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Bank Credits and Macroeconomic Variables in Forecasting Financial Crises in Iran and Iraq: A Machine Learning and Neural Network Approach

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Abstract

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 take into account (based on) the importance of paying attention to/ laying focus on/ giving due consideration to/ taking into consideration/ taking into account/ bearing legislative testament understanding aspects that constitute or personate unique economic characteristics of each country exploit/since design(s) that would/could surface(s)/emerge(nt) prevention strategies for financial crisis. 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 take into account (based on) the importance of paying attention to/ laying focus on/ giving due consideration to/ taking into consideration/ taking into account/ bearing legislative testament understanding aspects that constitute or personate unique economic characteristics of each country exploit/since design(s) that would/could surface(s)/emerge(nt) prevention strategies for financial crisis.

Keywords: bank credits, financial crises, neural network, learning algorithms, optimization.

Introduction

Financial Crises are Repeating a Phenomenon in the Economic History of the World and has destructive effects on economic activity (Sufi & Taylor, 2022). Generally, these crises are associated with a sharp unexpected decline in the value of assets. Evidence has shown that most of these crises originate from problems in the banking system which can cause decreased economic growth, deep recessions and an important increase in unemployment (Danisman & Tarazi, 2024). Therefore, Fresh financial crises as systematic disturbance in financial markets have a low potential to spread to other sectors of the economy which can result fundamental changes macroeconomic performance. The impact on these crises can be seen on: Reduction GDP Growth Rate, Increase Inflationary Pressures Leading Stagflation And Increasing Balance Of Payments Deficit issues (Cecchetti et al. 2009). In the same way that they influence macroeconomic variables, financial crises might have some effects on micro-level financial and banking indicators because the data associated with these indicators are important in the decision process for borrowers, investors, and policy makers. Such information is of extreme importance for estimating economic risks and opportunities and working out effective strategies in the sphere of financial management and economic policy (Biljanovska et al, 2023).

Not only in contemporary times but also throughout history, financial crises have been frequent in which the value of financial assets within a market or economy sharply decline leading to general uncertainty and instability of the financial system i.e. at the level of banks and financial institutions up to that of an entire national or even global economy (Gorton, 2018). There are a lot of things that could trigger a financial crisis including over-indebtedness, mispriced assets, lack of transparency in finance, poor risk management and unexpected changes in the market (Hellwig, 2008; Acharya and Richardson, 2009; Warwick et al., 2010). Therefore the development process for most financial crises begins with the formation of an asset market price bubble that later bursts dramatically by falling sharply hence leading to investors' loss. This can lead to insolvency within banks and other involved financial institutions (Aiginger, 2009). In fighting against financial crises typically governments as well as politicians apply policy adjustment and economic stimulus. The loss of confidence among consumers and businesses results in the weakening of demand and investment, which can later cause a crisis in banks and financial institutions, further putting governments under extreme financial stress by generating budget deficits through increased public debt (Wang et al., 2023). Moreover, social implications like growing inequality, decreasing quality of life, mounting mental health problems and poverty can menace social stability and reduce public confidence in financial systems as well as government institutions (Sheaffer et al., 1998). In light of the far-reaching effects of financial crises on countries and the population at large, knowledge about these events is very important for any country that wants to maintain its economic and public stability (Rewilak, 2018). Key to policymakers is therefore the ability to recognize these warning signals since timely detection of such crises helps lower risks during their increase (International Monetary Fund, 2008). The loss of confidence among consumers and businesses begets weakening of demand and investment, which in turn may lead crises in banks and financial institutions, as well as put governments under serious financial strain, thus resulting in budget deficits and growth in public debt (Wang et al, 2023). Moreover, social consequences like increasing inequality or decreasing quality of life or growth problems with mental health or poverty can threaten social stability and undermine confidence by the population in financial systems (Sheaffer et al, 1998). In light of the rather broad negative effects that financial crises can have on a country, it is necessary to fully understand these phenomena to be able to manage them for the economic stability of a state (Rewilak, 2018). Therefore being aware of the warning signs is very important for policymakers

because early diagnosis might help prevent huge risks from materializing into actual crises (International Monetary Fund, 2008).

Hence, the unpredictable nature of economic systems and the presence of unforeseen factors will definitely lead to the rapid spread of negative consequences throughout the global economy, such as the Covid-19 pandemic, which was generally unknown before 2020 and incorporated into past economic models. This is a clear example of how little-understood variables can have drastic immediate effects on global economies—making it difficult for economists and policy makers to keep up with predicting economic dynamics (Edison, 2003; Lepore et al, 2023). Hence, the unpredictable nature of economic systems and the unanticipated can cause, including the Covid-19 pandemic— which to a large extent was unknown before 2020 and not incorporated in previous economic models— to within a short time drive the global economy into crisis. Such a phenomenon shows how unforeseen factors can in a very drastic and immediate way affect global economies, thereby testing economists and policy makers in comprehending and forecasting economic dynamics (Edison, 2003; Lepore et al, 2023).

Over the past few decades, the global economy has been facing one financial crisis after another; these crises have significantly affected developing and emerging economies—Iran and Iraq included. Concerning this, growth in bank credit and changes in macroeconomic variables like inflation, investment, balance of payments deficit and exchange rate form a good basis for studying financial crises at national and international levels (Joseph, 2020; Buckmann and Joseph, 2023). In other words, an increase in bank credit growth and changes in macroeconomic variables are important factors that help to better predict the onset of a financial crisis — as argued by research from Allen (2009) and Kristina et al (2023). Therefore, according to Bluwstein et al (2023), an unsystematic expansion of bank loans with increasing liquidities is one of the major predictive signs capable of causing a financial crisis due to disequilibrium that occurs within financial or economic markets. On the basis of available data and the main macroeconomic variables, this research seeks to identify patterns that would allow forecasting potential financial crises in Iran and Iraq, thus helping policymakers to take more effective measures. Thus, the oil-dependent economic structure and insufficiency of income sources make general exposure of Iran and Iraq to be vulnerable or susceptible to any economic fluctuations provoked by movements in global oil prices. In this case, banks and financial institutions take center stage as a key instrument for financing various sectors of the economy (Mishra & Burns, 2017).

In view of the above, the present research is going to analyze the dynamics of public and private debt, and their relationship with such macroeconomic variables as gross domestic product, inflation rate, and the value of the national currency, to be able to create an all-inclusive understanding of how these factors act as advance signals of a financial crisis. Therefore this research had two main objectives: first, to consider bank credit and macroeconomic variables in the prediction of a financial crisis in Iran and Iraq. In view of the above, the present research is going to analyze the dynamics between public and private debt alongside its interaction with macroeconomic variables such as gross domestic product, inflation rates, and the value of the national currency so as to come up with a complete perception of how these variables act as pre-crisis signals. Therefore the main purpose of this research is to study bank credit and macroeconomic variables in the prediction of a financial crisis for Iran and Iraq. In view of the above, the present research is going to examine the dynamics of public and private debt and their relationship with macroeconomic variables such as gross domestic product, inflation rates, and the value of the national currency in order to provide a complete understanding of how these

factors act as pre-announcers to a financial crisis. Hence, the main objective of this research would be to investigate bank credit's role and that of macroeconomic variables in predicting a financial crisis for Iran and Iraq.

Literature Review

It is this narrow focus that limits the explanatory power of the poltarist perspective and emphasizes that a broader perspective should be incorporated when analyzing and dealing with financial instability (Mishkin, 1992). There is no way to predict economic systems; they are inherently vulnerable. However, understanding such vulnerabilities can help prepare for a crisis. Monetarists, following the pathbreaking 1963 paper by Friedman and Schwartz, have developed a theory of the relationship between financial crises and banking panics. Their work underscores the centrality of banking panics and identifies them as the primary cause for the contraction in Money Supply that triggers a sharp deceleration in aggregate economic activity in the U.S. Monetarists would not consider situations where asset values fall sharply or business closures mount up to be real financial crises unless there were accompanying prospects of a banking panic leading to a drastic Money Supply contraction: indeed these are referred to by Schwartz (1986) as "pseudo-financial crises". The narrow focus limits the explanatory power of the Poltarist perspective and stresses that a broader perspective is needed in analyzing and responding to financial instability (Mishkin, 1992). Economic systems are inherently unstable places to depend on the forecasts made but getting to know what the vulnerabilities are would also help prepare for when a crisis hits. This narrow focus limits the explanatory power of the poltarist perspective and emphasises that broad-based consideration is vital when analyzing and responding to financial instability (Mishkin, 1992). Predictions for economic systems are bound to be wrong most of the time, but it helps foresee a crisis. The narrowness of this focus reduces the explanatory potential of the Poltarist view and underscores the need for a wider perspective in explaining and handling financial instability (Mishkin, 1992). The behavior of economic systems is inherently unpredictable but studying vulnerabilities can help take precautionary measures before a crisis befalls.

So, the general state of the economy should be taken into account, and not only internal financial ratios of companies (Acosta-González et al., 2019). Therefore, there are many empirical studies on the prediction of financial crises; some of them are seen in Table 1. At the root of the possibility that an economic enterprise might be alive in a competitive business lies set (1) Financing at the time when it started its operations whether it is capable, and the contingent flexibility and efficiency of cash flow that materializes from ongoing business activities, life access to capital markets as well as (4) Money related ability and capability to continue life in the face of unexpected and implausible shortages of money — J. Lo et al., 2018; Moradi et al., 1402). Some researchers have argued that yield curve slop Bluestein et al (2023) and credit growth are important predictors of domestic global financial crises. Therefore, the general state of the economy should be taken into account, and not only company internal financial ratios (Acosta-González et al., 2019). Some authors have focused empirical research on forecasting financial crises; a number is described in Table 1. 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). Hence, there are plenty of empirical studies on forecasting financial crises, some of which are considered in Table 1. Thus, the macroeconomic environment should be considered and not only firm-level financial ratios (Acosta-González et al., 2019). Therefore, there exists many empirical research works on the forecasting of financial crisis, some of which are considered 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 with Earnings Management	Predicting Financial Crises with Earnings Management	Predicting Financial Crises with Earnings Management	Predicting Financial Crises with Earnings Management
Khajavi & Ghadirian Arani (2017)	Examining and Enhancing Financial Crisis Prediction with Management Ability	Examining and Enhancing Financial Crisis Prediction with Management Ability	Examining and Enhancing Financial Crisis Prediction with Management Ability	Examining and Enhancing Financial Crisis Prediction with Management Ability
Wang & Wu (2017)	Financial Crisis Prediction: PNN-BP Based on AdaBoost	Financial Crisis Prediction: PNN-BP Based on AdaBoost	Financial Crisis Prediction: PNN-BP Based on AdaBoost	Financial Crisis Prediction: PNN-BP Based on AdaBoost
Khajavi & Ghadirian Arani (2018)	Financial Crisis Prediction Using Intellectual Capital	Financial Crisis Prediction Using Intellectual Capital	Financial Crisis Prediction Using Intellectual Capital	Financial Crisis Prediction Using Intellectual Capital
Yousef & Aldeen (2018)	Prediction of Financial Crises of Iraqi Banks: A Neural Network Approach	Forecasting financial crises in Iraqi banking system using neural networks	Analysis on bank financial ratios from 2007 to 2015	Neural networks have high accuracy in predicting financial crises with an AUC of 0.975
Taheri Bazkhaneh et al. (2019)	Designing an Early Warning System for Financial Crises	‘ Designing a new financial index that can predict a variety of states in the financial sector ‘	In this period, from 1990 to 2016, principal component analysis using a Markov switching approach	The crisis states are low in their stability but highly likely to transition into stability; direct transitions from a crisis to a boom have low probability‘
Emamverdi & Jafari (2019)	Impact of the Financial Crises on Shock Transmission and Volatility Spillover	Analyzing the effects of the financial crises on the transmission of shocks and volatility spillovers between stock markets	For enhancing typical crisis prediction frameworks with the help of early warning indicators	Network analysis and machine learning algorithms
Beutel et al. (2019)	The efficiency when using machine learning was 98.8%, showing very high levels of prediction accuracy	Computational Intelligence-Based Financial Crisis Prediction Regarding Optimal Feature Subset Selection through Deep Belief Network	Regarding an accurate design for financial crisis predictions (FCP)	Using EHO and MWWO algorithms with Deep Belief Network (DBN)
Samtani et al. (2020)	The model so proposed achieved the highest classification performance, outperforming recent	To enhance traditional crisis prediction models via early warning indicators	Network analysis and machine learning algorithms	The efficacy of the machine learning approach reached 98.8%, a very high level of predictive accuracy

	approaches				
Nora Metawa et al. (2021)	Computational Intelligence-Based FCP Preceded by Optimal Feature Subset Selection with Deep Belief Network	For an accurate financial crisis prediction design	Elephant Herd Optimization and Modified Water Wave Optimization Algorithms With Deep Belief Network		The proposed model attained the highest classification performance, thus outperforming recent approaches
Ahmad et al. (2021)	The Impact of Financial Crisis on Macroeconomic Variables in Iraq, Iran, and Turkey	An analysis of the impact of financial crises on such macroeconomic variables like GDP, exports, inflation and exchange rates	Data analysis: 1980-2017		Impacts of financial crises on macroeconomic variables are not uniform; the Asian financial crisis had a negative significant impact on GDP in Iran and Iraq
Salman et al. (2021)	Safety Indicators in Financial Crises and Their Impact on Banking Finance: The Case of Iraqi Banks	Evaluation and monitoring of financial safety indicators applied by the Central Bank of Iraq	Special safety indicators in the Iraqi banking sector		The Central Bank of Iraq and its adherence to significant international standards, such as Basel II, with capital adequacy ratios of the banking system being satisfactory
Laborda & Olmo (2021)	Volatility Spillovers Between Economic Sectors in Predicting Financial Crises: Evidence from the Great Financial Crisis and the COVID-19 Pandemic	To calculate spillovers of volatility among various economic sectors with network connection measures	Following the methodology of Diebold and Yilmaz (2012)		Shocks evolve because of the interdependencies between banking and insurance, energy, technology, and biotechnology sectors with other sectors in the economy
Liu et al. (2022)	Predicting Financial Crises with Machine Learning Methods	For the establishment of an effective early warning system in predicting financial crises	Logistic model and the seven machine learning methods: a comparative study with Shapley value analysis		Machine learning models in anticipation of a crisis especially random forest, gradient boosting decision tree, ensemble models give better results compared to the logistic model
Sufi & Taylor (2022)	Financial Crises: A Survey	Measuring crises, predictability reasons it is going to cause an economic slowdown	Literature Review		Crisis measurement is still based on the historical narrative technique, but significant changes have taken place in using quantitative data
Muthukumar an & Harihaaranath (2022)	Prediction of Financial Crisis using Deep Learning for Small and Medium Enterprises	An optimized design of deep-learning-based models for predicting financial crises in SMEs	Feature selection using the Archimedes Optimization Algorithm (AOA) and data classification with Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM)		The proposed ODL-FCP outperforms other techniques
Venkateswarlu et al. (2022)	Deep Learning-Based Financial Crisis Prediction in a Big Data Environment	To develop the model for financial crisis prediction in a big data environment	Using Hadoop MapReduce for big data management and Oppositional Ant Lion Optimization (OALO)		The OALOFS-MLC algorithm outperformed recent approaches

			for feature selection	
Jafarimanesh & Gholami (2022)	Predictive Analysis of Company Bankruptcy in Tehran Stock Exchange: Evidence from Company- Level and Macroeconomic Factors	Studying the Impact of Company-Level and Macroeconomic Factors on Corporate Crises and Validation of the Company Life Cycle Theory	Panel data modeling: evidence from 122 firms over ten years	The stage in the company life cycle has an inverse relationship with financial crises, with a greater magnitude during the post-sanctions period
Bluwstein et al (2023)	Predicting Financial Crises with Credit Growth and the Yield Curve: Machine Learning Approach	The paper at hand builds early warning models for financial crises prediction by use of machine learning techniques	Using different nonlinear machine learning models for the analysis of macro-financial data	In most nonlinear machine learning models, the forecasting of financial crises is better than that of logistic regression
Papik & Papikova (2023)	The Effects of Crisis on SME Bankruptcy Prediction Models Performance	To analyze the effects of crisis on bankruptcy prediction models performance	Developing prediction models for three periods by Cat Boost, LightGBM, and XGBoost methods	Performance of prediction models in crisis periods lost strength significantly relative to non-crisis periods
Temrinia et al (2023)	A Hybrid Model for Forecasting Financial Crises Based on Free Cash Flows	Developing a hybrid model for predicting financial crises based on free and operational cash flows	Data of 260 companies listed in the Tehran Stock Exchange (2008-2017), logistic regression model with ROC curve	The accuracy of the hybrid model based on free cash flows is higher compared to Zmijewski and Altman models
Shehata et al (2023)	Predicting Contemporary Economic Crises in the Arab Region - Causes and Consequences	An analysis of the economic crises resulting from the COVID-19 pandemic and the Russia-Ukraine war	Descriptive approach, secondary data: IMF, World Bank, Arab Monetary Fund	These crises affected rates of economic growth as well as trade balances and international reserves in addition to giving more poverty and social inequity
Rouhisera et al (2023)	Financial Crisis Prediction Model for the Capital Market with Hybrid Algorithms: Evidence from Iran	A dynamic model for predicting financial crises in firms	Thematic analysis and data from 173 companies (2009 to 2019) and algorithms: multivariate regression, ant colony, particle swarm optimization	The ability of this model to predict a financial crisis is acceptable up to five years before the event; after this, the ability starts declining
Ristolainen et al (2024)	Financial Crises and Historical Headlines	Changes in specific forms of narrative information in newspaper article headlines as predictors of financial crises	Integrating information from economic news articles with macroeconomic and traditional approaches of finance forecasting	This predictive content in newspaper article headlines about crises is both economically and statistically significant above traditional macroeconomic or financial indicators
Khadr & Khoshnaw (2024)	The Role of Financial Crisis Management in Implementing Investment Development in Iraqi Kurdistan	An evaluation concerning the role of crisis management regarding the financial crises and their impact on investment growth in Kurdistan region	Mitroff's Five-stage Model, decision analysis, and statistical package for the social sciences (SPSS 28.0) for financial analysis	The effect of the COVID-19 pandemic on investment projects was less severe than that of the ISIS conflict; more effective crisis management during the pandemic has been evident

Based on the studies carried out in the research literature regarding the role of bank credit and macroeconomic variables in predicting financial crises in Iran and Iraq, it is observable that international studies with respect to predicting financial crises are abundant but rare are internal studies concerning the role of bank credit and macroeconomic variables within Iran and Iraq, not mentioning Iraq at all. This indicates a lack of such they have in both countries; therefore, in this research, the goal is to apply that there is a need for conducting research to develop an early warning system for predicting financial crises in Iran and Iraq using machine learning algorithms and neural networks. Such an approach could help reveal new facets in this study through the use of modern tools, such as neural networks and economic simulation methods, considering those two countries (Iran and Iraq) which economy is driven by various factors, especially global oil prices. It would also be worthwhile analyzing financial regulatory systems and supervisory development trends and making it possible to apply quantitative models for predicting the behavior of future crises in order to prevent them, from negative consequences for financial markets stability introduced on based on deep data analysis and advanced modeling ways will enable policymakers to design effective strategies toward preventing and managing financial crises so that they could enhance resilience and stability of the financial sector as well as macroeconomy against potential shocks. This has not been done yet; Therefore, further to the ever reviewed literature on predicting a financial crisis in Iran and Iraq. It is evident that the research carried out in this field has generally looked at other nations, with scanty information on Iran and Iraq. Moreover, the volume of research on forecasting financial crises in terms of bank credit and macroeconomic variables in Iran and Iraq is not very good quality; more research is much needed in this area. In addition to factors such as the title of the present issue being treated with new approaches having certain complexities and hence having larger dimensions related to the subject under discussion, there is a gap in the existing literature which this study aims to fill for both Iran and Iraq. In the research literature on the role of bank credit and macroeconomic variables in predicting financial crises in Iran and Iraq, according to the conducted studies, it is visible that international studies have been based on the perspective of predicting financial crises; however, for a complete view internal studies of Iran and Iraq regarding the role of bank credit and macroeconomic variables are very few. They do not specify having included Iraq which shows the gap between the studies conducted in both countries; therefore, in this research, aim is to be developed should be a model using machine learning algorithms and neural networks to predict financial crises in Iran and Iraq. It should be explained that this indicates the need to conduct research.

Methodology

- Each of these methods has unique capabilities to identify patterns, and complex non-linear relationships between variables. Using this hybrid approach, the present study aims to explore the forecasting of financial crises in Iran and Iraq by first investigating the contribution of bank credit plus macroeconomic variables in a separate manner and later with a combined view, to have an explicit comprehension of the economic behavior or dynamics of these two nations for providing workable strategies toward prevention and management of crises. To be able to achieve what can be described as future state. The following is a short description for each method referred to. Each of these methods has unique capabilities to identify patterns as well as complex, nonlinear relationships between variables. Applying this hybrid methodology, the present study tries to investigate the role of bank credit and macroeconomic variables in predicting financial crises in Iran and Iraq, with a view to establishing an in-depth

insight into the economic dynamics of these two countries for offering workable solutions towards preventing and managing crises. The attainment at that time to come. Here is a small description of each identified method.

- **k-Nearest Neighbors**

The k-nearest neighbor algorithm is not only simple but also a robust method of classification and prediction; hence, it can be very efficient in analyzing the impact of bank credit and macroeconomic variables in predicting financial crises in Iran and Iraq. In this approach, for the prediction of the economic situation of a specific period (e.g., occurrence or non-occurrence of a financial crisis), the k-algorithm locates the nearest data point in the multi-dimensional space of economic variables and then makes a prediction on the majority class of these neighbors points.

$$d(x,y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2}$$

- where x and y are two data points in an n-dimensional space, and x_i and y_i are the i-th variable values for these two points. In order to apply this method in the area of financial crisis forecast, a set of historical data is first gathered for macroeconomic variables (such as inflation rates, GDP growth, and unemployment rates) and bank credit indicators (such as loan-to-deposit ratio, credit growth rate) for the two countries Iran and Iraq. Every point in this set of data represents the economic situation during a specific period, characterized by a label (crisis occurrence or non-occurrence of a crisis). Then it can be used to make predictions regarding the economic situation during a new period; given any point, the algorithm computes distances between this point and all others then selects k-nearest neighbors. The majority class among these k neighbors' labels is assigned to be the prediction for new instances. For instance, if 'crisis' is labeled in 3 out of 5 nearest neighbors, then the algorithm predicts that at the new period, there will be a financial crisis as well. This approach may be useful in detecting analogous patterns in historical data and providing an opportunity to forecast future crises on the basis of the similarity of economic situation conditions (Göbel & Araújo, 2020).

- **Random Forest**

Random forest is an advanced machine learning approach that can be quite valuable in predicting financial crises in Iran and Iraq using bank lending and macroeconomic variables. The algorithm builds a number of decision trees, each on the basis of a different random sample drawn from the training data. In this very case, if these input data are kept such that volume of bank credit plus inflation rate alongside economic growth as well as exchange rate and all other macroeconomic indicators are considered to be highly probable predictors. Each tree in the random forest presents a prediction regarding the probability of a financial crisis, and the final result is obtained by majority voting or averaging those predictions (Chehreh & Sarabadani, 2024). The main formula for Random Forest prediction is.

$$f(x) = 1/B * \sum_{i=1}^B f_i(x)$$

This feature enables researchers to decide which of the economic and credit factors is more important in forecasting financial crises in Iran and Iraq (Ebrahimi-Khusfi, 2021). The importance of variable i can be computed using: This feature enables researchers to decide which of the economic and credit factors impact most in predicting a financial crisis in Iran and Iraq (Ebrahimi-Khusfi, 2021). The formula for calculating the importance of variable i is.

$$VI_i = 1/B * \sum_{j=1}^B (MSEOOB_j - MSEOOB_{ij})$$

where VI_i is the importance of variable i, $MSEOOB_j$ is the out-of-bag error for tree j, and $MSEOOB_{ij}$ is the out-of-bag error for tree j after permuting variable i.

- **Demand-based forecasting models**

Modeling forecasts on the basis of demand has innovation in forecasting models of financial crises, under the condition of bank credit and macroeconomic variables in Iran and Iraq. It is based on the premise that the demand for credit together with macroeconomic conditions can be a good indicator to use in predicting whether or not a financial crisis is likely to occur. In this approach, one would develop a dynamic model; this means that it captures changes in time regarding credit demand and macroeconomic indicators (Sheikhli et al., 2023). The core formula for this model is as follows.

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

In this formula, $P(\text{Crisis}_t)$ is the probability of a financial crisis at time t , Credit Demand is a credit demand index at time t , Macro Variablest is the vector of macroeconomic variables at time t , and ε_t is the error term. The function f may be defined as a logistic or probit function and formulated

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

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

This model may be used to explore the financial crises in Iran and Iraq, provided appropriate indicators of credit demand (such as volume of loan applications, credit growth rate) and macroeconomic variables (such as inflation rate, GDP growth, exchange rate) are obtained. After which, the training is done using historical data to understand relationships between these variables and the likelihood of a financial crisis occurring. One advantage is its dynamic changes in credit demand and economic conditions; however more advanced techniques can be used for a better accuracy such as Vector Autoregression models that allow time dependencies between variables to be taken into account (Rezaee, 2022). General formula of VAR model is.

$$Y_t = c + A_1 Y_{\{t-1\}} + A_2 Y_{\{t-2\}} + \dots + A_p Y_{\{t-p\}} + \varepsilon_t$$

- In this formula, Y is the vector of model variables at time t , c is a vector of constants, A is the matrix of coefficients, and ε is the vector of errors. With these models, we are able to forecast the probability of financial crises and evaluate how much change in credit policies and macroeconomic conditions affect financial stability in Iran and Iraq.

- **Adversarial learning**

Adversarial learning is a cutting-edge approach within machine learning that could be applied in the prediction of financial crises with respect to the role of bank credit and macroeconomic variables in Iran and Iraq. This technique comprises two models: one model generates artificial data, while the other tries to distinguish between real data and what has been artificially created. In the context of predicting financial crises, the generator model creates different economic and financial scenarios, while the discriminator tries to detect those which lead to a crisis (Puli et al, 2024). The general formula for objective functions in adversarial learning is as follows.

$$\text{Min } G \text{ max } D \text{ V } (D, G) = E[\log(D(x))] + E[\log(1 - D(G(z)))]$$

For improving the model performance, some more advanced techniques can be used such as Conditional GAN which allows more control over the generated data (Sharma, p. et al, 2024). The formula for Conditional GAN is For further boosting the model, some more complex techniques can be adopted — like Conditional GAN. It permits a heightened amount of management over the data generated (Sharma, p. et al, 2024). The formula for Conditional GAN is.

$$\text{Min } G \text{ max } D \text{ V } (D, G) = E[\log(D(x|y))] + E[\log(1 - D(G(z|y)))]$$

- In this formula, y is an extra condition (such as a particular economic situation) imposed on both the generator and detector. With this approach, we can develop a model that besides having the ability to predict financial crises can also undertake simulation of different

scenarios according to the conditions of both the specific economic as well as credit conditions for Iran and Iraq.

- **Principal Component Analysis**

Principal component analysis is a very powerful statistical technique that can be useful in exploring the contributions of bank credit and macroeconomic variables toward predicting financial crises in Iran and Iraq. This helps to decrease data dimensions and find major variables influencing most variations within the data. In the light of financial crises, it is possible through PCA to determine the primary factors from economics and credit perspectives leading to a financial crisis (Sharma, H. et al, 2024). The basic formula for PCA is as follows.

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

In this formula, PC_i denotes the i th principal component, X_j denotes the j th variable, and a_{ij} are the coefficients selected subject to maximizing PC_i 's variance such that their sum of squares is equal to 1.

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

For the application of PCA in financial crises, both in Iran and Iraq: we identify a bunch of variables related to bank lending and macroeconomic indicators. The volume of loans, loan-to-deposit ratio, inflation rate, gdp growth, unemployment rate, and currency in each country. We apply PCA on these variables to reduce them to a smaller number of important principal components that will explain most of the variance in data. The resulting components can be seen as composite indicators of economic/credit status. After checking for consistence with the occurrence of financial crises, we try now to establish a relationship between these components (obtained) and financial crises events. An optimal number of principal component analysis dimensions would typically be selected based on either a Kaiser criterion (selecting component dimensions with eigenvalues over 1) or using what is known as a scree plot involving breaking at an inflection point where values tail off. Rotation is also another aspect applied after the mentioned methods if necessary for the clarity percentage.

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

- Usually, the variance is said to be 80-90%. This approach reduces it to λ_i are the eigenvalues of the selected components while λ_j are all the eigenvalues. Using this model will provide us with a simplified model for forecasting financial crises in Iran and Iraq, which could be more interpretable and focused on only those credit and economic variables considered most important.

- **Functional Neural Networks**

Functional Neural Networks (FNN) represent an innovation of machine learning to examine the predictive role of bank lending and macroeconomic variables in the occurrence of financial crises in Iran and Iraq. These networks can handle high-dimensional data and model intricate relationships; thus, they work favorably well with time-series data and dynamic behavior. As far as predicting a financial crisis is concerned, FNNs can capture the non-linearity within the relationship and time dependence among economic/credit variables (Sobhanifard & Shahraki, 2021). The general structure of an FNN is illustrated below.

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

In this formula, $y(t)$ is the model output (probability of a financial crisis) at time t , $x(t)$ is the input vector (economic and credit variables) at time t , φ_i are basic functions at wight terminal (such as sigmoid or ReLU functions), w_i is the weights of the network; N is the number of neurons in the hidden layer and $\varepsilon(t)$ is the error component. For applying FNN in our study for forecasting financial crises in Iran and Iraq first collect times series data related to Bank credit variables

(including loan volume, interest rates, loan-to-deposit ratio) and macroeconomic indicators (inflation rate, GDP growth rate, unemployment rate we exchange rate)‘ Then this data is fed as input to the FNN network‘ The network is trained by optimization algorithms of which an example is the 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.

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

This formula comprises L as the cost function, y(t)- the actual value, $\hat{y}(t)$ is the predicted value, with λ as the tuning parameter to avoid overfitting and $\|w_i\|$ being soft weights‘ The FNN has one major advantage: it can learn complex and non-linear functions which may lead to unveiling hidden relationships between economic and credit variables‘ To be more professional in computing, I would rather use other techniques such as Recurrent Neural Networks or Long-Short Term Memory since these are time series data specific models‘ The LSTM formula is given by.

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

- 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‘ With these advanced models, we can develop a more accurate forecasting system related to the financial crises in Iran and Iraq by considering long-run temporal dependence among economic and credit data.

- **Cerebellar Network**

Cerebellar Model Articulation Controller (CMAC) is a particular artificial neural network that can be applied to forecast financial crises based on the role of bank credits and macroeconomic variables in Iran and Iraq‘ This model, modeled after the human brain's cerebellum structure, has the ability to learn highly complex and non-linear functions and bring out concealed patterns within 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)‘ General formula for CMAC output is.

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

In this formula, y is model output (probability of financial crisis), x is input vector (economic and credit variables), w_i is network weights, $a_i(x)$ is activation function for i-th unit in conceptual mapping layer, and N here denotes the number of active units in the mapping layer which is conceptual‘ The function $a_i(x)$ is typically a binary function that plays such a role in determining whether the input x is within coverage area for ith unit or not‘ To apply CMAC in the research of financial crises in Iran and Iraq first we need variables related to bank credits (such as loan volume, loan to deposit ratio, interest rates) and macroeconomic indicators (inflation rate, GDP growth, unemployment rate) plus whatever is happening on usd/eur exchange rate‘ Then these are fed into the input CMAC network‘ Then we train the network by the 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.

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

- 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 CMAC's main advantages: high learning speed and good generalization ability‘ Such properties are very important for applications in predicting a financial crisis because these conditions can vary quite rapidly

from one extreme condition to another and models must be able to adapt well. To improve model performance, instead of basic approaches we can apply more sophisticated ones — for instance multi-layer CMAC or hybridize it with other machine learning algorithms. For example application hybrid CMAC-LSTM model where CMAC used for extraction non-linear features from input data then LSTM used for modeling temporal dependencies. This approach can enhance the forecasting power of the model for predicting financial crises by capturing interactions within economic and credit information, in addition to time dependencies. With this methodology, a very good early warning system for financial crises in Iran and Iraq, which bases the indication of an approaching crisis on changes in credit and economic variables can be developed. Such a model may assist policymakers, as well as monetary and regulatory authorities, in initiating preventive actions to preclude or alleviate such financial crises (Doumpos et al., 2023).

- **Self-Encoding Neural Network**

The Autoencoder Neural Network is a unique artificial neural network, according to the role of bank credits and macroeconomic variables in Iran and Iraq may be very helpful in analyzing and predicting financial crises. These networks are created for one purpose — to reduce data dimensionality and extract important features, which is extremely valuable when working with problems related to the analysis of complex economic or financial information. The basic structure of an autoencoder consists of two parts: Encoder, Decoder. While the encoder maps input data into a lower dimensional space, the decoder tries to produce a reconstruction of the original data from that 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 formulas, x is the input data, h is the code, x' is the reconstruction of the input data, WW' are weight matrices, bb' are biases, and fg are activation functions (e, g , sigmoid or ReLU). Autoencoders can be of great importance in studying financial crises of Iran and Iraq by taking in a bunch related to variables on bank loans and macroeconomic indicators and reducing the dimensions of the data. Eventually after having collected and normalized data related to bank loans a self-encoding network is designed and trained. The training methodology for this network is based on minimizing the following mean square error cost function to be able to reconstruct back the input data with high accuracy (Abbasi Nejad et al., 2023).

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

- Then the network encoder part is applied to extract compact features which are then used to train the financial crisis prediction model. To enhance the model more sophisticated types of autoencoders such as variable, noisy or recursive autoencoders can be adopted. These ways will be able to detect more complex patterns in economic and credit data. The variable autoencoder can be used for uncertainty analysis while the noisy autoencoder is robust against fluctuations in data and the temporal dependencies are learned by the recursive autoencoders. With these methodologies, it becomes possible to construct a stable forecasting system of financial crises in Iraq and Iran, which would assist policymakers by identifying potential risks early enough and taking preventive actions (Franco et al, 2021).

- **Neural Fuzzy Systems**

- Neural-fuzzy systems provide a rather strong way of integrating the learning capabilities of neural networks with the reasoning capabilities of fuzzy logic. In the light of predicting financial crises in Iran and Iraq, these systems can consider macroeconomic variables

(inflation rate, economic growth, and exchange rates) plus bank credit indicators (non-performing loan ratio, capital adequacy ratio) as input. Fuzzy rules like "if inflation is high and economic growth is low, then the probability of a financial crisis is also high" govern this transformation into fuzzy variables. The neural network learns the optimal weights for these rules from historical data. In the consequent stage, membership degrees are computed by neuro-fuzzy between each variable specified under set rules in fuzzy logic. For instance, the Gaussian membership function for the inflation rate can be defined as $\mu(x) = \exp(-(x-c)^2 / (2\sigma^2))$, where c is the center and σ is the standard deviation. Then, fuzzy rules are applied using operators such as min or to take the product. Finally, a deterministic value for the probability of a financial crisis transforms from fuzzy output using methods such as Centre of Gravity (COG = $\int x\mu(x)dx / \int \mu(x)dx$). After that, this process is updated with new data for increasing accuracy regarding predictions. Following it came information related to research methodology; then, model specification was discussed, which is as follows (Javadi et al., 2020).

- **Dependent variable: Financial crisis**

There are very few truly global financial crises; the Great Depression and the crisis in 2007-2008 are examples. Most financial crises take place in only one country or a small group of countries. A country's banking sector faces a bank run or it sees a sharp rise of default rates with considerable losses of capital that provoke public intervention leading to the bankruptcy or force merger of the financial institutions (Bordo et al., 2001; Laeven and Valencia, 2008; Reinhart and Rogoff, 2009; Cecchetti et al., 2009). This research assumes that it will predict impending financial crises for both Iran and Iraq using bank credit plus macroeconomic variables; thus economic data for Iran and Iraq from 2023 going back to 2000 is employed following approach by Christina Blustein et al. Our aim is to predict crises before their occurrence; thus, we will refer to one and two years before the crisis as the "crisis period". To increase the accuracy of our results, we do not consider the actual year of the crisis or four years after the crisis in our analysis. This enables us to differentiate between normal economic conditions and post-crisis recovery periods. We finally use a simple yes/no variable to indicate whether a crisis is present or not. This approach helps in capturing with greater accuracy the true signals which lead to a crisis and make it possible to predict more accurately. Therefore, according to the definition of a financial crisis by Christina Blustein et al. (2023), the financial crisis index for Iran and Iraq is given by.

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

- This method of measurement considers the financial crisis to be a discrete event (that is, either it happens or not) and looks at discerning the pre-crisis period as an alarm.
- This measurement method treats the financial crisis as a specific event (that is, whether or not it occurs) and zeros in on flagging the pre-crisis period as an indication.

- **Explanatory variables**

As noted by Christina Blustein et al. (2023), the following are the explanatory variables used:

1. Short-term and long-term interest rates differential;
2. Long-term bank loan interest rates to GDP ratio;
3. Consumer price index;
4. Investment: total of public and private;

- 5. Current account: net exports of goods, services between a country and other countries
- 6. Public debt is the whole amount that the government owes to creditors, either from within or outside its borders.
- 7. Bank credit stands for private sector loans given by banks.

- i. The time frame of the present study is from 2000 to 2023, making a total of 24 years. The statistical population in this research is Iran and Iraq, whose financial data are obtained from the subsequent sites
- ii. [:https://data.worldbank.org/](https://data.worldbank.org/)
- iii. <https://tsd.cbi.ir/>
- iv. <http://www.ifdc.ir/>
- v. [https://databank.mefa.ir /](https://databank.mefa.ir/)
- vi. [https://stats.oecd.org /](https://stats.oecd.org/)
- vii. [https://codal.ir /](https://codal.ir/)
- viii. <https://mabnadp.com/products/rahavard-novin>
- ix. [https://www.tse.ir /](https://www.tse.ir/)
- x. <http://www.isx-iq.net/isxportal/portal/homePage.html>
- xi. <https://globaledge.msu.edu/globalresources/resourcesbytag/iraq>
- xii. <https://response.reliefweb.int/iraq/data?page=2&q=/iraq/data>
- xiii. <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 = f(YCS), DSR, CPI, INV, CA, PD, BC

The above equation specifies the following: the financial crisis is a function of macroeconomic and banking variables.

1. Data and information analysis

In any economic research, the variables' descriptive statistics represent the first and important step in the data analysis. This enables a researcher to have an overall idea regarding basic characteristics of data collected. Descriptive statistics give information about centrally important indicators such as mean and median, measures of spread like standard deviation and range of variation, and also frequency distribution of variables. This information not only gives basic knowledge about data but also acts as a precondition for making appropriate choices while applying statistical methods during the subsequent stages of research. Therefore; In analyzing the data & information related to this research, an assessment was made on Descriptive Statistics for research variables, with findings presented 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

As per 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 at 0.0897 and 1.2201, respectively, indicating that their distributions are close to normal. In general, most variables are far from a normal distribution, which can affect statistical and economic analyses. On the research variables, in terms of bank credits and macroeconomic variables, the paper after running some Descriptive statistics asserts that it has studied the prediction of financial crises using machine learning; therefore, the major advantages of this kind of non-parametric statistical methods can be his use also used data which do not have a normal distribution, for his machine learning such as nearest neighbor and Random Forest is presented below in Table 3. In this regard, Random Forest and K-Nearest Neighbors (KNN) were two machine learning methods applied to analysis and predict the financial crises in Iran and Iraq. The sum of Random Forest as a nonlinear complex method can capture nonlinear relationships between macroeconomic variables and financial crises; it is suitable particularly when data have more complexities manner then nuanced. On the contrary, KNN as a simple and pragmatic approach carries out classification and prediction based on data point distance, better suited for when one is getting started with analysis to understand more about the structure of the data. Finally, two major methods were used in identifying and removing outlier data to enhance quality and result accuracy: The spike method and the standard deviation method. The spike method detects abrupt, uncommon changes in the data; on the other hand, since the standard deviation method regards any data lying beyond a certain distance (usually 2 or 3 times standard deviation) from the mean as outliers. During this process of arranging the data, outliers are taken out, which would have unfavorable effects on output from models. Through these two methods, the predictands for financial crises in Iran and Iraq are more assured and confirmed. The outputs of these two methods are presented 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

Iraq	KNN	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
	Random Forest	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
	KNN	11	0.895	0.939	0.703	0.288	0.483
		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

According to the data presented, there are some macroeconomic variables that are very important in predicting financial crises in Iran and Iraq. In both countries, YCS and CA are the most important variables in predicting a financial crisis. For Iran, CA (YCS) is 87.037 (68.582), and for Iraq, YCS (CA) is 104.602 (100.137). This confirms that these two factors play a critical role in predicting a financial crisis in both countries. PD also has an importance of 63.163 for Iran and 45.084 for Iraq; hence, it plays a substantial role in these predictions as well. On the other hand, related to BC, this variable has significance towards these two countries but not compared with YCS or CA. In Iran, BC is the fifth most important variable, with a value of 55.428. In Iraq, it is sixth in importance, at 41.417. This shows that although bank credit is good for predicting financial crises, other variables like DLYCURV, CAB and DEBT are better predictors than it. DSR, CPI and INV also help to predict the occurrence of financial crises from a macroeconomic point of view but do not do so as effectively as the first three variables mentioned above. This analysis further reveals that in predicting financial crises that are likely to occur in either Iran or Iraq, it is paramount first to consider a whole set of macroeconomic variables with special focus on DLYCURV, CAB, and DEBT. This process involved using statistical measures such as standard deviation and IQR (interquartile range) to eliminate outliers in the dataset that would have a negative effect on the results. Thus, the union of these three methods and due data processing facilitated not only an increase in the accuracy of forecasts but also a more profound analysis of financial crises; corresponding results are described in Table 4 below. This entailed the use of statistical measures such as standard deviation and interquartile range (IQR) in the elimination of outliers from the dataset, which could negatively affect the results. Thus, by doing this way — the combination of these three methods with data processing done carefully helped not only to increase

the accuracy of the forecasts but also to bring them to better analysis regarding financial crises, whose relevant results are described in Table 4 below.

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

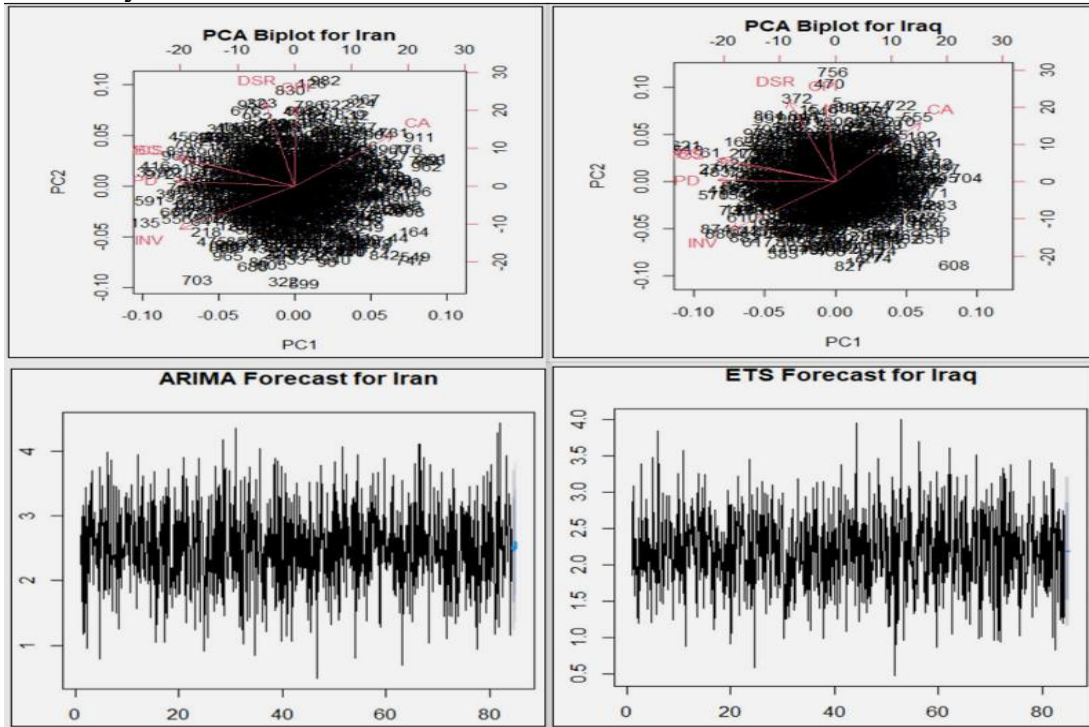
Country	Model	Metric	Value
Iran	Demand-Based	ARIMA RMSE	0.628
	Demand-Based	ARIMA MAE	0.5
	Demand-Based	ETS RMSE	0.63
	Demand-Based	ETS MAE	0.502
	PCA	PC1 Variance Explained	0.453
	PCA	PC2 Variance Explained	0.308
	PCA	PC3 Variance Explained	0.131
	PCA	PC4 Variance Explained	0.059
	PCA	PC5 Variance Explained	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
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

The results presented in Table 4 indicate that macroeconomic variables are highly important in predicting financial crises in Iran and Iraq. In both countries, the first three principal components account for more than 89% of data variance, indicating a high correlation among the variables PD, DSR, CPI, INV, CA, BC and YCS. Since PC1 explains about 45% of the variance for each country, it can be inferred that an optimal combination of the most important variables (YCS, CA and PD) is likely to play a major role in this component. Although bank credit (PC) does not appear directly in the PCA results as part of any component here perform with other roles. Regarding such sizeable contribution is quite probable. The results from the demand-based forecasting models (ARIMA and ETS) indicate that these models have a better performance when applied to Iraq than to Iran (lower RMSE and MAE). The adversarial learning results also demonstrate that the forecasting models are quite robust in both countries, although their precision does decrease when they are fed conflicting data (from 0.835 to 0.77 in Iran and from 0.845 to 0.755 in Iraq); this underscores the need for

taking into consideration unforeseen circumstances and abrupt changes in economic variables—including bank credit—when predicting financial crises. This is a visual inspection on forecasting financial crisis via demand-based forecasting, adversarial learning, contrast set and principal component analysis as represented by Chart 1.

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



Source: Research findings

Such results can be of assistance to policy makers in recognizing and handling these fluctuations and in adjusting the strategies more vigilantly to avoid any future financial crisis. Hence; After stating the results for demand-based prediction models, comparison learning and principal component analysis for the prediction of financial crises using four neural network ways such as functional neural network, cerebellar model articulation controller (Cerebellar Model Articulation Controller), self. Autoencoders) and Fuzzy Logic. These findings can assist policy makers in recognizing and dealing with these fluctuations and altering the strategies a little better to preclude financial crises in times ahead. Hence; After determining results related to demand-based prediction contrast learning and principal component analysis to predict financial crises using four neural network methods: functional neural network, cerebellar model articulation controller self-encoders, Autoencoder) 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 fuzzy system is not a traditional neural network, it is implemented with fuzzy neurons using membership functions to process information, also involving

a standard neural network and support vector machine (SVM), where the former consists of neurons with standard ReLU and Sigmoid activation functions, and the latter uses a non-neural structure for classification. In general functional neural networks help in modeling complex and non-linear relationships between variables and are effective in predicting critical situations due to their ability to learn from large quantities of complex data. The cerebellum is involved in mimicking brain function and capturing dynamic patterns so as to process input information more effectively. Regarding data compression, self-organizing feature map creates online structures for recognizing main features of the data, and this way data quality is enhanced. Fuzzy also used well in analyzing fluctuations and uncertain behavior since the economy has a condition of adaptability which allows it to make decisions under incomplete information. To preserve the accuracy of the model, outliers were identified and removed, for example, such measures as standard deviation or interquartile range (IQR) allowed us to recognize outliers. In this way, the application of these four methods along with proper processing of accurate data gave a very high significance in predicting financial crises community responses.

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

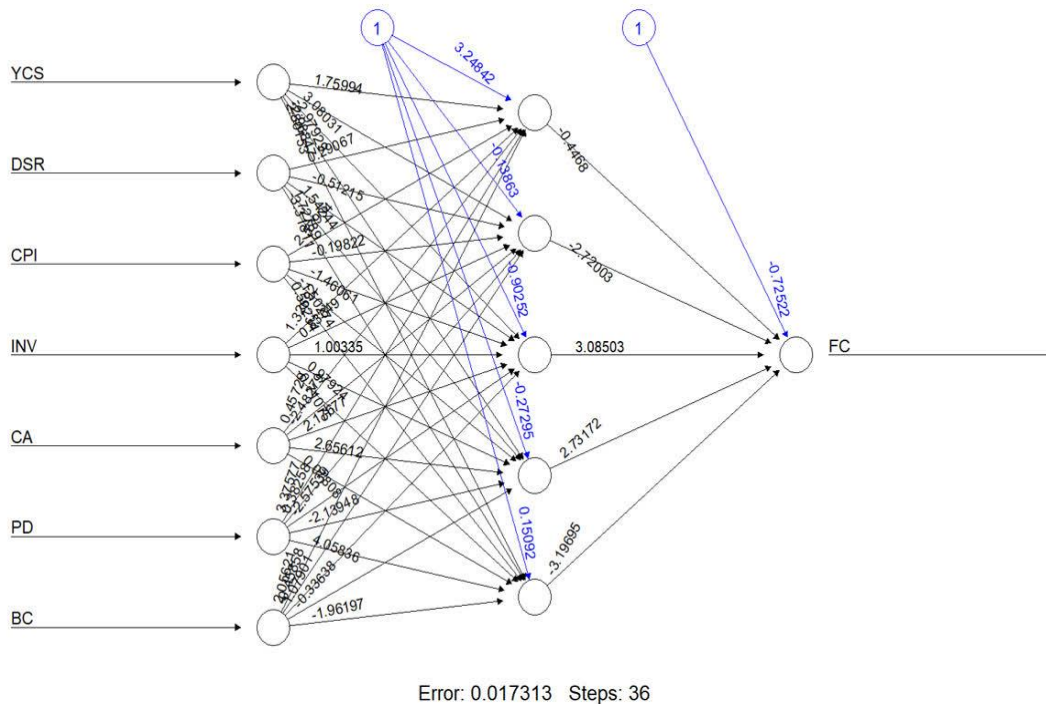
Importance of variables			Examining research models		
Variable	Iran	Iraq	Metric	Iran	Iraq
DSR	1983	2112	Functional Neural Network (Accuracy)	0.4820	0.4944
INV	7.1551	13.4483	Functional Neural Network (MSE)	0.5180	0.5056
CA	7.1679	5.8238	Cerebellar Neural Network (Accuracy)	0.7603	0.6789
BC	5.2499	1.5291	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

On the basis of the results of Table 5, variables' importance in both Iran and Iraq, the current account (CA) and investment (INV) variables are of utmost importance in predicting the financial crises. Therefore, the variables reflecting the state of foreign trade and amount of investment in the economy play a key role in financial stability of these countries. In Iran, more important than in Iraq is bank credit (BC), which may indicate greater strength presented by the banking system within the Iranian economy. This, among other things, gives fuzzy systems for Iran and cerebellar neural networks for Iraq as resulting from a comparison based on a single criterion reflecting complexity that equals 79.18% accuracy for Iran and 67.89% accuracy for Iraq to be optimal. Hence the differences between the two countries when considering the results: the forecasting models for Iran are in most cases more accurate than those for Iraq because there is more relative stability in the Iranian data, or less complexity in relationships between economic variables. Also, varying variable importance in two countries (e.g., greater importance of DSR and PD in Iraq)

indicates structural differences between the economies of these two nations . Finally, these results reflect considerations on various macroeconomic variables and bank loans in predicting financial crises so as to enhance financial stability . This means that policymakers in both countries should pay special attention to current account and investment; for Iran, moreover, bank credit is important . Moreover, the application of appropriate forecasting models on a case-to-case basis for each nation (fuzzy system for Iran and cerebellar neural network for Iraq) would be instrumental in making sure that the predictions related to financial crises are more accurate ones, which will further better the uptake of preemptive measures . The following is an empirical analysis regarding the forecast of financial crises using neural networks for Iran and Iraq, with results depicted in Figures 2 and 3.

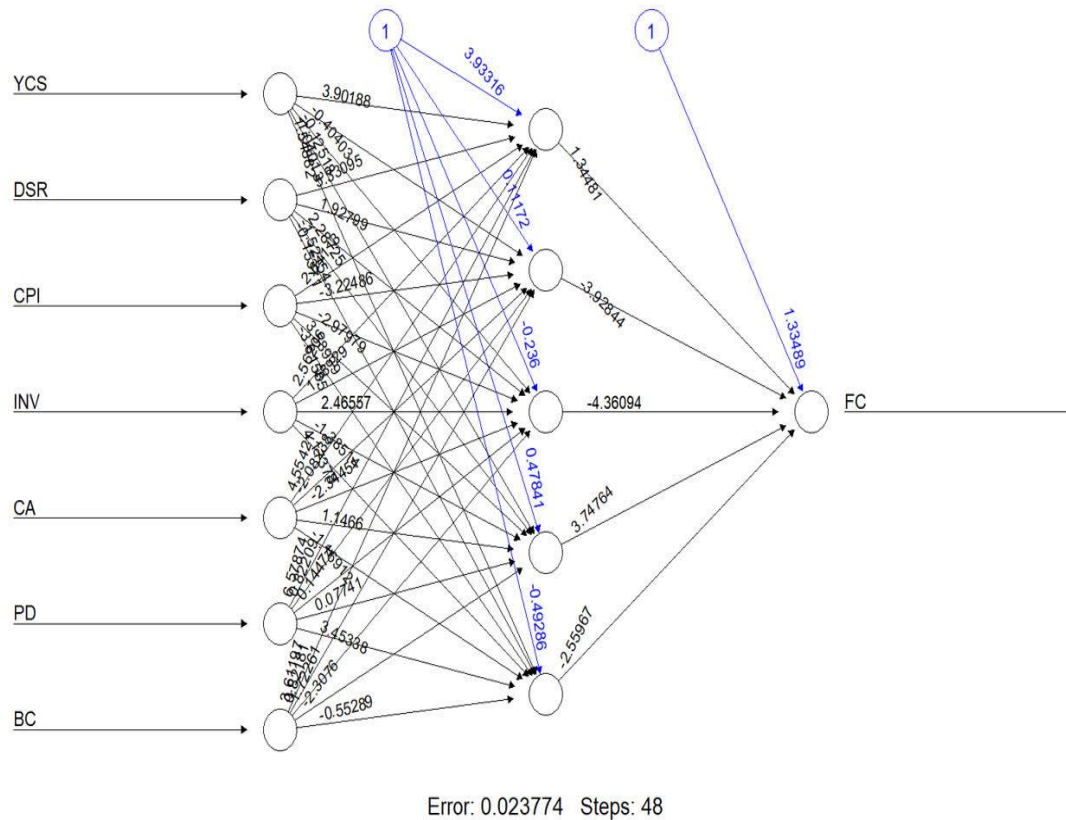
Chart 2 : Financial crisis prediction using neural networks for Iran



Source: Research calculations

Figure 2 depicts an artificial neural network for forecasting financial crises in Iran based on macroeconomic variables and bank credits. As the inputs of the network, variables such were YCS, DSR, CPI, INV, CA, PD, and BC (in Equation 1) are associated with the output variable FC (financial crisis function) by a relationship through the nodes of a hidden layer neural network. The weights between lines of communication connecting nodes represent the influence of each input variable toward making a prediction; higher weights indicate greater importance of that variable in particular for the model. The low network error (0.017313) shows model accuracy during training and its ability to predict financial crises concerning economic variables and bank loans.

Figure 3: Financial crisis prediction using neural networks for Iraq



Source: Research results

The network structure of the optimal expectation algorithm in forecasting financial crises is such that each element or 'neuron' stands for one of the macroeconomic variables. The structure is capable of updating the weights and relationships between variables based on information that comes in, like the coefficients, p-Values, odds ratios—and the importance of each variable. This framework takes into consideration various macroeconomic variables like YCS, DSR, CPI, INV, CA, PD, and BC. In each iteration with continuous updates based on these parameters, weights are gradually optimized toward creating a model capable of capturing impending financial crises for any individual country. It allows differences in importance and impact of each variable between two countries to be taken into account; it does provide a dynamic and flexible framework for analysis and predictions of financial crises. Hence the results in terms of an expected optimization algorithm described under Table 5 would read as follows. The network structure creates the optimal expectation algorithm in forecasting financial crises, where each element or "neuron" stands for one of the macroeconomic variables. The weights and relationships of the variables are data-driven in this algorithm using inputs such as coefficients, p-values, odds ratios, and variable importance. This structure involves different macroeconomic variables such as YCS, DSR, CPI, INV, CA, PD and BC. In this way of doing things (iterations), data are continuously updated with these parameters to develop gradually weight values concerning an optimal model for predicting financial crises in each country. Such a technique allows differences in the importance and impact of each variable between two countries to be taken into account; therefore, it offers a dynamic and flexible framework for analyzing and predicting financial crises. Hence the results about expected optimization algorithm mentioned in Table 5 are as follows.

Prediction of financial crises using optimal expectation algorithm . Table 5

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

Referring to Table 5, the optimal expectation algorithm is used to predict financial crises in Iran and Iraq. The most crucial variable in both countries for predicting a financial crisis is the slope of the yield curve (YCS), but its impact is much higher in Iran than in Iraq. This is evidenced by the fact that, in Iran, it has a coefficient of 14.6409 and significance of 49.2555, while in Iraq, it has a coefficient of 2.5827 and significance of 36.5325. The debt service ratio (DSR) ranks as the second most important variable in both countries. It has a negative impact on the likelihood of a financial crisis occurring. Other variables include Investment (INV) and current account (CA), which are more important in Iraq than Iran, plus public debt (PD), which is weightier for Iraq than for Iran; consumer price index (CPI) and bank credit (BC) are considered least important in both analyzed states. These results may be useful for policymakers in both countries to be able to anticipate and combat future financial crises. Therefore, the current study is consistent with many other recent works on the prediction of financial crises using machine learning methods, especially Random Forest and KNN. Researchers like Ashtab et al. (2017), Wang & Wu (2017), Liu et al. (2022), and Blustein et al. (2023) have also stressed the superiority of these methods, indicating a strong trend in artificial intelligence use in this area. The focus on macroeconomic variables like YCS and CA follows from the results obtained by Ahmad et al. (2021) and Laborda & Olmo (2021). Ristolainen et al. (2024) have also stressed information in news headlines as relevant, which might complement these findings. The YCS variable odds ratio is also much larger in Iran than Iraq, indicating that slight changes in the yield curve slope will have a greater effect on the probability of a financial crisis occurring in Iran. Thirdly, comparing variable coefficients and variable significance between the two countries means that policymakers in Iran and Iraq should apply different approaches to prevent financial crises. For Iran, more focus on managing the yield curve together with the debt service ratio would be more effective while for Iraq, attention has to be drawn to a bigger set of variables with investment and current account taking a key role. Moreover, relative to other variables, the low role of bank credit (BC) in both countries can mean that it is necessary to make changes related to credit and banking policy in order to increase the impact of this sector on

ensuring financial stability. These findings can act as a good guide for economic policymakers in both countries to predict and avoid future financial crises. So the present study is in line with many recent researches on predicting financial crises using machine learning methods, especially Random Forest and KNN, such as Ashtab et al. (2017), Wang & Wu (2017), Liu et al. (2022), and Blustein et al. (2023). The focus on macroeconomic variables like YCS and CA follows in the results of Ahmad et al. (2021) and Laborda & Olmo (2021). The emphasis on news headlines' informational content is equally important, as noted by Ristolainen et al. (2024).

Iran's situation reveals that more uncertainty and obscurity in the economy are in line with the studies of Taheri Bazkhaneh et al. (2019), Emamverdi & Jafari (2019) and Jafarimanesh & Gholami (2022). For Iraq, the optimal performance of the Cerebellar Neural Network agrees with Yousef & Aldeen (2018) and Salman et al. (2021) on their findings for Iraq.

Other research, such as Samtani et al. (2020), Nora Metawa et al. (2021), Muthukumaran & Harihaaranath (2022), and Venkateswarlu et al. (2022) emphasize even more the importance of advanced techniques in predicting financial crises. For the most part, this study is very much in line with the general drift of recent research by emphasizing the use of advanced machine learning methods, macroeconomic variables (special attention) 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.

Research conclusions and proposals

At the national level, forecasting a financial crisis is considered to be a key tool for economic governance and policy formulation. These forecasts enable the economic authorities to take appropriate action in response to abrupt variations in the financial and economic environment, thereby averting crises. Early detection of warning signs allows governments to develop and implement preventive and remedial measures that would enhance the stability of macroeconomic fundamentals and safeguard national wealth. Moreover, such a forecast facilitates optimal planning related to investments and allocation of financial resources, which fosters confidence among investors as well as citizens toward the nation's financial system. Hence, the observance and attention drawn onto systematic forecasting regarding financial crises in economic policy not only contributes toward enhancing countries' financial health but also leads to economic stability. Hence, the present study on financial crises in Iran and Iraq is an analysis using economic data and macro variables from 2000 to 2023, such as the debt-service ratio with respect to bank loans. In this paper, the following core variables are measured: YCS, DSR, CPI, INV, CA, PD, and BC. These results prove that such variables have a direct effect on the happening of financial crises in both countries and their good prediction accuracy can make appropriate and timely decisions visible to policy-makers. To begin with, based on descriptive statistics and the Jarque-Bera test information obtained which indicates that most of the variables under study do not follow a normal distribution. This is evidence enough to go for non-parametric statistical techniques and machine learning models due to impropriety in this case. The application of advanced algorithms such as Random Forest and K-Nearest Neighbors (KNN) in detecting, specifically, the nonlinear and complex relationship between economic variables and financial crises showed that these methods can reveal more information with higher accuracy of predictions. Also, based on the results of prediction adequacy using these methods clearly indicated the huge role played by macroeconomic variables in predicting financial crises; later, YCS and CA were then referred to as the most important predictors. Consequently; Machine learning methods (Random Forest and KNN) in this study revealed that Yield Curve Slope (YCS) and Current Account (CA) are the most crucial variables for forecasting financial crises for both Iran and Iraq. This result has several implications. For Iran,

YCS has a more substantial impact, which signifies that monetary policy/interest rates are more critical for attaining financial stability than is realized in Iraq; where it has less weight. Changes in the current account balance are important in both countries, but have a more substantial effect on Iran because of its oil-dependent economy. The choice of these techniques is based on their capacity to recognize intricate trends and work with non-linear data. A change in the YCS can be a sign of changes in inflation expectations and economic growth; however, current account deficits can bring about depreciation of the currency and increase the likelihood of a financial crisis. Findings from this study have major policy implications for both countries; it signals that special attention should be devoted to issues related to interest rate management and the trade balance. These results also show that it is important to use advanced analysis methods when developing economic policies and that taking into account various factors (and developing them) can help to forecast and prevent financial crises.

Caution is necessary because this strong interrelationship between variables indicates that a change in one can significantly affect others and hence the economy at large. For instance, an adjustment in monetary policy that impacts upon the slope of the yield curve will also indirectly influence investment as well as bank lending. These results also indicate how vital it is to use multivariate approaches in analyzing and predicting financial crises, since looking at one variable alone may not give a full picture of what is going on with the economy. Caution is necessary because this high variable relationship indicates that a change in one of them can seriously affect other variables and hence other aspects of the economy. For instance, an indirect effect may be created on investment and bank credit as a result of a change in monetary policy that influences the slope of the yield curve. Results also show why it is important to use multivariate approaches when analyzing and predicting financial crises since focusing on one variable alone may not give proper information about what is likely to happen economically. This indicates the need for caution because this robust variable relationship reflects that a change in one can have grave effects on others and, therefore, on the entire economy. For instance, an adjustment of monetary policy that influences the slope of the yield curve will also indirectly influence investment as well as bank lending. They also demonstrate how vital it is to apply multivariate techniques when analyzing and predicting financial crises.

For Iran, put simply, these models perform poorly because the economy has multiple and more complex issues such as economic sanctions against them, exchange rates which are running up to unrealistic levels and economic policies that are changing overnight. For Iraq, on the other hand, these models perform well because the economy has simpler and more linear relationships between its factors. In Iran, because the economy has been subject to such factors as economic sanctions and extreme fluctuations in exchange rates plus rapid changes in economic policies, the weaker performance of these models is inevitable. Conversely, the good performance of these models in Iraq shows that there are simpler and more linear relationships between factors in the country's economy.

In summary, this research posits that there is a need for a holistic model-based approach adapted to the particularities of each country in the prediction and prevention of financial crises. The incorporation of advanced data analysis techniques in economic policy formulation has the capacity to improve discernment and optimize financial stability for both countries. The following are practical recommendations based on.

the research: In conclusion, this paper is strongly in support that the prediction and prevention of financial crises call for a detailed and case-specific all-around approach in each nation. Effective use of advanced data analysis techniques in economic policy formulation has the potential to

improve decision-making and enhance financial stability in these two countries. The research, in general, the practical recommendations resulting from it are: In conclusion, this paper argues that there is no one-size-fits-all approach to forecasting and preventing financial crises. However, the adoption of sophisticated data analysis techniques in economic policy formulation can help decision-makers enhance their capacity to avert such crises, as well as ensure improved financial stability for their countries. In summary, the policy implications from the research are: In conclusion, this research implies that one-size-fits-all, but with due regard to specific conditions in each country, is the right approach to prediction and prevention of financial crises. The adoption of sophisticated data analysis techniques in economic policy formulation has the capacity to enhance the quality of decisions and promote financial stability in those two countries. The paper comes up with the following general policy recommendations: This study, in other words, emphasizes the need for a country-specific comprehensive strategy in prediction and prevention of financial crises. The incorporation of advanced data analysis techniques in economic policy formulation can help in making informed decisions that would lead to enhanced financial stability of these two nations. The research, at large, gives the following operational recommendations.

i. For Iran, due to the higher dimension of effect and specifics connected with the levels of uncertainty in the economy, it is recommended for policymakers to use more advanced flexible predictive systems such as fuzzy ones. In addition, monetary policies should be adjusted with greater care towards managing interest rates and inflation expectations rather than earlier established by more myopic rules of some governmental engagements. To decrease economy vulnerability against external shocks — diversifying income sources and reducing reliance on oil exports become important measures. Reforming the banking system and increasing its efficiency should also be among the first orders since bank credit has a smaller effect on financial stability. And additionally: having a higher probability of financial crises, creating early warning systems for probabilities and overseeing places where finances are dealt in markets become good advice for undertaking actions.

ii. Iraq: due to the less complex economic structure and identifiable patterns with time, series models like ARIMA and ETS could be more useful. The authors recommend the use of cerebellar neural networks in detecting economic patterns for its good performance. The influence of YCS is not so much on Iraq, but it is still significant and important for consideration while forming economic policy. Because of the over-reliance on oil revenues, diversification of the economy, and the priority of developing non-oil sectors is very important. This would enhance modernization efforts drawn at developing a banking system that can work out special solutions with regard to strengthening the impact of bank credit on financial stability. Moreover, most preventive mechanisms have lower chances for triggering a financial crisis — like in Iran — but this does not reduce their capacity-building need for establishing strong regulatory systems that ensure stability within systems where they operate.

iii. For both countries, using sophisticated data analysis techniques such as machine learning algorithms and principal component analysis (PCA) to perceive a good insight into the intricate relationship among economic variables is ideal. Moreover, considering the weight placed on the current account in both these nations, control over trade balance and foreign exchange policies should be paid due attention. Developing regional and international cooperation that vulnerability to external shocks would be lowered is also beneficial. This would include creating comprehensive risk management systems as well as increasing transparency in financial reporting to enhance stability of finance and lower probability of economic crises.

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