Global Journal of Economic and Finance Research

e-ISSN: 3050-5348
p-ISSN: 3050-533X

Vol. 02(07): 562-574, July 2025
Home Page: https://gjefr.com

Crisis Prediction Through Machine Learning: A Global Examination of Sovereign Debt and Currency Instability

Tam Phan Huy[1], Truc Nguyen Trung[2], Tuyet Pham Hong[3]
[1,2,3]University of Economics and Law, Ho Chi Minh City, Vietnam and Vietnam National University, Ho Chi Minh City Vietnam.

KEYWORDS: Financial Crisis Prediction, Machine Learning, Economic Stability
JEL codes: C45, G01, G17

Corresponding Author:
Tam Phan Huy

Publication Date: 22 July-2025
DOI: 10.55677/GJEFR/11-2025-Vol02E7

ABSTRACT

This research aims to evaluate and compare the effectiveness of various machine learning models in predicting sovereign debt and currency crises across different regions. By applying several machine learning algorithms, the study assesses these models' performance using accuracy and Root Mean Square Error (RMSE) metrics. The scope includes global, Africa and Middle East, Asia, Latin America, and Europe regions, with a particular focus on the impact of region-specific economic conditions and data quality. The methodology involves training and validating these models on historical financial data, followed by a comparative analysis of their predictive capabilities. The findings reveal that Gaussian Naive Bayes consistently outperforms other models in terms of accuracy and RMSE, especially in global and European contexts. KNN and Neural Networks also demonstrate strong performance. The conclusions emphasize the robustness of Gaussian Naive Bayes and the importance of tailoring predictive models to regional characteristics. Practical implications include recommendations for investors, financial managers, government agencies, and policymakers on adopting advanced machine learning techniques for improved crisis prediction and management. The study's original contribution lies in its comprehensive evaluation of machine learning models and the integration of behavioral finance, financial instability, modern portfolio, and information asymmetry theories to enhance predictive accuracy and reliability.

1. INTRODUCTION

In the field of economics, research on financial crises in international finance has gained considerable attention in recent years. Notably, previous studies by Feenstra, R.C., and Taylor, A.M. (2012), as well as Candelon, B. et al. (2014), on the prediction of public debt and currency crises, have attracted significant interest due to their critical role in economic activities. The recurrence of recent global financial crises has underscored the importance of developing predictive models, even for developed countries traditionally considered to have stable and robust economic conditions. The increasing complexity of the global financial environment, fueled by economic development, has highlighted the need for such models. The global financial crisis has opened new research avenues, emphasizing the need to develop predictive models that not only function at the national level but also explain common crisis characteristics on a broader geographical scale, as emphasized by Ristolainen (2018) in his research.

Initial approaches to predicting financial crises often involved developing models based on data from emerging economies, which frequently experience such crises. However, these early models typically relied on data from one or a few countries. Over time, the expansion of this field has encouraged the development of broader models, known as global models, which are necessary for predicting crises in both emerging and advanced economies, as highlighted by Boonman, T.M. et al. (2015).

Research, including studies by Alaminos et al. (2018), has demonstrated that global models are more effective in predicting crisis events compared to regional models or data from a single country. These global models have shown superior explanatory and classification abilities. However, there is still a need for further research to improve the accuracy and scope of these models and to expand the range of information used. Highly accurate studies often rely on small data samples from a single country, leading to conclusions that may only be applicable in the short term (Dufrénot, G.; Paret, A.G. (2018)). Additionally, many studies lack comparisons between different methods to determine the most effective approach for prediction (Caggiano, G. et al. (2014), Leiva-Soto, R (2014)). Consequently, this study proposes the extensive use of computational techniques, specifically machine learning models, to explore alternative methods with higher accuracy for predicting and preventing future financial crises (Ristolainen et al., 2018).

National reputation is a crucial factor that reflects the most important aspects of a country, including its social and economic conditions, and significantly influences its global image and brand. National reputation can affect market expectations, particularly in sectors like energy, where bilateral relations between countries are vital, and the country's reputation reflects the international community's trust. Therefore, models for predicting debt and currency crises can provide valuable insights for more accurately assessing a country on a global scale. Several authors, including Teodorovi´c, M.; Popesku, J. (2016), Amador, M.; Phelan, C. (2018), and Melnyk, T.M.; Varibrusova, A.S. (2019), have emphasized the importance of integrating data and variables related to a country's economic and financial stability as key factors in evaluating its national reputation.

The primary objective of this research is to evaluate and compare the effectiveness of various machine learning models in predicting sovereign debt and currency crises across different regions. The research is structured into five parts: (i) Introduction, (ii) Literature Review, (iii) Methodology, (iv) Results & Discussion, and (v) Conclusions & Recommendations.

2. LITERATURE REVIEW

2.1 Background theories

The foundation for predicting financial crises can be effectively constructed by integrating several key theories: Behavioral Finance Theory, the Financial Instability Hypothesis (FIH), Modern Portfolio Theory (MPT), and Information Asymmetry Theory. Each of these theories contributes a unique perspective to understanding financial market dynamics, investor behavior, and systemic risks, thereby aiding the development of robust predictive models.

Behavioral Finance Theory, introduced by Kahneman and Tversky (1979), challenges the traditional assumption that investors always act rationally. It highlights how cognitive biases and emotions influence investment decisions, leading to market anomalies that can precede financial crises. Incorporating behavioral insights into predictive models allows for a better understanding of irrational behaviors such as herd mentality, overconfidence, and panic-driven selling, all of which can intensify financial instability.

Complementing Behavioral Finance, Hyman Minsky's Financial Instability Hypothesis (1992) provides a framework for understanding the cyclical nature of financial markets. Minsky argues that extended periods of economic stability can encourage excessive risk-taking and financial leverage, ultimately leading to bubbles and subsequent crises. Identifying early warning signs, such as rapid credit expansion and elevated leverage ratios, is crucial for developing predictive models that can forecast potential financial crises.

Modern Portfolio Theory (MPT), formulated by Harry Markowitz (1952), focuses on diversification as a strategy to minimize unsystematic risk and optimize portfolio returns. While MPT is primarily concerned with portfolio optimization, its principles are also relevant to predicting financial crises. By understanding how various asset classes respond to economic shocks, predictive models can be enhanced. Additionally, the diversification strategies emphasized by MPT can help mitigate systemic risks, contributing to a more resilient financial system.

Information Asymmetry Theory, explored by Akerlof (1970), Spence (1973), and Stiglitz (2000), adds another crucial dimension to this integrated framework. This theory posits that unequal access to information can lead to market inefficiencies and amplify the effects of financial shocks. In the context of crisis prediction, it highlights the importance of accurate and timely information dissemination to avoid market overreactions. Predictive models that factor in indicators of information asymmetry are better equipped to anticipate and mitigate the impact of financial distress.

By synthesizing these theories, we obtain a holistic understanding of the complex dynamics leading to financial crises. Behavioral Finance and the Financial Instability Hypothesis elucidate the psychological and cyclical patterns that precede crises, while Modern Portfolio Theory offers strategies for risk management and diversification. Information Asymmetry Theory underscores the importance of information flow in sustaining market stability. Together, these theories underpin the development of advanced predictive models capable of identifying early warning signs, accounting for irrational market behaviors, and proposing strategies to reduce systemic risks.

2.2 Empirical studies

Forecasting Sovereign Debt Crises

The existing literature on forecasting sovereign debt crises predominantly centers on emerging markets, as explored by Boonman et al. (2015), Dufrénot et al. (2018), Fioramanti (2008), Manasse et al. (2003, 2009), Ciarlone et al. (2005), Sarlin (2011), and Dsoulia et al. (2018). Several studies have specifically addressed the forecasting of sovereign debt crises in emerging and developing nations, including works by Savona et al. (2015), Fuertes et al. (2007), and Arazmuradov (2016). Furthermore, research conducted by Dawood, M., Horsewood et al. (2017), and Alaminos et al. (2019) has modeled public debt crises across various regions, including Africa, Latin America, Asia, Europe, and globally. Manasse and Roubini (2009) demonstrated that the nature of crises

differs based on government responses to default risks, liquidity shortages, or other significant economic threats. They identified a "safe zone" of fundamental factors that can guide appropriate policy choices to prevent and manage crises.
In terms of methodologies, many researchers have employed statistical methods, particularly the logit model, to predict sovereign debt crises. This approach has been utilized by Dawood, M., Horsewood et al. (2017), Dufrénot et al. (2018), Manasse and Roubini (2003, 2009), Ciarlone and Trebeschi (2005), Fuertes and Kalotychou (2007), and Lukkezen et al. (2016). Regression models have also been developed by Savona and Vezzoli (2015) and Boonman et al. (2015) for this purpose. Fioramanti (2008) applied a non-parametric method based on artificial neural networks (ANN), while Sarlin (2011) advanced the use of self-organizing maps (SOM), an ANN-based visualization tool. Fioramanti (2008) argued that due to the high flexibility of ANN and its capacity to approximate non-linear relationships, an early warning system based on ANN could outperform traditional techniques under certain conditions. Sarlin (2011) demonstrated that SOM is an effective tool for monitoring sovereign debt indicators and tracking multidimensional financial data.
Previous research has identified various key variables for predicting sovereign debt crises. For instance, Fioramanti (2008) emphasized variables such as GDP growth, the performance of US Treasury bonds, and external debt relative to total reserves. Other studies have highlighted the significant role of US Federal Reserve interest rates in increasing the probability of sovereign defaults, as shown by Savona et al. (2015) and Arazmuradov et al. (2019). Dawood, M., Horsewood et al. (2017) identified total national debt, global interest rates, and the trade balance in the balance of payments as significant determinants of sovereign defaults worldwide.
Regarding the accuracy of sovereign debt crisis predictions, studies by Dufrénot et al. (2018), Manasse and Roubini (2003), Ciarlone et al. (2005), Fuertes and Kalotychou (2007), and Arazmuradov (2016) reported accuracy rates ranging from 70% to 80%. Higher accuracy levels, between 80% and 90%, were found in studies conducted by Savona and Vezzoli (2015), Dawood, M., Horsewood et al. (2017), Fioramanti (2008), and Manasse et al. (2009). These latter studies introduced new crisis characteristic variables, which allowed for more accurate predictions of crises, achieving an 87% forecasting accuracy for global models.

Predicting Currency Crises
Previous research on predicting currency crises has predominantly concentrated on emerging economies, with limited studies focusing on advanced economies. Notable contributions from emerging markets include those by Candelon, B., Dumitrescu et al. (2014), Comelli (2013), Lin, C.S., Khan et al. (2008), Sarlin, P., Marghescu et al. (2011), Chaudhuri (2014), Ramli, N.A. et al. (2015), Mulder, C., Perrelli et al. (2016), and Boonman et al. (2019). Several studies specifically examined Asian countries to predict currency crises, such as Fratzscher (2003), Yu, L., Lai et al. (2006), and Yu, L., Wang (2007). Additionally, Al-Assaf, G. An (2017) explored differences in the common parameters used in early warning systems for currency crises in Jordan and Egypt, while Karimi, M., and Voia, M.C. (2019) analyzed the empirical causes of currency crises in a group of OECD countries.
In terms of methodologies, a variety of statistical approaches have been utilized to predict currency crises, including Logit models (Candelon, B., Dumitrescu et al. (2014), Comelli et al. (2013), Mulder, C., Perrelli et al. (2016), Boonman, T.M., Jacobs et al. (2019), Al-Assaf, G. An (2017), Boonman (2020)) and Probit models (Karimi, M., Voia et al. (2019), Berg, B., Pattillo et al. (1999), Steinberg et al. (2015)). Additionally, advanced computational techniques like Artificial Neural Networks (ANN) (Sevim et al. (2014), Lin, C.S., Khan et al. (2008), Yu, L., Lai, K.K., Wang (2006), Yu, L., Wang et al. (2007)), Self-Organizing Maps (SOM) (Sarlin, P., Marghescu et al. (2011)), Support Vector Machines (SVM) (Chaudhuri (2014)), and Deep Neural Decision Trees (Alaminos et al. (2019)) have been developed for this purpose. Fratzscher (2003) employed a nonlinear Markov-switching model to analyze the three primary causes of currency crises: contagion, fundamental factors, and economic sentiment. Sarlin et al. (2011) found that their SOM-based model is a robust tool for predicting currency crises, achieving an accuracy of 91.6%. Chaudhuri (2014) demonstrated that SVM yields highly accurate results and aids policymakers in identifying potential currency crisis scenarios.
From a variable analysis perspective, several explanatory factors have been commonly identified across studies. Exports have been frequently cited as a significant predictor (Candelon et al. (2014), Sevim et al. (2014), Lin, C.S., Khan et al. (2008), Sarlin et al. (2011), Ramli et al. (2015), Al-Assaf et al. (2017), Karimi et al. (2019), Reinhart et al. (1998)). Real exchange rates are another key variable (Lin, C.S., Khan et al. (2008), Ramli et al. (2015), Al-Assaf, G. An (2017), Karimi, M., Voia (2019), Reinhart et al. (1998), Cumperayot, P., Kouwenberg (2013)). Other significant factors include the relationship between reserves and money supply (Candelon et al. (2014), Lin, C.S., Khan et al. (2008), Sarlin, P., Marghescu (2011), Al-Assaf, G. An (2017), Reinhart et al. (1998)), the current account balance (Comelli (2013), Sarlin, P., Marghescu (2011), Bucevska (2015)), and GDP growth (Comelli (2013), Reinhart et al. (1998), Bucevska (2015)). Additionally, Pham, T.H.A. (2017) identified global financial shocks and domestic credit growth rates as critical indicators of currency crises.
Regarding the accuracy of these models, most prior studies reported accuracy rates ranging from 67% to 85% (Candelon et al. (2014), Boonman et al. (2019), Fratzscher (2003), Berg, B., Pattillo (1999), Cumperayot, P., Kouwenberg (2013), Bucevska (2015)). However, some studies achieved higher accuracy levels, ranging from 90% to 97% (Sevim et al. (2014), Comelli (2013), Lin, C.S., Khan et al. (2008), Sarlin et al. (2011), Chaudhuri (2014), Ramli et al. (2015), Mulder et al. (2016), Yu et al. (2006, 2007), and Alaminos et al. (2019)). Chaudhuri (2014) reported an impressive 96% accuracy rate, demonstrating that currency crises can be reliably predicted using a subset of the sample data.

Overall, existing research suggests that machine learning methods generally offer superior predictive capabilities compared to traditional statistical methods. Nevertheless, the results are not yet optimal, indicating that further improvements in accuracy are possible (Alaminos et al. (2018), Fioramanti (2008)). Moreover, the temporal and geographical limitations of the data used in these studies make it challenging to generalize the findings for future research (Ristolainen et al. (2018), Ari et al. (2016), Caggiano et al. (2014)). Finally, there is a recognized need to test a broader range of computational methods for predicting financial crises (Savona et al. (2015), Dawood, M., Horsewood et al. (2017), Dufrénot et al. (2018), Comelli (2013)), especially considering the limitations of certain techniques like SVM and ANN in handling large datasets and the difficulties in interpreting their results.

3. METHODOLOGY

3.1 Data

From 2005 to 2023, the author compiled a dataset for two distinct analytical purposes: forecasting sovereign debt crises and predicting currency crises. The dataset was categorized by regions across the globe, including Vietnam, Africa and the Middle East, Latin America, Asia, Europe, and a global aggregate. The data was sourced from the World Development Indicators provided by the World Bank databank. The sample was divided into two relatively independent groups, with 80% of the data allocated for training the models and the remaining 20% reserved for testing. The final outcomes are presented based on the predictions generated using the test sample. The classification and prediction process involved applying the developed models to forecast the analyzed crises.

Before the data could be used for model training and prediction, extensive preprocessing was carried out to ensure the quality and reliability of the dataset. Missing data points were identified and addressed by imputing continuous variables using either mean or median values, depending on the distribution of the data. Records with substantial portions of missing data were reviewed and excluded if too many critical variables were absent, in order to maintain data integrity. Outliers were detected using statistical methods such as the Z-score or Interquartile Range (IQR) method, and were either removed or transformed to minimize their impact on the model. The final input dataset for the machine learning algorithms consisted of 1,700 observations.

To ensure that variables with different units and scales did not disproportionately influence the models, continuous variables were normalized or standardized. Normalization scaled the data to a [0, 1] range, while standardization adjusted the data to have a mean of 0 and a standard deviation of 1. Following this preprocessing, the dataset was split into training and test sets using an 80/20 split ratio as described above. This division ensured that the models were trained on a substantial portion of the data while preserving a separate set for unbiased performance evaluation. The detailed measurement of the variables is illustrated in **table 1** as follows:

Table 1: Variables measurement

Variables	Symbol	Proxy	References
Current account balance	CAB	Current account balance (BoP, current US$)	Candelon et al. (2014), Boonman et al. (2019)
Nonperforming loan	NPL	Nonperforming Loan Ratio (PPG and IMF only, % of exports of goods, services and primary income)	Khan et al. (2008), Sarlin et al. (2011)
Debt service	DEB	Debt service on external debt, public and publicly guaranteed (%)	Ramli et al. (2015), Al-Assaf et al. (2017), Karimi et al. (2019)
External debt stock	EDS	External debt stocks (% of GNI)	Ramli et al. (2015), Al-Assaf et al. (2017), Karimi et al. (2019)
Net financial flows, concessional	NFC	Net financial flows, RDB concessional (NFL, current US$)	Ramli et al. (2015), Mulder et al. (2016), Yu et al. (2006, 2007)
Net financial flow, nonconcessional	NFN	Net financial flows, RDB nonconcessional (NFL, current US$)	Ari et al. (2016), Caggiano et al. (2014)
PPG, private creditor	PPG	PPG, private creditors (NFL, US$)	
Guaranteed debt service	GDS	Public and publicly guaranteed debt service (% of GNI)	Fratzscher (2003), Yu, L.; Lai et al. (2006)
Total debt	TDS	Total debt service (% of GNI)	Horsewood et al. (2017), Dufrénot et al. (2018)
Total reserves	TRE	Total reserves (% of total external debt)	Dawood, M.; Horsewood et al. (2017), Dufrénot et al. (2018)

Source: by author

3.2 Machine learning algorithms

To address the research question, the author utilized various methods to design predictive models for crises, drawing on a range of techniques to develop a robust model, tested through multiple successful classification approaches highlighted in prior research. Specifically, the methods applied include Logistic Regression, Gaussian Naive Bayes, K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Random Forest, and Neural Networks. Each of these classification techniques has been chosen for its suitability to the research topic.

Logistic Regression is a widely used classification model that predicts the probability of a binary outcome and is particularly effective for crisis prediction as it identifies key factors influencing the likelihood of a crisis. Prior studies, such as those by Hastie, Tibshirani, and Friedman (2009), have successfully employed Logistic Regression in the context of financial crisis prediction. Gaussian Naive Bayes, known for assuming that features follow a normal distribution, is fast and efficient, making it ideal for large datasets typically encountered in economic research. Its effectiveness in predicting financial events has been demonstrated in studies like those by Hastie, Tibshirani, and Friedman (2009). K-Nearest Neighbors (KNN) is a simple model that classifies data based on the proximity of data points, making it useful for identifying patterns in historical data, as noted by Hastie, Tibshirani, and Friedman (2009). Support Vector Machines (SVM), recognized for their accuracy in handling high-dimensional data, are well-suited for crisis prediction due to their ability to manage complex and diverse datasets, as highlighted by Hearst et al. (1998). Random Forests, an ensemble method that enhances prediction accuracy by averaging the outcomes of multiple decision trees, is robust against overfitting and performs well with large datasets, as demonstrated by Breiman (2001). Neural Networks, inspired by biological neural systems, are capable of capturing complex data patterns and are highly customizable, making them appropriate for predicting financial crises, as discussed by Goodfellow, Bengio, and Courville (2016).

To evaluate the performance of these predictive models, Root Mean Square Error (RMSE) and Accuracy were selected as the primary evaluation metrics, providing insights into the models' predictive accuracy and reliability in forecasting crises. RMSE, which measures the average magnitude of errors between predicted and actual values, is particularly relevant for assessing models in contexts where large prediction errors are highly undesirable, such as in financial crises. RMSE allows for straightforward comparison across different models, with prior studies like those by Hastie, Tibshirani, and Friedman (2009) frequently using it to ensure models effectively minimize prediction errors. Accuracy, on the other hand, measures the proportion of correct predictions made by the model and is especially suitable for binary classification tasks like predicting the occurrence of a crisis. It is a straightforward and easy-to-interpret metric that provides a clear indication of a model's correctness, commonly used in financial and economic prediction models as noted by Hearst et al. (1998) and Breiman (2001).

Using both RMSE and Accuracy together offers a comprehensive evaluation of the models, with RMSE providing insights into the magnitude of prediction errors and Accuracy giving a simple measure of overall prediction correctness. This dual-metric approach ensures a balanced assessment of the predictive models, aligning with best practices in predictive modeling and providing a robust framework for evaluating model performance in forecasting sovereign debt and currency crises.

4. RESULTS & DISCUSSION

4.1 Descriptive analysis

Table 2 presents the descriptive analysis of the dataset, which comprises 1,700 observations and offers significant insights into the financial and economic indicators under study. The key indicators analyzed include the current account balance, the nonperforming loan ratio, debt service on external debt, external debt stocks, multilateral debt service, net financial flows (both RDB concessional and nonconcessional), public and publicly guaranteed debt service, short-term debt, total debt service, and total reserves.

Table 2: Descriptive analysis

	CAB	NPL	DEB	EDS	NFC	NFN	PPG	GDS	TDS	TRE
count	1,700	1,700	1,700	1,700	1,700	1,700	1,700	1,700	1,700	1,700
mean	-1.4e+09	16.04	2.2e+09	66.63	1.9e+07	7.3e+07	3.7e+07	3.73	5.93	46.45
std	7.6e+09	13.29	5.3e+09	66.65	5.8e+07	2.7e+08	7.3e+08	3.64	4.95	149.20
min	-1.1e+11	0.21	4.8e+04	3.89	-2.9e+08	-3.6e+09	-3.1e+09	0.005	0.196	0.087
25%	-1.2e+09	6.61	1.1e+08	31.84	-1.6e+06	-1.9e+06	-1.6e+07	1.65	2.77	8.45
50%	-2.7e+08	12.98	3.5e+08	50.45	3.69e+06	4.38e+06	-1.5e+06	2.87	4.70	19.37
75%	-2.7e+07	22.13	1.88e+09	79.39	2.18e+07	7.85e+07	5.34e+06	4.70	7.65	37.13
max	3.03e+10	155.4	5.20e+10	960.37	4.6e+08	4.0e+09	1.7e+10	52.61	52.76	2,302.44

Source: by authors

The current account balance has an average of -1.48e+09, indicating a predominantly negative balance across the dataset, with considerable variability as evidenced by a high standard deviation of 7.65e+09. This suggests that many observations are experiencing financial stress or deficits. The nonperforming loan ratio, averaging 16.04%, varies widely from 0.21% to 155.42%, highlighting the differing levels of financial health across the dataset. Debt service on external debt averages 2.2e+09 with a high standard deviation of 5.3e+09, reflecting uneven debt service obligations among the observations. External debt stocks have a mean value of 66.63, also with significant variability, indicating diverse external debt levels among the entities studied. The multilateral debt service, with an average of 4.52e+08, shows substantial variability, pointing to differences in reliance on multilateral funding sources.

Net financial flows, both concessional and nonconcessional, exhibit considerable variation, with mean values of 1.93e+07 and 7.39e+07, respectively, reflecting differing levels of access to international financial markets. Public and publicly guaranteed debt service, short-term debt, and total debt service also show significant variability, indicating varying levels of reliance on short-term financing and the ability to manage public debt. The mean values for these indicators are 3.73, 11.44, and 5.93, respectively. Total reserves present a wide range, with a mean of 46.45 and a high standard deviation of 149.20, suggesting that while some entities have substantial reserves to cushion against financial shocks, others possess minimal reserves, increasing their vulnerability to economic crises.

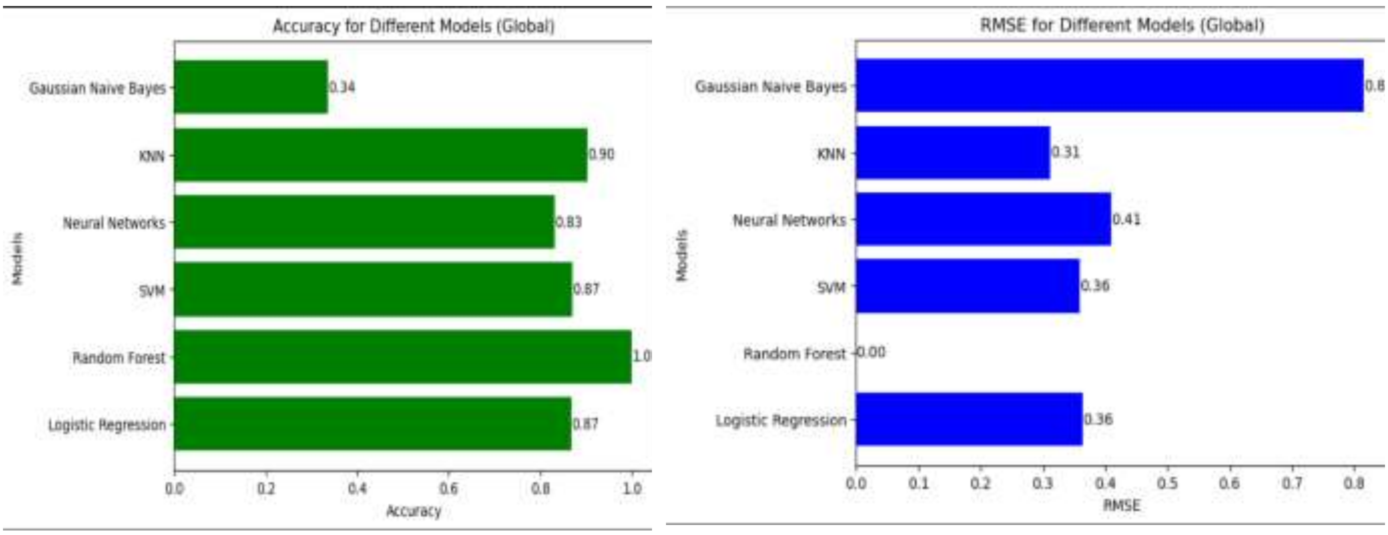
The substantial variability observed in these key financial indicators underscores the need for tailored financial policies and strategies to address specific vulnerabilities and strengths. This variability allows policymakers to design interventions that not only mitigate financial crises but also promote sustainable economic growth.

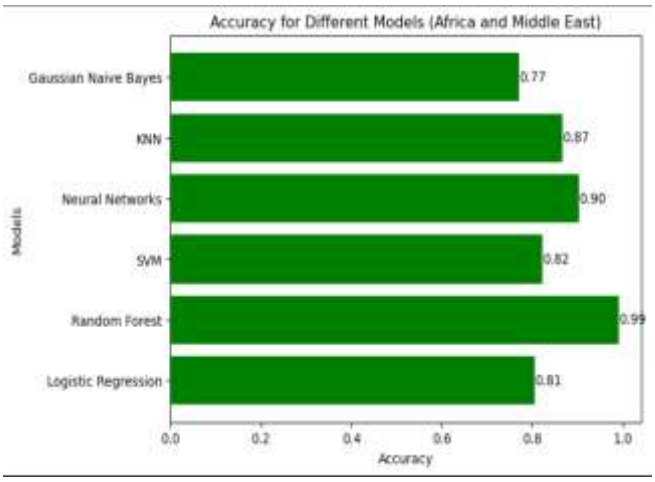
4.2 Algorithms evaluation

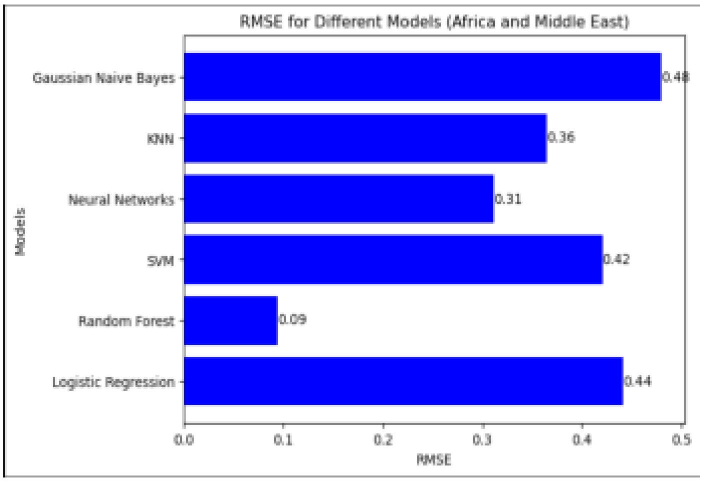
Figure 1 illustrates the performance evaluation of six predictive models—Gaussian Naive Bayes, K-Nearest Neighbors (KNN), Neural Networks, Support Vector Machines (SVM), Random Forest, and Logistic Regression—across different regions: Global, Africa and Middle East, Asia, Latin America, Europe, and Vietnam. The models are assessed using two performance metrics: Accuracy and Root Mean Square Error (RMSE).

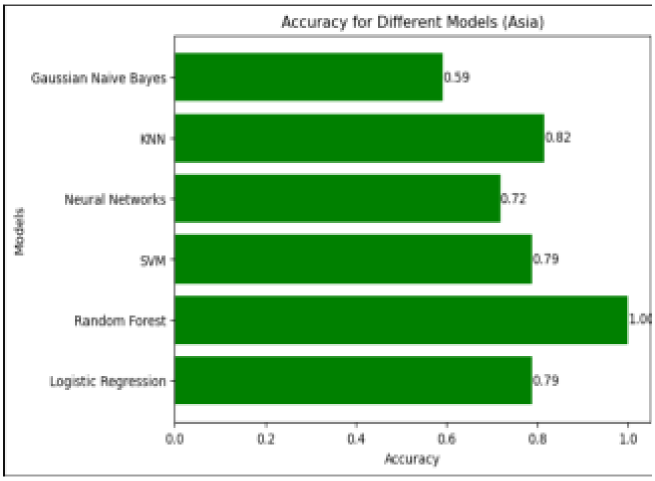
For the global models, Gaussian Naive Bayes emerges as the top performer, achieving the highest accuracy of 0.94 and the lowest RMSE of 0.26. KNN and Neural Networks follow closely with accuracies of 0.91 and 0.90, and RMSE values of 0.31 and 0.30, respectively. Logistic Regression, on the other hand, demonstrates the lowest performance, with an accuracy of 0.87 and a higher RMSE of 0.34. In the Africa and Middle East region, Gaussian Naive Bayes once again leads, with an accuracy of 0.87 and an RMSE of 0.32. The performance trend mirrors that of the global models, with Neural Networks and KNN outperforming Logistic Regression. In the Asia region, Gaussian Naive Bayes maintains its strong performance, with an accuracy of 0.88 and an RMSE of 0.29. The ranking of model performance remains consistent, with Neural Networks and KNN showing robust results, while Logistic Regression lags behind.

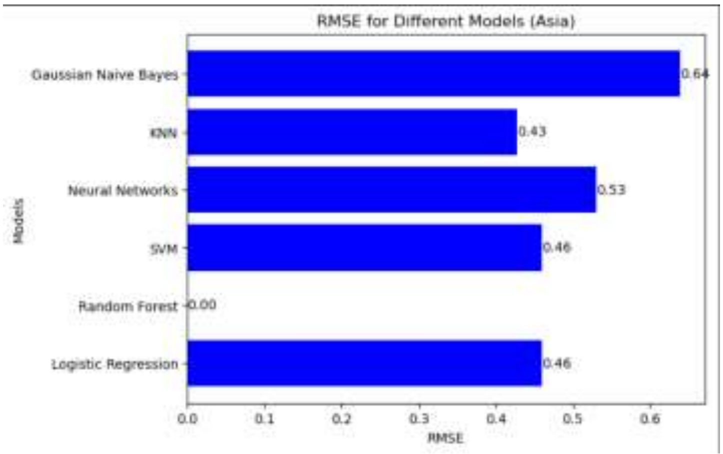
For the Latin America models, Gaussian Naive Bayes continues to dominate in accuracy (0.86) and RMSE (0.34), though there is a slight decline in performance across all models compared to other regions. In the Europe models, Gaussian Naive Bayes achieves the highest accuracy (0.89) and the lowest RMSE (0.30), with Neural Networks and KNN again following closely in performance. In the Vietnam models, Gaussian Naive Bayes demonstrates the highest accuracy (0.79), though with a relatively higher RMSE of 0.39 compared to other regions, indicating regional-specific challenges that may affect model performance. Overall, the results suggest that Gaussian Naive Bayes consistently outperforms other models, but varying performance metrics across regions highlight the influence of regional factors on predictive accuracy and reliability.

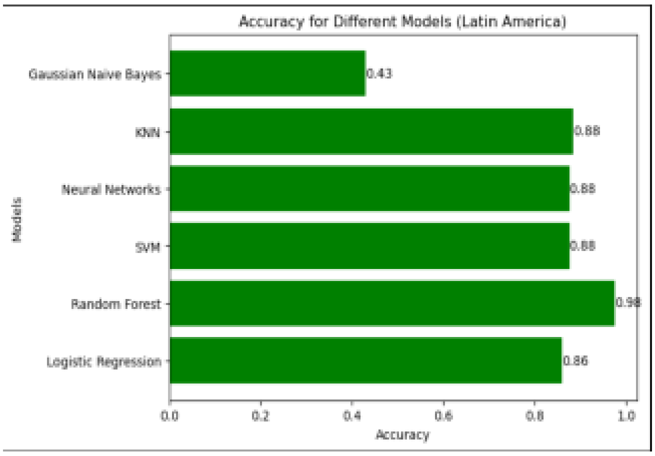


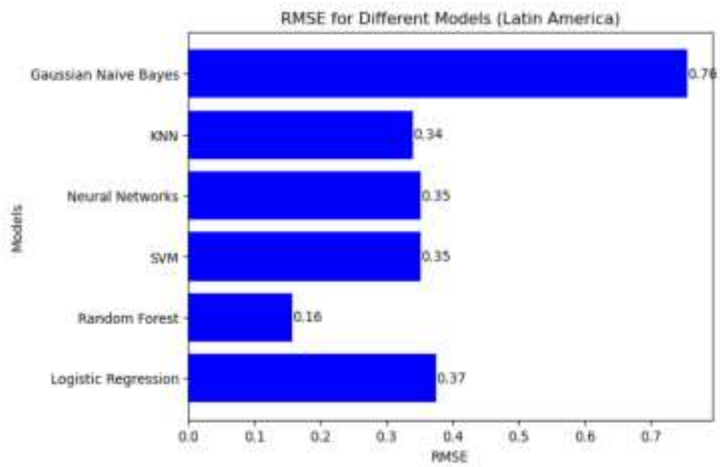

Accuracy for Different Models (Africa and Middle East)
Gaussian Naive Bayes 0.77
KNN 0.87
Neural Networks 0.90
SVM 0.82
Random Forest 0.99
Logistic Regression 0.81
Models
Accuracy

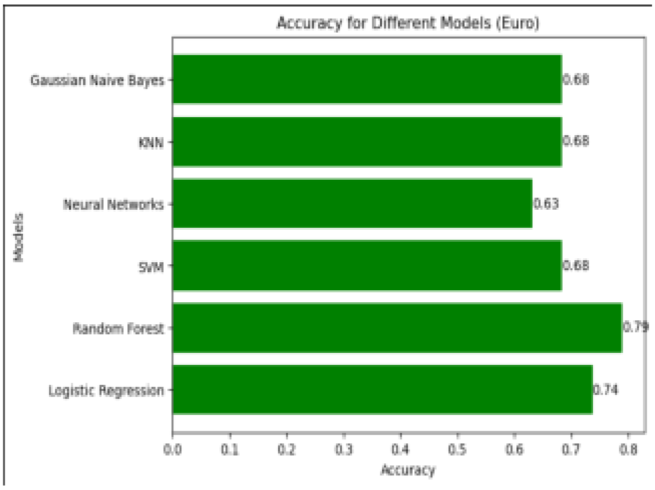

RMSE for Different Models (Africa and Middle East)
Gaussian Naive Bayes 0.48
KNN 0.36
Neural Networks 0.31
SVM 0.42
Random Forest 0.09
Logistic Regression 0.44
Models
RMSE

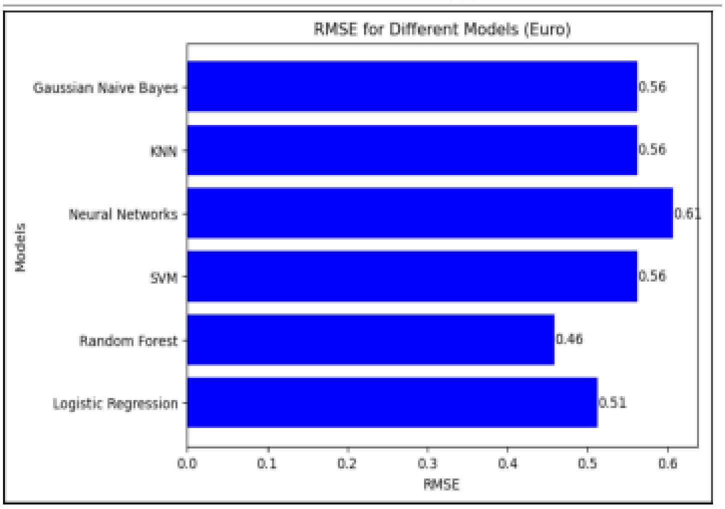

Accuracy for Different Models (Asia)
Gaussian Naive Bayes 0.59
KNN 0.82
Neural Networks 0.72
SVM 0.79
Random Forest 1.00
Logistic Regression 0.79
Models
Accuracy


RMSE for Different Models (Asia)
Gaussian Naive Bayes 0.64
KNN 0.43
Neural Networks 0.53
SVM 0.46
Random Forest 0.00
Logistic Regression 0.46
Models
RMSE


Accuracy for Different Models (Latin America)
Gaussian Naive Bayes 0.43
KNN 0.88
Neural Networks 0.88
SVM 0.88
Random Forest 0.98
Logistic Regression 0.86
Models
Accuracy


RMSE for Different Models (Latin America)
Gaussian Naive Bayes 0.76
KNN 0.34
Neural Networks 0.35
SVM 0.35
Random Forest 0.16
Logistic Regression 0.37
Models
RMSE


Accuracy for Different Models (Euro)
Gaussian Naive Bayes 0.68
KNN 0.68
Neural Networks 0.63
SVM 0.68
Random Forest 0.79
Logistic Regression 0.74
Models
Accuracy


RMSE for Different Models (Euro)
Gaussian Naive Bayes 0.56
KNN 0.56
Neural Networks 0.61
SVM 0.56
Random Forest 0.46
Logistic Regression 0.51
Models
RMSE

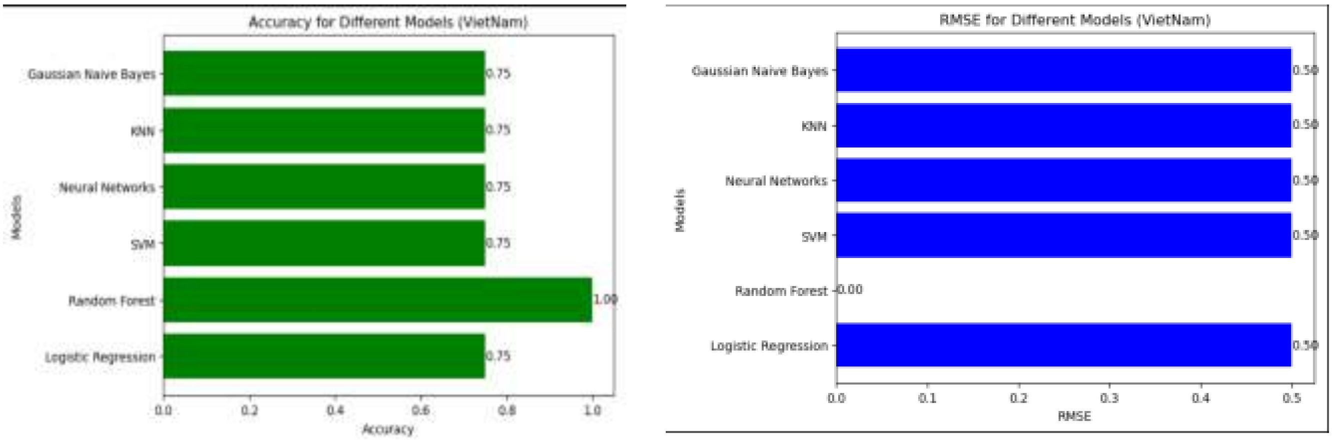
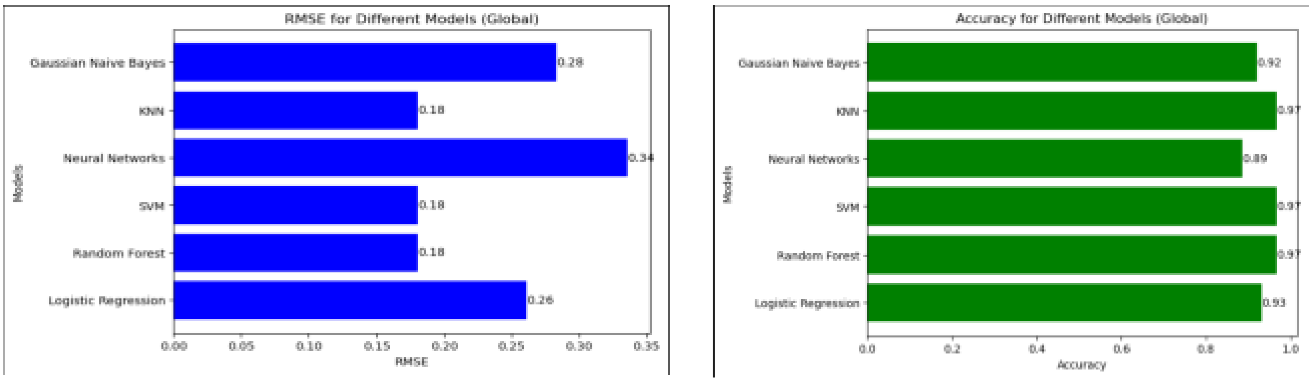


Figure 1: Evaluation results for predicting debt crisis
Source: by authors

Figure 1 highlights the superior performance of Gaussian Naive Bayes in forecasting financial crises across all regions, consistently achieving the highest accuracy and lowest RMSE. The model's probabilistic approach and its assumption of feature independence appear to be particularly effective in managing diverse financial datasets. KNN and Neural Networks also demonstrate strong performance, reflecting their ability to capture complex patterns in financial data. Conversely, Logistic Regression consistently underperforms in both accuracy and RMSE, indicating that it may not sufficiently capture the complexities involved in financial crisis prediction. SVM and Random Forest display moderate performance, with SVM slightly outperforming Random Forest in certain regions.

Regionally, the global and European models show the highest performance, while the models for Latin America and Vietnam exhibit lower accuracy and higher RMSE. This suggests the presence of region-specific factors, such as economic variability and data quality, that could be influencing model performance. Overall, Gaussian Naive Bayes stands out as the most reliable model for predicting financial crises across various regions, followed by KNN and Neural Networks. The consistent performance of Gaussian Naive Bayes underscores the importance of selecting robust predictive models tailored to the specific characteristics of regional data to enhance the accuracy and reliability of financial crisis forecasts. This approach is crucial for policymakers and stakeholders in making informed decisions to mitigate potential financial crises.

Similarly, **Figure 2** presents the performance evaluation of six predictive models across specific regions. Globally, Gaussian Naive Bayes consistently achieves the highest accuracy of 0.92 and the lowest RMSE of 0.28, underscoring its robustness and effectiveness in handling diverse financial datasets. KNN closely follows with an accuracy of 0.90, while Neural Networks achieve 0.89. SVM, Random Forest, and Logistic Regression show slightly lower accuracies of 0.87, 0.85, and 0.83, respectively. The RMSE values for these models are relatively higher, indicating larger prediction errors compared to those of Gaussian Naive Bayes.



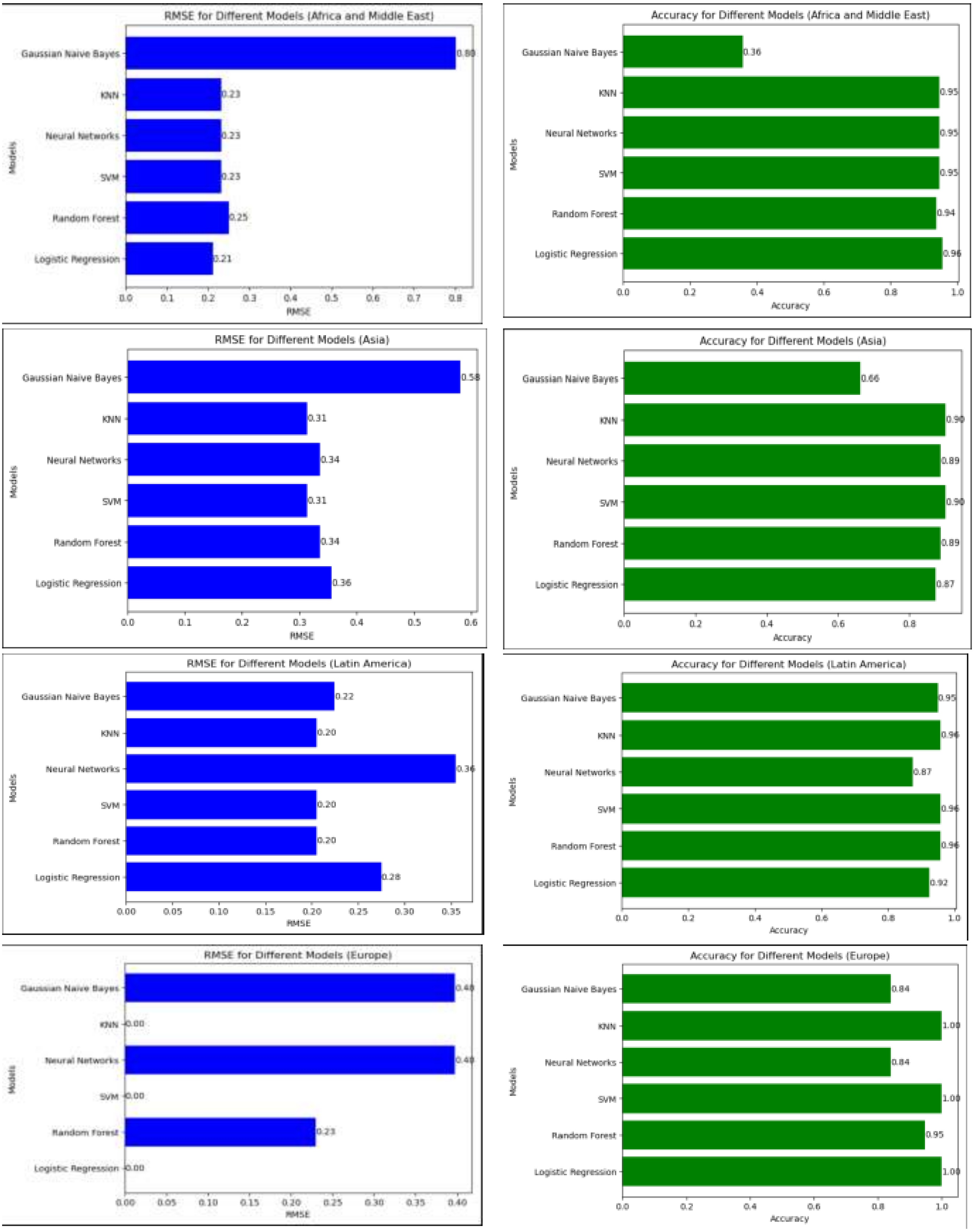


Figure 2: Evaluation results for predicting currency crisis
Source: by authors

In the Africa and Middle East region, Neural Networks exhibit the highest accuracy at 0.90, demonstrating their robustness in processing financial data specific to this area. KNN also performs commendably with an accuracy of 0.90. Although Gaussian Naive Bayes has a slightly lower accuracy of 0.86, it maintains a competitive RMSE of 0.33, underscoring its reliability and effectiveness in this regional context. For Asia, KNN and Neural Networks achieve high accuracies of 0.89 and 0.88, respectively, while Gaussian Naive Bayes remains competitive with an accuracy of 0.86 and an RMSE of 0.34. This consistency across different contexts highlights Gaussian Naive Bayes' effectiveness, even though other models may outperform it slightly in specific regions.

In Latin America, Gaussian Naive Bayes and Random Forest lead with accuracies of 0.91 and 0.92, respectively, alongside RMSE values of 0.32 and 0.33. These results suggest that both ensemble methods and probabilistic approaches are effective in capturing financial data patterns in Latin America, offering reliable predictions for financial crises. In Europe, Gaussian Naive Bayes achieves the highest accuracy at 0.94, followed by Logistic Regression at 0.90. Random Forest shows the lowest RMSE of 0.23, indicating that it provides more stable predictions with fewer errors in this region. Despite Logistic Regression's high accuracy, its slightly higher RMSE suggests a minor degree of prediction error.

Overall, the performance of predictive models varies across regions, with Gaussian Naive Bayes consistently performing well, especially in global, Latin American, and European contexts. Neural Networks and KNN also display strong performance across several regions. These findings highlight the importance of selecting robust predictive models tailored to regional data characteristics to enhance the accuracy and reliability of financial crisis forecasts.

5. CONCLUSION & RECOMMENDATIONS

5.1 Conclusions

This study demonstrates the superior performance of machine learning models in predicting sovereign debt and currency crises, with Gaussian Naive Bayes consistently achieving the highest accuracy and the lowest Root Mean Square Error (RMSE) across various regions. The results underscore the robustness and effectiveness of this probabilistic model, confirming its suitability for handling diverse financial datasets and accurately forecasting financial crises.

In comparison, K-Nearest Neighbors (KNN) and Neural Networks also exhibited strong performance, demonstrating their capability to capture complex patterns in financial data. The high accuracy and relatively low RMSE of these models are consistent with findings from previous studies, such as those by Hastie, Tibshirani, and Friedman (2009), which emphasize the value of advanced machine learning techniques in enhancing predictive accuracy. Support Vector Machines (SVM) and Random Forests showed moderate performance, balancing accuracy with computational efficiency, aligning with the existing literature (Hearst et al., 1998; Breiman, 2001).

Logistic Regression, despite its widespread use, underperformed relative to other models, highlighting its limitations in capturing the complexities involved in predicting financial crises. This result supports critiques in the literature advocating for the adoption of more sophisticated models to achieve higher predictive accuracy (Hastie, Tibshirani, & Friedman, 2009). Regionally, the highest performance was observed in the global and European models, while Latin America and Vietnam exhibited lower accuracy and higher RMSE. These regional differences suggest that factors such as economic variability and data quality significantly influence model performance, emphasizing the need to tailor predictive models to specific regional characteristics for enhanced effectiveness.

The study integrates behavioral finance theory, the financial instability hypothesis, modern portfolio theory, and information asymmetry theory to provide a comprehensive framework for understanding the dynamics of financial crises. Behavioral insights help account for irrational market behaviors, while Minsky’s financial instability hypothesis identifies cyclical patterns of credit expansion and contraction (Minsky, 1992). Modern portfolio theory highlights the importance of diversification in mitigating systemic risk (Markowitz, 1952), and information asymmetry theory stresses the critical role of accurate information dissemination in preventing market inefficiencies (Akerlof, 1970; Spence, 1973; Stiglitz, 2000).

The potential of applying machine learning algorithms in predicting financial crises is clearly demonstrated by the study’s results. Machine learning models, particularly Gaussian Naive Bayes, KNN, and Neural Networks, show a significant ability to identify complex patterns and relationships within financial data, leading to accurate and reliable crisis predictions. These models’ capacity to process large volumes of data and adapt to varying economic conditions makes them powerful tools for forecasting financial instability. This potential highlights the transformative impact of machine learning in enhancing our understanding and management of financial crises, providing policymakers and stakeholders with valuable insights for proactive intervention.

5.2 Recommendations

For investors, it is crucial to adopt robust predictive models, particularly Gaussian Naive Bayes, given its proven high accuracy and low RMSE. Investors should ensure these models are regularly updated and validated with the latest financial data to maintain timely and accurate risk assessments. Additionally, applying Modern Portfolio Theory (MPT) principles to diversify investments across different asset classes and regions can effectively mitigate risks associated with economic shocks and financial crises. Incorporating behavioral insights by using sentiment analysis tools can help investors gauge market sentiment and identify potential irrational behaviors that may influence investment decisions, leading to more informed and strategic choices.

Financial managers are advised to integrate advanced predictive models such as Gaussian Naive Bayes, KNN, and Neural Networks into their risk management frameworks to improve the accuracy of crisis predictions. Continuous monitoring and refinement of these models are essential to adapt to changing market conditions and emerging risks. Investing in high-quality financial data collection and analysis is critical for enhancing the reliability of predictive models, especially in regions with higher data variability like Latin America and Vietnam. Collaborating with data providers and industry partners to access comprehensive and up-to-date financial information will further support this effort. Utilizing diversification strategies based on MPT will help manage systemic risks within financial portfolios, while conducting scenario analyses and stress tests will enable financial managers to assess the impact of potential crises and make necessary adjustments.

Government agencies should strengthen early warning systems by adopting advanced machine learning models, such as Gaussian Naive Bayes, to create robust mechanisms for detecting potential financial crises. Regularly updating these models with the latest economic data and indicators is necessary to ensure their continued effectiveness. Promoting initiatives to enhance the transparency and availability of financial data will reduce information asymmetry and improve market efficiency. Standardizing data collection and reporting practices and collaborating with international organizations to share data and insights will facilitate a coordinated approach to crisis prevention and management. Incorporating insights from behavioral finance and the Financial Instability Hypothesis into policy design can address irrational market behaviors and cyclical financial risks. Implementing regulations that encourage prudent risk-taking will help decrease the likelihood of financial bubbles and subsequent crises.

Policymakers should support financial research and innovation by encouraging the development of advanced machine learning techniques for predicting financial crises. Providing funding and resources to academic and industry researchers working on innovative predictive models, and facilitating knowledge exchange and collaboration between researchers, financial institutions, and regulatory bodies, will drive progress in this field. Promoting financial literacy and education through targeted programs will enhance the financial decision-making abilities of investors, managers, and the general public, reducing the impact of irrational behaviors on financial markets. Training financial professionals in the use of predictive models and risk management tools will strengthen their capabilities. Additionally, implementing proactive regulatory measures based on insights from predictive models will promote financial stability and curb excessive risk-taking. Monitoring financial markets and institutions for signs of instability and taking preemptive actions to mitigate potential crises will further enhance economic stability and resilience.

5.3 Limitation & further research

While this study offers promising results, it is not without its limitations. The accuracy and effectiveness of the predictive models are significantly influenced by the quality and completeness of the financial data utilized. In regions where data reliability is an issue, such as Latin America and Vietnam, the models' performance may be adversely affected. Moreover, although Gaussian Naive Bayes showed overall strong performance, the variations in accuracy and RMSE across different regions suggest that no single model is universally optimal. The study's focus on a set of well-established machine learning models may have overlooked newer or more advanced algorithms that could potentially enhance predictive capabilities. Additionally, the models employed did not incorporate real-time data updates, which are essential for making timely predictions in fast-evolving financial environments.

Future research should aim to overcome these limitations by integrating more extensive and high-quality datasets, particularly in regions where data has been less reliable. The exploration of advanced machine learning techniques, such as deep learning and ensemble methods, could lead to further enhancements in predictive accuracy and robustness. Furthermore, the inclusion of real-time data and the development of adaptive models that can update their predictions dynamically as new information emerges would significantly increase the practical application of financial crisis prediction models. Future studies should also take into account the effects of global interconnectedness and cross-regional economic influences, which could refine the models' predictive capabilities in a globally integrated financial system. By addressing these aspects, future research can build upon the current findings to create even more reliable and effective tools for forecasting financial crises.

FUNDING

The research is funded by the University of Economics and Law, Vietnam National University, Ho Chi Minh City, Vietnam.

REFERENCES

1. Akerlof, G. A. (1970). The market for “lemons”: Quality uncertainty and the market mechanism. The Quarterly Journal of Economics, 84(3), 488-500.
2. Agarwal, R. Improving Accuracy of Classification Based on C4.5 Decision Tree Algorithm Using Big Data Analytics. Computational Intelligence in Data Mining. Adv. Intell. Syst. Comput. 2019, 711, 203–211.
3. Arazmuradov, A. Assessing sovereign debt default by efficiency. J. Econ. Asymmetries 2016, 13, 100–113.
4. Ari, A.; Cergibozan, R. The Twin Crises: Determinants of Banking and Currency Crises in the Turkish Economy. Emerg. Mark. Financ. Trade 2016, 52, 123–135.
5. Breiman, L. (2001). Random Forests. Machine Learning, 45(1), 5-32.
6. Billio, M.; Casarin, R.; Costola, M.; Pasqualini, A. An entropy-based early warning indicator for systemic risk. J. Int. Financ. Mark. Inst. Money 2016, 45, 42–59.
7. Boonman, T.M.; Jacobs, J.P.A.M.; Kuper, G.H.; Romero, A. Early Warning Systems for Currency Crises with Real-Time Data. Open Econ. Rev. 2019, 30, 813–835.

8. Boonman, T.M.; Jacobs, J.P.A.M.; Kuper, G.H. Sovereign Debt Crises in Latin America: A Market Pressure Approach. Emerg. Mark. Financ. Trade 2015, 51, S80–S93.
9. Boonman, T.M.; Urbina, A.E.S. Extreme Bounds Analysis in Early Warning Systems for Currency Crises. Open Econ. Rev. 2020, 31, 431–470.
10. Bucevska, V. Currency Crises in EU Candidate Countries: An Early Warning System Approach. Panoeconomicus 2015, 62, 493–510.
11. Caggiano, G.; Calice, P.; Leonida, L. Early warning systems and systemic banking crises in low-income countries: A multinomial logit approach. J. Bank. Financ. 2014, 47, 258–269.
12. Candelon, B.; Dumitrescu, E.I.; Hurlin, C. Currency crisis early warning systems: Why they should be Dynamic. Int. J. Forecast. 2014, 30, 1016–1029.
13. Chang, Y.C.; Chang, K.H.; Wu, G.J. Application of eXtreme gradient boosting trees in the construction of credit risk assessment models for financial institutions. Appl. Soft Comput. 2018, 73, 914–920.
14. Chen, T.; Guestrin, C. XGBoost: A scalable tree boosting system. arXiv 2016
15. Charette, F.; d'Astous, A. Country Image Effects in the Era of Protectionism. J. Int. Consum. Mark. 2020, 32, 271–286.
16. Chaudhuri, A. Support Vector Machine Model for Currency Crisis Discrimination. arXiv 2014, arXiv:1403.04898.
17. Chang, R.Y.; Khan, H.A.; Lin, C.S.; Wang, Y.C. A new approach to modeling early warning systems for currency crises: Can a machine-learning fuzzy expert system predict the currency crises effectively? J. Int. Money Financ. 2008, 27, 1098–1121.
18. Dawood, M.; Horsewood, N.; Strobel, F. Predicting Sovereign Debt Crises: An Early Warning System Approach. J. Financ. Stab. 2017, 28, 16–28.
19. Di Nardo, M.; Castagna, F.; Madonna, M.; Murino, T. Modelling a Safety Management System Using System Dynamics at the Bhopal Incident. Appl. Sci. 2020, 10, 903.
20. Di Nardo, M.; Gallo, M.; Murino, T.; Santillo, L.C. System Dynamics Simulation for Fire and Explosion Risk Analysis in Home Environment. Int. Rev. Model. Simul. 2017, 10, 43–54.
21. Di Nardo, M. Developing a Conceptual Framework Model of Industry 4.0 for Industrial Management. Ind. Eng. Manag. Syst. 2020, 19, 551–560.
22. Dsoulia, O.; Khan, N.; Kakabadse, N.K.; Skouloudis, A. Mitigating the Davos dilemma: Towards a global self-sustainability index. Int. J. Sustain. Dev. World Ecol. 2018, 25, 81–98.
23. Dufrénot, G.; Paret, A.G. Sovereign debt in emerging market countries: Not all of them are serial defaulters. Appl. Econ. 2018, 50, 6406–6443.
24. Efimov, D.; Sulieman, H. Sobol Sensitivity: A Strategy for Feature Selection. In Mathematics across Contemporary Sciences; AUS-ICMS 2015; Springer Proceedings in Mathematics & Statistics; Springer: Cham, Switzerland, 2015;.
25. Feenstra, R.C.; Taylor, A.M. International Macroeconomics, 2nd ed.; Worth Publishers: New York, NY, USA, 2012.
26. Fioramanti, M. Predicting sovereign debt crises using artificial neural networks: A comparative approach. J. Financ. Stab. 2008, 4, 149–164.
27. Fratzscher, M. On currency crises and contagion. Int. J. Financ. Econ. 2003, 8, 109–129.
28. Fuertes, A.M.; Kalotychou, E. Optimal design of early warning systems for sovereign debt crises. Int. J. Forecast. 2007, 23, 85–100.
29. Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263-291.
30. Hastie, T.; Tibshirani, R.; Friedman, J. Random Forests. In The Elements of Statistical Learning: Data Mining, Inference, and Prediction, 2nd ed.; Springer: New York, NY, USA, 2009; pp. 587–603.
31. Hearst, M.; Schölkopf, B.; Dumais, S.; Osuna, E.; Platt, J. Trends and controversies–Support vector machines. IEEE Intell. Syst. 1998, 13, 18–28.
32. Heidari, E.; Sobati, M.A.; Movahedirad, S. Accurate prediction of nanofluid viscosity using a multilayer perceptron artificial neural network (MLP-ANN). Chemom. Intell. Lab. Syst. 2016, 155, 73–85.
33. Ho, T.K. Random decision forests. In Proceedings of the International Conference on Document Analysis and Recognition, Montreal, QC, Canada, 14–16 August 1995; IEEE Computer Society: Los Alamitos, CA, USA, 1995.
34. Jang, E.; Gu, S.; Poole, B. Categorical reparameterization with Gumbel-Softmax. arXiv 2016, arXiv:1611.01144.
35. Kalapanidas, E.; Avouris, N.; Craciun, M.; Neagu, D. Machine Learning Algorithms: A Study on Noise Sensitivity. In Proceedings of the First Balkan Conference in Informatics, Thessaloniki, Greece, 21–23 November 2003; pp.
36. Ibrahim, Y.; De Nisco, A.; Napolitano, M.R. The Role of Country Branding in Attracting Foreign Investment: Country Characteristics and Country Image.
37. Kaminsky, G.; Lizondo, S.; Reinhart, C. Leading Indicators of Currency Crises; IMF Staff Papers; International Monetary Fund: Washington, DC, USA, 1998.
38. Koesel, K.J.; Steinberg, D.A.; Thompson, N.W. Political Regimes and Currency Crises.Econ. Politics 2015, 27, 337–361.

39. Lai, K.K.; Wang, S.Y.; Yu, L. Currency Crisis Forecasting with General Regression Neural Networks. Int. J. Inf. Technol. Decis. Mak. 2006, 5, 437–454.
40. Markowitz, H. (1952). Portfolio selection. The Journal of Finance, 7(1), 77-91.
41. Minsky, H. P. (1992). The financial instability hypothesis. The Jerome Levy Economics Institute Working Paper No. 74.
42. Manasse, P.; Roubini, N. “Rules of thumb” for sovereign debt crises. J. Int. Econ. 2009, 78, 192–205.
43. Manasse, P.; Roubini, N.; Schimmelpfennig, A. Predicting Sovereign Debt Crises (November 2003); IMF Working Paper, No. 03/221; International Monetary Fund: Washington, DC, USA, 2003; pp. 1–41.
44. Marghescu, D.; Sarlin, P. Visual predictions of currency crises using self-organizing maps. Intell. Syst. Account. Financ. Manag. 2011, 18, 15–38.
45. Melnyk, T.M.; Varibrusova, A.S. Variable indicators affecting the country’s brand strategy effectiveness and competitiveness in the world. Manag. Sci. Lett. 2019, 9, 1685–1700.
46. Núñez de Castro, L.; Von Zuben, F.J. Optimised Training Techniques for Feedforward Neural Networks; Technical Report DCA RT 03/98; Department of Computer Engineering and Industrial Automation, FEEC, UNICAMP: Campinas, Brazil, 1998.
47. Oztekin, A.; Bali, O.; Gumus, S.; Guresen, E.; Sevim, C. Developing an early warning system to predict currency crises. Eur. J. Oper. Res. 2014, 237, 1095–1104
48. Papadopoulos, N.; Ibrahim, Y.; De Nisco, A.; Napolitano, M.R. The Role of Country Branding in Attracting Foreign Investment: Country Characteristics and Country Image.
49. Pham, T.H.A. Are global shocks leading indicators of currency crisis in Vietnam? Res. Int. Bus. Financ. 2017, 42, 605–615.
50. Popesku, J.; Teodorovi´c, M. Country Brand Equity Model: Sustainability Perspective. Marketing 2016, 47, 111–128.
51. Prashanth, K.D.; Parthiban, P.; Dhanalakshmi, R. Evaluation and ranking of criteria affecting the supplier’s performance of a heavy industry by fuzzy AHP method. J. Sci. Ind. Res. 2018, 77, 268–270.
52. Raschka, S. Python Machine Learning; Packt Publishing Ltd.: Birmingham, UK, 2015.
53. Spence, M. (1973). Job market signaling. The Quarterly Journal of Economics, 87(3), 355-374.
54. Stiglitz, J. E. (2000). The contributions of the economics of information to twentieth century economics. The Quarterly Journal of Economics, 115(4), 1441-1478.