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Currency and Financial Crisis: A Review Study of Prediction Models and Crisis Management Strategies

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Keywords: Currency, Currency Crisis, EWS (Early Warning System), Financial Crisis, Prediction.

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Abstract

Predicting currency and financial crises has garnered a lot of attention and research, with notable developments and a variety of methodological approaches. This review article summarizes current research from 2019 to 2024 with an emphasis on the kinds of datasets, timeframes, and models used. The examination displays a wide range of data, from the 1970s to 2022, with the majority of studies depending on data collected after the 1990s because of its increased dependability and availability. Many models have been used, such as Markov switching models, artificial neural networks (ANN), signal approaches, deep neural decision trees (DNDTs), and traditional econometric models like logit and probit. The results emphasize that there isn't a single model that is always better; rather, they emphasize the significance of choosing models based on context and the advantages that hybrid or ensemble approaches may have. Our review highlights that to improve prediction accuracy, a variety of datasets and models must be used. Because currency crises are inherently complex, a multifaceted strategy that makes use of both conventional econometric and contemporary machine learning techniques is required. To better capture the complex dynamics of economic indicators, future research should investigate higher frequency data and keep improving hybrid methodologies.

This thorough analysis contributes to the current discussion on currency and financial crisis forecasting by offering insightful analysis and directing future research paths.

Keywords: Currency, Currency crisis, EWS (Early Warning System), Financial crisis, Prediction.

أزمات العملة والأزمات المالية: دراسة مراجعة لنماذج التنبؤ واستراتيجيات إدارة الأزمات

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الخلاصة

تحظى عملية التنبؤ بالأزمات النقدية والمالية بقدر كبير من الاهتمام والبحث، مع تطورات ملحوظة ومجموعة متنوعة من الأساليب المنهجية. تلخص هذه المقالة الأبحاث الحالية من عام ٢٠١٩ إلى عام ٢٠٢٤ مع التركيز على أنواع مجموعات البيانات والأطر الزمنية والنماذج المستخدمة. يستعرض البحث أيضا مجموعة واسعة من البيانات المستخدمة في هذه الأبحاث، من سبعينيات القرن العشرين إلى عام ٢٠٢٢، حيث تعتمد غالبية الدراسات على البيانات التي تم جمعها بعد التسعينيات بسبب زيادة موثوقيتها وتوافرها. تم استخدام العديد من النماذج، مثل نماذج التبديل ماركوف، والشبكات العصبية الاصطناعية (ANN)، ونهج الإشارة، وأشجار القرار العصبية العميقة (DNDTs) والنماذج القياسية الاقتصادية التقليدية مثل لوجيت وبروبيت. تؤكد النتائج انه لا يوجد نموذج واحد أفضل من بقية النماذج، بل يعتمد أهمية اختيار النموذج بناءً على السياق والمزايا التي قد تتمتع بها الأساليب الهجينة أو المجمعة وسنسلط الضوء على أنه من أجل تحسين دقة التنبؤ، يجب استخدام مجموعة متنوعة من مجموعات البيانات والنماذج. ولأن أزمات العملة معقدة بطبيعتها، فإن الأمر يتطلب استراتيجية متعددة الأوجه تستفيد من كل من القياس الاقتصادي التقليدي وتقنيات التعلم الآلي المعاصرة. ومن أجل التقاط أفضل للديناميكيات المعقدة للمؤشرات الاقتصادية، ينبغي للبحوث المستقبلية أن تحقق في البيانات ذات التردد الأعلى وتحسين المنهجيات الهجينة باستمرار. ويساهم هذا التحليل الشامل في المناقشة الحالية حول التنبؤ بالعملة والأزمات المالية من خلال تقديم تحليل ثاقب وتوجيه مسارات البحوث المستقبلية.

الكلمات المفتاحية: أزمات العملة، التنبؤ، الأزمات المالية، العملة، نظام الإنذار المبكر.

1. Introduction

1.1. Definition

Currency crises are periods of extreme volatility and depreciation of a country's currency, which can have significant impacts on the economy and society. Price increases for both domestic and imported products and services are one effect of the currency crisis. Customers, however, may not always view price rises similarly. While some price increases could be viewed as justifiable, others might be perceived as exploitative and unfair [1]. A financial crisis is a disruption to the financial markets that exacerbates issues with moral hazard and adverse selection. Financial markets are therefore unable to effectively direct money to individuals who provide the most profitable investment possibilities [2]. And there are significant occurrences that may have detrimental effects on society and the world economy [3]. Therefore, Early warning systems (EWS) are crucial since they can identify the early warning indicators of a crisis and offer policy solutions to avert or lessen it. However, the majority of EWS rely on ex-post data, which can be delayed and revised frequently and may not accurately represent the status of the economy right now [4].

Financial and currency crises are connected, due to their reliance on each other. They are occurrences that are often analyzed separately because of their unique characteristics and impacts. Financial crises can result in declines as they typically lead to disturbances in financial sectors like stock market collapses or banking emergencies [5]. A rapid devaluation of a country's currency is commonly referred to as a currency crisis [6]. These situations often occur due to market speculation or a loss of trust from investors. To grasp the reasons, processes, and government reactions to these crisis types, researchers distinguish between the two crises in that financial crises often occur by asset bubbles and excessive borrowing while currency crises are commonly associated with balance of payments issues and foreign exchange reserves [7].

1.2. The challenge

Determining and quantifying currency crises objectively is one of the difficulties in analyzing them. The literature has put forth a variety of strategies, including indicators based on market pressure, balance of payments, or currency rates. Among these, the Exchange Market Pressure Index (EMPI) is frequently employed as a combined gauge of currency pressure that accounts for variations in international reserves, interest rates, and exchange rates. Finding the causes or aggravating variables of a currency crisis, such as market expectations, contagion effects, macroeconomic fundamentals, or policy actions, is another difficulty [8]. The identification and analysis of current financial crisis variables is also not easy, assessment of the likelihood and seriousness of potential risks and provision of a scientific foundation for risk mitigation and control constitute early warning systems for financial risk. Building a strong financial risk early-warning mechanism is crucial due to the fragility of the financial system and the severity of the financial crisis [9]. Consequently, it's critical to create reliable and accurate models that can foresee and avert these kinds of problems. However, financial crisis prediction (FCP) is a difficult endeavor that requires handling high-dimensional, complicated data, in addition to choosing the most pertinent features that can reflect the problem's underlying patterns [3].

1.3. Objectives of the study

In this paper, we aim to unify and compile the current state of knowledge on the subject of currency crises and the financial crisis, and we will attempt to collect and summarize the research, theories, methodologies, and results that have been reached. Through our review of existing literature, we can identify trends in research, such as emerging predictive models or evolving crisis indicators, as well as evaluate the strengths and weaknesses of the methodologies used and discuss their applicability, accuracy, and robustness. In this paper, we will attempt to inform policymakers, financial analysts, and researchers about effective strategies for crisis prevention and early warning systems and political interventions. This can help improve financial stability and resilience.

1.4. Importance of predicting crisis

Forecasting currency and financial crises plays a role in upholding stability and averting significant economic downturns. Accurate predictions empower policymakers to proactively address issues thereby minimizing effects on economies and societies. Research has shown that rapid surges in credit and asset values often foreshadow crises underscoring the importance of monitoring these signals for detection **[10]**. In addition, having a grasp of how types of financial crises, like currency and banking crises, are interconnected can help in creating well-rounded plans to reduce possible weaknesses **[11]**. It is advantageous to forecast these crises as it helps in safeguarding stability and safeguarding individual national economies **[12]**.

2. Literature review

2.1. Historical overview:

The examination of crisis occurrences within finance has garnered interest in the realm of economics over the past twenty years, particularly concerning the anticipation of financial and currency crises due to their substantial impact on economic activities **[13]**. Since the 1930s a few academics have introduced the idea of a "financial crisis" for the time and have delved into exploring and researching this business phenomenon **[14]**. A number of European nations experienced a crisis related to the Exchange Rate Mechanism (ERM) in 1992, which was one of the first currency crises. In December 1994, there was a currency crisis involving the peso. It all started when the Mexican government suddenly decided to devalue its currency, leading to a decline in the peso's value and triggering an economic downturn that saw a substantial decrease in GDP. Despite this, the notable event was the Asian Financial Crisis of 1997 **[15]**. Initially, two common approaches prevailed in financial crisis analysis: the signal method and the logit model. Despite occurrences of crises, the adoption of early warning models emerged as a relatively recent development in the late 1990s. Recent studies have delved into utilizing machine learning techniques for predicting crises. These techniques encompass decision trees, networks, random forests, support vector machines, and various deep-learning models [16]. This extensive research endeavor has generated an array of prediction models backed by varied methodologies [13]. There have been three types of models, for understanding currency crises. The first set of models emerged in response to the balance of payment crises in countries, like Argentina, Chile, and Mexico during the 1970s and 1980s. The second-generation models were developed following the Exchange Rate Mechanism (ERM) crisis in 1992 and the crisis of 1994–1995. Lastly, efforts to create third-generation models began after the crisis that occurred between 1997 and 1998. An in-depth look at the literature can help a researcher between a currency crisis and other types of financial crises such as balance of payments crises. The term "financial crisis" seems to be the comprehensive covering forms of instability linked to financial and monetary systems. A balance of payment crisis stems from an imbalance between a deficit in the account and the capital and financial account leading to a currency crisis after foreign reserves are depleted. Many sources suggest that these two concepts are interchangeable. Numerous theories have been proposed to explore the occurrence of currency crises [17].

2.2. Currency crisis

According to [18], using logit regression on monthly data from 1992 to 2011, an early warning system (EWS) was developed to predict currency crises in emerging economies in Asia and Latin America. This system includes analyzing currency crisis history, selecting an ideal cut-off criterion, identifying key predictors, and testing variables using a sound statistical approach. Institutional and macroeconomic factors were used to forecast future crises. EWS's performance was compared with other techniques like the probit model and the signal approach. High foreign conflict combined with weak law and order can also trigger a crisis. Ultimately, a lack of democracy, indicated by high government stability and the absence of internal strife, leads to a currency crisis. The logit model performed better than the probit model and the signal approach in accuracy and timeliness.

Statistika and Maret [19] used a neural network approach (ANN) to identify the Indonesian currency crisis by analyzing macroeconomic data. The authors choose 12 indicators that are often used in literature using monthly data from January 1990 to December 2018. They contrast the ANN model's performance with that of a logit model and a signal approach. They discovered that compared to the other two approaches, the ANN model has a greater accuracy rate and a lower false alarm rate. The most important indicators for forecasting currency crises, including interest rates, foreign reserves, inflation, and exchange rates, are likewise identified by the ANN model. According to the paper's conclusion, the ANN approach is a useful instrument for creating an early warning system for Indonesia's currency crisis.

Arya and Soenardi [20] use a combination of volatility and Markov switching models to identify currency crises in Indonesia based on real deposit rate indicators, utilizing monthly data from January 1990 to July 2022 and applying ARCH, GARCH, and EGARCH volatility models. They assume that the Markov switching models have two or three states. They use log-likelihood, AIC, BIC, and HQIC criteria to evaluate the models and find that MS-ARCH(1) is the best model for currency crisis modeling on the real deposit rate indicator, detecting crises from 1997 and 2008 and showing how Indonesian crisis eras can be identified using smoothed probabilities from the integrated models. They identify four crisis periods: Jan 1998–Aug 1997, Jun 1998–Oct 1998, Aug 2000–Jun 2000, and Oct 2008–Dec 2008. They conclude that Markov switching models combined with volatility effectively capture data condition changes and are valuable for Indonesia's currency crisis detection.

In Ref. [15], Deep neural decision trees (DNDTs), a method based on decision trees and deep learning neural networks, were used to create a global model for currency crisis prediction by Alaminos et al. They employed a sample of 162 nations, covering both emerging and developed regions, to account for regional heterogeneity in warning indicators. They compared DNDTs with other widely used methods like support vector machines, random forests, and logistic regression. The DNDTs approach achieved an average accuracy of 93.75% for currency crisis prediction, surpassing the other techniques in accuracy, precision, recall, and F1 score. Their research concluded that DNDTs offer tools that contribute to global financial stability and hold significant potential for macroeconomic policy adaptation to currency value decline risks.

Based on interest rates and inflation, Amri, Chamidah, and Sugiyanto [21] created early detection models for currency crises in Indonesia. To simulate the large fluctuations and regime changes of the 1998 and 1997 crises, they combined Markov regime-switching and volatility models, using smoothed probability values to assess the models' effectiveness on monthly data from January 1990 to December 2018. They found that MRS-AR (2,1) is best for inflation, and MRS-GARCH (2,2,0) is most suitable for interest rates. MRS-GARCH (2,2,0) identified currency crises from January to December 1998, while MRS-AR (2,1) identified crises from August 1997 to December 1998. They concluded that Indonesia did not face a currency crisis in 2019 based on the smoothed probability estimates from the two models and proposed using these indicators as early warning systems for currency issues.

Based on the stock price index, Prasasti et al. [22] identified a suitable model and forecasted the Indonesian currency crisis from November 2022 to October 2023, and they made use of three models: a hybrid of the Markov switching model and the volatility model. A situation when the depreciation of the exchange rate surpasses a predetermined threshold is referred to as a currency crisis. The combination model outperforms the others in terms of accuracy, sensitivity, and specificity, they discovered. Additionally, based on the combination model, they projected that Indonesia would not experience a currency crisis between November 2022 and October 2023. Then, based on the stock price index, they concluded that volatility and the Markov switching model could be employed together as an early warning system for Indonesia's currency problem, and they recommended that to prevent a currency crisis, the government and central bank should keep an eye on changes in the stock market and take preventative measures.

Sugiyanto et al. [23] use the real interest rate on deposit indicators from 1990 to 2018 to try and identify Indonesia's currency crisis. To explain the oscillations and regime shifts of the indicator, they used models of volatility and Markov Switching. The MRS-ARCH (2,1) model is suggested as the most appropriate model to elucidate the currency crisis. After analyzing the data using the MRS-ARCH (2,1) model, they came to the following conclusions: There are two states in the model: state 1 is regular, and state 2 is a crisis state. The smoothed probability values indicate that the model can account for the crisis that transpired in 1997/1998 and 2008. Based on the indicator, the model forecasts that there was no indication of a catastrophe in 2019. Ultimately, they concluded that a good way to identify Indonesia's currency issue is to look at the real interest rate on deposits. and the MRS-ARCH (2,1) model is a good fit for explaining how the indicator behaves.

Adams and Metwally [24] used yearly data from 1977 to 2017 to identify the markers of Egypt's currency crisis. Based on 16 economic indicators, they discovered that the following five factors had the best forecasting ability: real interest rate, real exchange rate, USA interest rate, domestic current account, and domestic interest rate spread. They suggested the creation of the market turbulence index (MTI) to gauge the severity of the currency crisis and compare it to other indices. They determined eight episodes of the Egyptian currency crisis that align with historical occurrences. According to their findings, 90.6 percent of non-crisis episodes and 87.5 percent of crisis episodes are accurately predicted by the probit model. The MTI outperforms other indices in reflecting the intensity of the currency crisis, including the Speculative Pressure Index (SPI) and the Exchange Market Pressure Index (EMPI).

In Ref. [25], the recent history of currency crisis (stress periods) and the factors determining their likelihood in India were studied by Mohana Rao and Padhi. Using signal extraction methodology and a logistic regression model for the years 1986–2015, they sought to build an early warning system (EWS) to predict the likelihood of an impending crisis within the 12-month crisis window. They determined 22 crisis months (stress periods), of which only the early ones (1990–1991) had a devaluation; the later ones (after 1991) did not. In terms of accuracy, the logistic regression model performs better than the signal extraction method. They concluded that creating an EWS can be a useful diagnostic tool for tracking how susceptible the Indian economy is to exchange rate fluctuations.

In Ref. [26] a model for forecasting the Iranian currency crisis was presented by Davari et al.; it combined machine learning techniques with macroeconomic indices and classified times of peace and crisis using quarterly data from 1990 to 2018 with logistic regression, support vector machine, and random forest techniques. The most significant indicators are the real effective exchange rate, inflation rate, current account balance, and foreign exchange reserves. The random forest approach has the highest accuracy and reliability. A currency crisis is defined as an exchange rate depreciation of more than 15% in a quarter or more than 25% in a year. The study identified six periods of crisis: 1994Q4, 1995Q1, 2002Q3, 2012Q2, 2018Q2, and 2018Q3. The random forest technique outperforms the other methods and is valuable for forecasting the currency crisis in Iran.

According to [13] a nation's ability to develop depends on its sovereign debt and currencies, which makes international relations and efficient funding crucial. Forecasting sovereign debt and currency crises is important, but current models are not accurate or diverse in terms of geography. David Alaminos and colleagues introduce new predictive models that outperform conventional statistical methods. The models take into account a global sample that includes countries from Africa, the Middle East, Latin America, Asia, and Europe. Significant variables for currency crises are FCF, M2M, M2R, TRO, CACC, DUR, and YEAR; key variables for sovereign debt crises are TDEB, IMFC, FXR, M2R, SCFR, and SBS. Models with high prediction accuracy include fuzzy decision trees, AdaBoost, extreme gradient boosting, and deep learning neural decision trees; some of these models can predict sovereign debt up to 100% of the time, and currency crises up to 99.07%.

Using Egypt as a case study, Mamdouh and Hany [27] suggest the best early warning system (EWS) for foreseeing currency crises in developing nations. The research combines forecasts from separate models using equal weighting (EW) and dynamic model averaging (DMA) techniques, which support time-varying weights. The results show that these combined forecast methods perform better in both in-sample and out-of-sample predictions than individual models. The research demonstrates that a combination of forecasts provides superior predictive power, which contrasts with prior studies that support particular models, such as Probit, Logit, or extreme value models. In addition to estimating and combining density forecasts rather than point forecasts, the paper recommends future research investigate various combination schemes for other financial crises.

Using the Signal, Logit/Probit, BMA, and 2SLS techniques, Dao and colleagues **[28]** present a novel early warning system (EWS) for predicting currency and systemic banking crises in emerging markets like Vietnam. Focusing on indicators such as the securities index, real effective exchange rate, exports, and banking metrics like M2/reserves and NPLs, the EWS projects a low crisis probability for 2017–2018. Vietnam's economic stability was affected by dollarization and the 2008–2009 global financial crisis. Vietnam, a net importer until 2011, briefly had a trade surplus in 2012, leading to periodic deficits by 2015. Significant currency appreciation weakens export competitiveness, while severe depreciation increases foreign debt risk. From 2002 to 2016, the study's EWS identifies 11 macroeconomic variables influencing currency crises and 15 influencing systemic banking crises, showing a low crisis probability in subsequent years.

To predict currency crises across 17 developing countries, Gulden Poyraz's study uses a dynamic random effects probit model. It highlights the important effects of lagged crisis indicators, particularly the 12th, 3rd, 2nd, and 1st lags, showing short-term state dependence on crisis probability. Their study concludes that, although static models are more common in the literature currently in publication, a dynamic approach can uncover intertemporal relationships and identify actual state dependence in crisis occurrence by using lagged dependent variables. This emphasizes the importance of incorporating endogenous factors into early warning systems to enhance their ability to accurately forecast currency crises **[29]**.

In Ref. **[30]** the goal of the study by Ahmad Googerdchian, Babak Saffari, and Fatemeh Farzina is to use an early warning system to forecast currency crises in Iran. The study uses artificial neural networks, specifically a Multi-Layer Perceptron Neural Network with a Hard-Limit function, along with econometric techniques to analyze seasonal data from 2001 to 2015 and forecast that there won't be a currency crisis in 2019. Important conclusions show that the export index is the main factor affecting Iran's currency stability. The model's 97% predictive accuracy, as demonstrated by comparisons with earlier research, suggests that it is more reliable than traditional econometric techniques, which have higher prediction errors because of serial correlation in time-series data.

2.3 Financial crisis:

Altunöz [31] used the probit model, logit model, and KLR signal methodology to assess the predictability of the 2008 financial crisis in Turkey, selecting nine indicators related to financial stability with data from January 2003 to December 2012. He evaluated the approaches based on lead time, type I and type II errors, and accuracy. The KLR signal technique had a high accuracy rate of 97.5% but a high false alarm rate of 50%. The probit model had a lower accuracy rate of 78.31% and a false alarm rate of 16.67%. The logit model had the highest accuracy rate of 92.18% and a moderate false alarm rate of 33.33%. The lead times were 12 months for the logit model, 10 months for the probit model, and 8 months for the KLR signal method. Altunöz concluded that the logit model is the most effective technique for forecasting the financial crisis due to its high accuracy rate, tolerable false alarm rate, and extended lead time. He recommended monitoring indicators like the credit to GDP ratio, real exchange rate, and current account balance.

In Ref. [32], the authors utilize machine learning methods to anticipate financial problems by integrating multiple models within a sequential prediction framework. This framework covers France, Germany, Italy, and the United Kingdom, using macroeconomic factors like inflation, current account balance, loan growth, and currency rate to forecast crises. They evaluate their predictions out-of-sample, finding that their method can identify systemic financial crises three years ahead with a high signal-to-noise ratio. The approach outperforms any single model in the long run, adapting over time and across nations. Machine learning proves useful for creating macroprudential regulations and forecasting crises, though the method faces limitations, such as small crisis sample size and potential economic structural shifts.

Bluwstein et al. [33] utilized machine learning techniques to analyze macro-financial data from 17 nations between 1870 and 2016 to build early warning models for financial crisis prediction. They found that machine learning models generally outperform logistic regression in forecasting and out-of-sample predictions. Significant indicators of crisis risk include the slope of the yield curve and credit expansion. Machine learning methods like random forests, neural networks, and support vector machines showed better performance than logistic regression, particularly in terms of AUC-PR and AUC-ROC. A framework based on Shapley values revealed that credit growth and yield curve slope are consistently key predictors. Additionally, a flat or inverted yield curve, especially when nominal interest rates are low and credit growth is high, is particularly concerning.

In Ref. [34] Sumaira and colleagues evaluated the performance of traditional distress prediction models before, during, and following financial crises by comparing their predictive accuracy for Pakistani firms between 2001 and 2015. The Z-score model is excellent at predicting insolvency, but the probit model has the best overall accuracy. All models exhibit decreased accuracy during economic downturns. The study emphasizes the importance of defining financial distress broadly and considering warning signs such as listing fees and dividend failures. Metrics like profitability and liquidity show significant differences between troubled and stable firms. The study acknowledges limitations in generalizability and advocates broader research encompassing multiple emerging markets.

Hossein Dastkhan [35] investigates the use of Conditional Value at Risk (CoVaR), a forward-looking systemic risk measure, in an emerging market—the TSE, in particular—in this study. He creates new network-based indices and builds a network representation of firm interconnections based on ΔCoVaR values. As early warning systems, these indices can be used to anticipate firm-level and market-wide downturns and crises. According to the findings, these indicators may be able to predict crises up to seven periods ahead of time. This indicates that investors and policymakers alike may find these indicators useful in managing their portfolios according to risk assessments and in developing micro- and macro-prudential policies to reduce systemic risks.

According to [36] the collapse of the US housing market in 2007 marked the beginning of the global financial crisis, exposing large undervaluation's in mortgage-backed securities and causing a general decrease in bank profitability and liquidity because of intricate financial instruments. Investigations into the effects of securities like mortgage-backed securities, repurchase agreements, and interbank market securities on bank profitability were prompted by predictive models' inability to predict the crisis. Repurchase agreements and banks' return on capital correlated positively, but overall, these factors were not very good at predicting crises. Rather, stable, time-invariant bank characteristics and underlying risks undermined the efficacy of early warning indicators and contributed to the severity of the crisis. To improve crisis anticipation and management in international financial markets, these variables must be included in future prediction models.

During the COVID-19 pandemic, Feixiong-Ma and associates evaluated financial crisis prediction techniques for publicly traded firms. Support vector machines and RPROP artificial neural networks were used to analyze two years' worth of panel financial indicators from 162 different companies. By combining these techniques in a novel way, they were able to create a strong early warning system that improved risk supervision and stability for both listed businesses and the overall economy. According to the research, combining these algorithms predicts financial crises with accuracy and provides stakeholders—investors, creditors, and regulators—with information about the financial health of the company and risk-reduction tactics. Notwithstanding its merits, the study recommends that nonfinancial indicators and longitudinal data be incorporated into future research for thorough examination and ongoing model validation **[37]**.

High-tech enterprises (HTEs) should embrace sustainable development strategies, according to Houfang Guo, especially for "carbon neutrality" and "carbon peak" objectives. In the face of market competition, he addresses the need for HTEs to manage financial risks using machine learning models like XGBoost, BP neural networks, and logistic regression. The study aims to improve the accuracy of financial crisis early warning (FCEW) systems by combining these models with the stacking method. It examines fusion techniques such as voting and averaging and concludes that the stacking fusion model, particularly when combining logistic regression and XGBoost, produces better performance metrics like accuracy and AUC. Stacking fusion models perform better than single models and other techniques, providing strong predictions essential for sustainable business growth **[38]**.

The temporal convolutional network (TCN), introduced by Shun CHEN, Yi HUANG1, and Lei GE, is an advanced model for financial crisis forecasting that outperforms other deep learning techniques and conventional logit models. TCN processes multiple time points simultaneously, has a larger receptive field than RNNs, and handles long-range dependencies effectively with less computational power. The study uses Shapley value decomposition to interpret the model and finds that real GDP growth and stock prices are important variables in crisis prediction. The study validates the efficacy of TCN using the Jórda-Schularick-Taylor macro-history database, demonstrating precision increases of more than 10% and up to 50% compared to RNNs and logit models. These results highlight the potential of TCN to improve early warning systems and guide policy choices **[16]**.

The goal of the study by Jin Kuang, Tse-Chen Chang, and Chia-Wei Chu **[14]** is to provide a strong financial early warning model for Chinese enterprises amid market competition and economic globalization. The research shows better predictive accuracy with a combined approach using time series methods and the BP neural network algorithm, rather than individual methods. Examining 816 companies listed on the Shanghai Stock Exchange, the study concludes that the BP neural network is the most effective model for forecasting potential crises. Future research should increase sample sizes and integrate internal corporate factors and external economic indicators for more complete prediction models. The results highlight implications for strengthening crisis management, boosting asset appreciation, encouraging wise investments, and assisting policymakers in resource allocation and economic stability.

3. Summary of Literature Review:

This section offers a thorough overview of studies that have been done on the prediction of currency crises using various machine learning models. A variety of studies are covered in the literature review, demonstrating the variety of dataset types and ranges that researchers in this field have used. We aim to provide a concise and understandable summary by looking at known models used and selecting the models that work best based on the results. The main points of these studies are summarized in **Table 1**, providing a convenient way to quickly review the pertinent data.

Table 1: A Summary of the Studies of Literature Review.

Ref.	Pub. year	Dataset type	Dataset range	Known Models Used in the Study	Best model (depending on the results)
[18]	2022	Monthly data	From 1992 to 2011	logit regression and probit model	logit model
[19]	2023	Monthly data	From January 1990 to December 2018	ANN model, logit model, and signal approach	ANN method with Multilayer Perceptron Backpropagation algorithm
[20]	2023	Monthly data	From January 1990 to July 2022	Combination of volatility and Markov switching models (applying the ARCH, GARCH, and EGARCH volatility models)	MS-ARCH
[15]	2019	Annual data	From 1970 to 2017	deep neural decision trees (DNDTs), Logistic Regression, Support Vector Machines, ANN (Multilayer Perceptron), and AdaBoost	DNDTs
[21]	2020	Monthly data	From January 1990 to December 2018	combined Markov regime-switching and volatility models (applying the MRS-AR (2,1) and MRSGARCH (2,2,0))	MRS-AR (2,1)
[22]	2023	Monthly data	From November 2022 to October 2023	combination of volatility and MARKOV switching models	MSARCH (2,1) model with the AR(1) model
[23]	2019	Annual data	From 1990 to 2018	volatility and Markov Switching	MRS-ARCH (2,1)
[24]	2019	Annual data	From 1977 to 2017	probit model	probit model
[25]	2019	Annual data	From 1986 to 2015	signal extraction methodology and a logistic regression model	logistic regression model
[26]	2022	Quarterly data	From 1990 to 2018	the logistic regression, support vector machine, and random forest techniques	random forest
[13]	2021	Annual data	From 1970 to 2017	Multilayer Perceptron (MLP), Support Vector Machine (SVM), Fuzzy Decision Trees	for the sovereign debt crisis: FDT, AdaBoost, XGBoost, and DNDT. for the prediction of the

Ref.	Pub. year	Dataset type	Dataset range	Known Models Used in the Study	Best model (depending on the results)
				(FDT), AdaBoost, Extreme Gradient Boosting (XGBoost), Random Forest (RF), Deep Belief Networks (DBN), Deep Neural Decision Trees (DNDT)	currency crisis: DNDT, XGBoost, RF, and DBN
[27]	2020	Monthly data	From February 1995 to July 2018	Probit, Logit, Grompit, Switching regression model, equal weighting (EW), and dynamic model averaging (DMA)	EW- and DMA-based EWS
[28]	2022	Monthly data	From January 2002 to December 2016.	the Signal approach, Logit/Probit models, Bayesian Model Averaging (BMA), and Two-Stage Least Squares (2SLS).	the combined approach of these methods.
[29]	2019	Panel data	From 1991 to 2017	The dynamic panel probit model	The dynamic panel probit model
[30]	2021	Seasonal data	From 2001 to 2015	Multi-layer Perceptron Neural Network and Hard-Limit function	Multi-layer Perceptron Neural Network and Hard-Limit function
[31]	2019	Monthly data	From January 2003 to December 2012.	the probit model, the logit model, and the KLR signal methodology	the logit model
[32]	2021	Quarterly data	From 1985q1 to 2019q3	based on model aggregation and is “meta-statistical”	can incorporate any predictive model of crises in the analysis and test its ability to add information
[33]	2023	Annual data	From 1870 to 2016	Neural network, Extreme trees, SVM, Random Forest, Logistic regression, and Decision tree	Machine learning models outperform logistic regression
[34]	2019	Annual data	From 2001 to 2015.	Z-Score, O-Score, Probit, Hazard, and D-Score	The probit model and the Z-score model
[35]	2021	Daily data	From January 2010 and September 2016	Forward-looking Conditional Value at Risk (CoVaR), Network Analysis of Asset Exposures, Network-based Indices (derived from CoVaR values)	Network-based indices based on CoVaR values
[36]	2020	Annual data	From 2004 to 2008	Linear Multiple Regression Analysis, Fixed-Effects Regression Analysis	linear multiple regression analysis
[37]	2020	Panel data	From 2015 to 2016	RPROP artificial neural network and support vector machine	Combine the two methods
[38]	2023	Not mentioned	From 2018 to 2020	logistic regression, XGBoost, and BP neural networks	combine the models using the stacking method
[16]	2024	Annual data	From 1870 to 2016	Temporal Convolutional Network (TCN), Multilayer perception (MLP), Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU)	temporal convolutional network (TCN)
[14]	2022	Not mentioned	Not mentioned	the time series forecasting method (an autoregressive integrated moving average (ARIMA)) model, Backpropagation Neural Network (BPNN), and Combined Forecasting Method	combined forecasting method

4. Analysis and methodology:

After studying a large group of previous and more recent research in the field of predicting currency and financial crises, we can conduct a comprehensive analysis and focus on some important points below:

1. Publication Years and Types of Datasets: Through the date of research publication, there is continued interest in and progress in the field of currency and financial crisis prediction, spanning from 2019 to 2023. While monthly data is used in most studies, higher frequency data may be able to capture more subtleties in economic indicators that are important for forecasting currency and financial crises.

2. Dataset Ranges: The datasets span different periods; the most recent data goes back to July 2022, while the oldest data dates to 1970. The diverse range of dataset periods is indicative of distinct historical and economic contexts, thereby augmenting the findings' resilience and applicability. Most research uses data from the 1990s and later, most likely because this is when more complete and trustworthy economic data became available.

3. Models Used in the Studies: Many models have been used, such as deep neural decision trees (DNDTs), artificial neural networks (ANN), signal approaches, Markov switching models, and classic econometric models (logit and probit). The combination of the advantages of contemporary computational methods and classical econometrics through the use of both conventional and sophisticated machine learning models suggests a multidisciplinary approach.

4. Best-Performing Models: The findings show that no single model performs better than all others. The optimal model varies based on the research, dataset, and particular situation. For example, one study determined that the logit model performed best, while other studies found that the ANN method with Multilayer Perceptron Backpropagation, MS-ARCH, DNDTs, and MRS-AR performed best. This variation emphasizes the value of choosing models that are appropriate for the given context as well as the possible advantages of hybrid or ensemble approaches.

The analysis emphasizes how crucial it is to use a variety of models and data sets. Combining different models can potentially result in predictions that are more accurate because they each capture different aspects of the data. The ability of machine learning models to handle intricate, non-linear relationships in economic data is evident in the noticeable shift towards their integration in the prediction of currency and financial crises. The optimal model depends heavily on the context. Model performance is heavily influenced by variables like the dataset period, frequency, and particular economic conditions.

5. Discussion

The efficacy of distinct models in diverse settings implies that a combined or collaborative approach could prove advantageous. Researchers can take advantage of each model's advantages by combining them, which could result in more reliable and accurate predictions. The prevalence of data from the 1990s emphasizes how crucial current economic circumstances are for forecasting currency and financial crises. Nonetheless, incorporating more ancient data can improve the findings' generalizability and offer insightful historical context. The intrinsic complexity and unpredictable nature of currency and financial crises is a significant obstacle. Many variables affect the state of the economy, many of which are hard to measure or forecast. Overfitting is a further drawback, especially with intricate models like artificial neural networks. Ensuring that models generalize well to new data is crucial for reliable predictions. Higher frequency data (weekly or daily, for example) could be explored in future research to capture even more precise economic indicators. To increase prediction accuracy, more research is also required on hybrid and ensemble approaches, which combine machine learning and conventional econometric models. Including a wider range of historical eras and geographical areas in the datasets can improve model robustness and offer a more thorough understanding of currency and financial crises.

6. Conclusions

In this research, we reviewed literature on currency crisis prediction, highlighting the significant progress and diversity in methodologies. Predicting a currency crisis is a complex task due to the numerous variables and uncertainties involved, such as macroeconomic imbalances, external vulnerabilities, institutional weaknesses, political instability, and global shocks. Our review revealed that there is no universally best model or technique for predicting currency crises; each method has its strengths and weaknesses, which depend on factors such as the specific context, country characteristics, model assumptions, and data quality and availability. We examined a variety of methods, including logit and probit models, artificial neural networks, Markov switching models, and deep neural decision trees. Each method's sensitivity, robustness, accuracy, and applicability were discussed. This comprehensive analysis contributes to the body of knowledge on currency crisis prediction, providing insights into the current approaches and models used in the field.

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