iii. For both countries, utilizing advanced data analysis methods like machine learning algorithms and principal component analysis (PCA) to gain a better understanding of the complex relationships between economic variables is recommended. Furthermore, given the importance of the current account (CA) in both nations, careful management of the trade balance and foreign exchange policies should receive special attention. Strengthening regional and international cooperation to reduce vulnerability to external shocks could also be beneficial. Ultimately, creating comprehensive risk management systems and improving transparency in financial reporting could help enhance financial stability and reduce the likelihood of economic crises.

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