Key Indicators Influencing BRICS Countries' Stock Price Volatility through Classification Techniques: A Comparative Study

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Abstract: - The stock market is crucial for a country's economy. It reflects the economic health and investment status of a country. While it has attracted the interest of many scholars, the volatility of stock prices and the indicators influencing this volatility has not been extensively studied, particularly using classification techniques. This study aims to fill this gap in the literature by identifying an effective classification technique to classify the data of BRICS countries using eight classification techniques via WEKA software from 2000 to 2021. Additionally, the study seeks to explore the common indicators that significantly impact stock price volatility in BRICS countries. Findings reveal that tree algorithm-based techniques performed well in terms of accuracy and reliability, although no single common classification technique was identified. Among the eight techniques, Random Tree classified the data of BRICS countries with high accuracy, except for India, where the J48 technique was more efficient. Furthermore, the study indicates that there are no common indicators affecting stock price volatility, as these indicators vary across countries due to the distinct economic and sociopolitical structures of BRICS countries. These findings provide valuable insights for investors and policymakers to better understand and manage stock market dynamics in BRICS countries.

Key-Words: - Stock price volatility, Classification, Data Mining, BRICS countries, Indicators, WEKA

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1 Introduction

The stock market plays a crucial role in the country's economy and is extremely sensitive to social, economic, and political news events around the world. It works as a mirror to reflect the country's socio-economic and political structures.

In existing literature, a myriad of works studied the stock markets of emerging economies in different aspects, however, the indicators influencing the stock price volatility (SPV) have not been extensively explored. To fill the gap in the literature, this study examines indicators influencing the SPV of BRICS countries from 2000 to 2021. As emerging economies, BRICS countries have been selected because they have diverse political, demographic, and economic structures, [1]. The acronym BRICS is the abbreviation of five fast-growing markets in the universe of emerging market economies, [2]. The story of BRICS started in the early 2000s and Goldman Sachs analyst Jim O'Neill coined the term BRIC for the group of Brazil, Russia, India, and China to describe four fast-growing countries, [3]. In 2010, South Africa joined that group and formed the acronym BRICS, [4]. In terms of economic structures, Brazil has a liberalized and market-driven economic structure, Russia, India and China have dominant government-controlled economic structures and South Africa has a driven, structured, and open economic structure, [5]. BRICS countries have more than 40% of world's population, 28% of the world's massive land 24% of the global GDP, and more than 16% of global commerce, [6]. They established the New Development Bank in 2015 to mobilize resources for infrastructure and sustainable development projects, [7]. Being major recipients of foreign investments, they play an important role in the current pattern of global investments, [8].

The rest of the paper is structured as follows: Section 2 presents the literature review; Section 3 describes the data and methodology of the study; Section 4 presents the findings and discussion of empirical results; Section 5 presents the conclusions, research, and recommendations.

2 Literature Review

The economic structures of countries, particularly emerging countries such as BRICS, have become a focal point for many scholars. Research on this topic has been approached from a various perspective. Scholars have searched bank development and stock market performance [1] and the correlation between oil volatility and stock markets, [9], [10]. Additionally, studies have explored the interplay between economic growth, financial development, and income inequality, [11], as well as the relationship between exchange rates and stock market indices, [12], [13], [14], [15]. Other areas of investigation include volatility indices [14], the impact of crises on economic growth [13], [16], [17], and the effects of innovations on economic growth, [18]. Moreover, scholars have examined stock market efficiency [19], [20], [21], [22], green finance and climate change, [23], [24], [25] and the relationship between tourism and economic growth, [26]. Additionally, some scholars focus on the effects of exchange rates, [20], [27], the interconnectedness between Bitcoin and equity markets, [28], the impacts of private credit shocks on economic growth, [29] while some others have studied the relationship between entrepreneurial activity and economic growth [30], the effects of financial shocks [31] and the impacts of exports and imports on economic growth, [32]. Other than those, some scholars have worked on the relationship between trade openness and economic growth, [33], [34], the impact of market crashes on sector indices and volatility [35] and stock market efficiency before and after the COVID-19 pandemic, [36].

Stock markets and banks have been key drivers of economic growth and financial system development. Bank development is measured by credit facilities to the private sector relative to GDP, while stock market development is assessed by market size and liquidity, [1]. In existing literature, the bank and stock market indicators have not been studied together. This study addresses this gap by using both indicators to explore which common indicators impact stock price volatility in BRICS countries. One scholar studied in cross-country and panel form the interactions of bank development, stock market development, and global equity index for the BRICS countries from1990 to 2018, [1]. Their findings indicated that the models for bank development and market performance respond differently in the short term compared to the long term. Furthermore, they concluded that the growth of the global stock market is predominantly influenced by the global financial situation rather than the development of banks within BRICS countries.

Among the BRICS countries, Russia and Brazil are net oil exporters, while India, China, and South Africa are net oil importers. Consequently, their stock returns react oppositely to changes in oil volatility. One scholar examined the quantile dependence and directional predictability from oil volatility to stock returns in BRICS countries using the cross-quantilogram model, [37]. The findings reveal that low quantile oil volatility has a minimal impact on stock returns, whereas high quantile oil volatility amplifies losses in stock returns. Moreover, the influence of oil volatility on stock returns varies depending on whether a country is a net exporter or importer of oil. Oil volatility is not included in this study because its impact on the SPV of BRICS countries varies depending on whether they are net oil exporters or net oil importers.

The BRICS countries have experienced years of rapid trade and economic growth, now accounting for nearly a quarter of the global economy, [8]. These factors make the BRICS countries key players in global investment, as they are major recipients of foreign direct investment and increasingly significant for outward investors, [8]. The exchange rate is a crucial factor for investors. Several scholars have explored the relationship between exchange rates and stock market indices within BRICS countries. Reference [12], assessed the impact of exchange rates on stock market returns using the auto-regressive distributed lag (ARDL) method, concluding a significant effect of exchange rates on stock market indices returns. Similarly, the information linkages of the volatility index, a forward-looking measure of volatility, across BRICS countries were examined using a multivariate generalized autoregressive conditional heteroscedasticity model, [14]. This research highlighted varying degrees of connectedness among BRICS countries over the study period. Similar to the reference [12], another scholar worked on the dynamic linkages between exchange rates and stock market returns in a regime-switching environment across BRICS countries, [15]. The findings suggested that stock markets have more influence on exchange rates during both calm and turbulent periods. In the existing literature, scholars have used various methods, such as the auto-regressive distributed lag model [12], the dynamic five-factor parametric model, the multilayer feed-forward neural network [8], and the multivariate generalized autoregressive conditional heteroscedasticity model [14], to perform their analyses. However, there is a lack of comparison among the data mining (DM) methods and classification techniques. To address this gap, this study compares DM classification techniques to identify a common method for classifying the SPV data of BRICS countries.

The efficiency of stock markets has a significant interest among researchers. Reference [14], conducted a comparative study on the efficiency of stock markets across BRICS countries, evaluating the profitability of four trading rules: Simple Moving Average, Relative Strength Index, Moving Average Convergence Divergence, and Momentum, spanning from 1995 to 2008. The findings revealed that these indicators were most profitable in the Russian stock market. Additionally, they identified the Brazilian stock market as the most efficient among the BRIC countries. In 2020, Panda examined the financial structure of BRICS countries and the USA was examined to focus on investment opportunities within BRICS from 1997 to 2017, [20]. Considering factors such as market depth, market microstructure, portfolio weights, and various macroeconomic indicators, it was found that all BRICS countries, except Brazil, exhibited high investment rates. The financial and macroeconomic indicators suggest that BRICS countries are attractive destinations for investors, offering substantial economic value. These findings contributed to the findings in [17]. They also highlighted high investment rates in BRICS countries, excluding Brazil, [17]. In another study, the relationship between gold and stock markets in BRICS countries was explored using weekly data from 2000 to 2014, [21]. The research indicated that dynamic conditional correlations between gold and stock markets were generally low to negative during significant financial crises, suggesting that gold could serve as a safe haven during times of extreme market volatility.

Several scholars have examined individual stock markets within the BRICS countries during financial crises. For instance, the financial contagion effects on African stock markets, including South Africa's, during global financial crises such as the European debt crisis, Brexit, and the COVID-19 pandemic were studied, [38]. The findings indicated that the regional impact of these crises varied based on their nature. Financial contagion was observed to increase with country-level risk, market capitalization, and export-to-GDP ratio, but decreased with lower corruption levels. Moreover, financial interconnectedness was investigated by analyzing volatility spillovers and movements between equity and foreign exchange markets in BRICS countries from 1997 to 2018, [39]. That research showed that shocks originating from equity markets had a stronger impact on foreign exchange markets at the individual level. Conversely, foreign exchange markets had a greater influence on their corresponding equity markets. Interdependencies were found between the equity and foreign exchange markets of most BRICS countries, except for China, which displayed relative isolation. Brazil was identified as the main source of volatility spillovers to other BRICS markets, while South Africa showed the highest level of integration within the BRICS countries. These findings show the diverse social, economic, and geopolitical structures within BRICS countries. Under the consideration of diverse economic and sociopolitical structures in BRICS countries, two questions arise regarding the analysis techniques and the indicators affecting their stock price volatility (SPV): Is there a common classification technique that can classify the SPV data for all BRICS countries? And is it possible to identify common indicators that affect the SPV of BRICS countries? This paper aims to answer these questions by applying eight data mining (DM) classification techniques to twenty-seven indicators.

3 Aim and Methodology

The BRICS countries hold strategic significance in the global economy. As a group of fast-growing emerging economies, they account for 26% of the global GDP and 40.8% of the world's population. Numerous scholars have studied their economies, stock markets, and trade volatilities using various methods. However, there is a lack of comparative studies on stock price volatilities using DM classification techniques, as well as a lack of studies identifying common indicators affecting the SPV of BRICS countries. To address these gaps, this study aims to identify a common classification technique for classifying the SPV data of BRICS countries using eight distinct DM techniques through the open-source software WEKA. Additionally, the study seeks to determine which common indicators have the greatest impact on SPV in BRICS countries based on the classification outcomes. To achieve these objectives, the following hypotheses are formulated:

H1: There are common indicators that significantly influence the SPV of BRICS countries.

H2: A common classification technique effectively classifies the data of BRICS countries.

3.1 Data

The annual data from 1994 to 2022 were collected from The World Bank Indicators and the OECD Data Bank, [5]. To ensure data quality, only indicators with minimal missing values were included in the statistical analyses, so the data from 2000 to 2021 were utilized to perform the analysis. 27 indicators were chosen based on availability for each country. Table 1 presents these 27 indicators along with their definitions and SPV. The dependent variable in this analysis is SPV. The SPV data were initially collected in US dollars. However, since many classification techniques require binary data in WEKA, the SPV data were transformed into a categorical format by calculating the difference between the current year's SPV and the previous year's SPV. A positive difference was denoted by "P", and a negative difference was denoted by "N".

Table 1. Indicators and their definitions

Variables	Indicator Definition
X1	Exports Merchandise Customs current Us dollars millions not seas adj
X2	GDP at market prices current Us dollars millions seas adj
X3	Imports Merchandise Customs current Us dollars millions not seas adj
X4	Nominal Effective Exchange Rate
X5	Total Reserves
X6	Real Effective Exchange Rate
X7	Bank capital to total assets percent
X8	Central bank assets to GDP percent
X9	External loans and deposits of reporting banks vis a vis the nonbanking sectors percent of domestic bank deposits
X10	Financial system deposits to GDP percent
X11	Gross portfolio equity assets to GDP percent
X12	Gross portfolio debt liabilities to GDP percent
X13	Gross portfolio equity liabilities to GDP Percent
X14	Insurance company assets to GDP percent
X15	Liquid liabilities to GDP percent
X16	Mutual fund assets to GDP percent
X17	Non life insurance premium volume to GDP percent
X18	Outstanding domestic public det securities to GDP percent
X19	Pension fund assets to GDP percent
X20	Private credit by deposit money banks and other financial institutions to GDP percent
X21	Private credit by deposit money banks to GDP percent
X22	Provisions to nonperforming loans percent
X23	Remittance inflows to GDP percent
X24	Stock market capitalization to GDP percent
X25	Stock market return percent year on year
X26	Stock market total value traded to GDP percent
X27	Stock market turnover ratio percent
Y	Stock price volatility (P: increase; N: decrease)

As highlighted in Section 2, the BRICS countries are key players in global investment, both as major recipients of foreign direct investment and as significant outward investors, [8]. Trade is also vital for these economies. Brazil depends on exporting commodities and agricultural products. Similarly, Russia's economy is predominantly based on natural resources and commodity exports, [20]. China and India benefit from cheap labor and resources, exporting manufactured goods, agricultural products, technology, and services. South Africa's economy is diverse, relying on mineral resources like gold, platinum, and diamonds, as well as agriculture, tourism, and financial services. Given this context, the independent variables, X1-X27, were meticulously selected from financial and economic indicators that influence SPV and are available for each BRICS country. These include ten economic and seventeen financial indicators. The economic indicators are Exports of Merchandise (Customs) in current US dollars (X1), GDP at market prices in current US dollars (X2), Imports of Merchandise (Customs) in current US dollars (X3), Nominal Effective Exchange Rate (X4), Total Reserves (X5), Real Effective Exchange Rate (X6), Stock Market Capitalization to GDP percentage (X24), Stock Market Return percentage (X25), Stock Market Total Value Traded to GDP percentage (X26), and Stock Market Turnover Ratio percentage (X27). The remaining indicators are financial, as detailed in Table 1.

3.2 Classification Techniques

Classification in Data Mining (DM) is an important technique that groups the data into distinct categories by employing mathematical and statistical techniques. The main objective of classification is to accurately predict the target class for each data, [40]. It enables accurate predictions and better decision-making. In literature, various classification methods have been proposed. In this study, WEKA implementation software is used to classify SPV data of BRICS countries. WEKA is a DM implementation software program developed by the University of New Zealand under the General Public License, [41]. In WEKA, there exist seven classification algorithms, namely bayes, functions, lazy, meta, misc, rules, and trees, each including various sub-classification modules. WEKA employs many classification techniques depending on the data type, nominal ordinal, or interval. Based on the data type, a suitable algorithm can be chosen to effectively extract information from the dataset. For this study, all applicable classifications were utilized on the dataset, but only eight of them demonstrated effective classification. These are Naïve Bayes (NB), Simple Logistic (SL), Meta-Bagging (MB), Classification via Regression (CVR), Decision Table (DT), Decision Stump (DS), J48, and Random Tree (RT).

The NB is a sub-classification module of the bayes algorithm. The NB technique is based on the Bayesian theorem of probability. The Bayesian Network Classifier efficiently computes the most likely output based on the input. In the NB, the presence of a particular attribute is considered independent of the presence of any other attribute when the class variable is given. Bayesian networks are directed acyclic graphs (DAGs) where nodes represent random variables, [42]. The edges denote conditional dependencies, while unconnected nodes represent independent variables. Each node is associated with a probability function that provides the probability of the variable it represents. For the

NB, numeric estimator precision values are chosen based on the analysis of the training data. This algorithm can be used when the variables are binary class, missing class values, and nominal class. The SL is a sub-classification module of the functions algorithm. For the SL, LogitBoost with simple regression functions as base learners are used for fitting the logistic model. In SL classification, the model predicts the probability of each class. The logistic function transforms the linear combination of the input features into a probability value between 0 and 1. The logistic function is defined as:

$$P(Y = 1|X) = \frac{1}{1-e^{-z}} \tag{1}$$

where $P(Y = 1|X)$ represents the probability of the dependent variable being 1 given the values of the independent variables X and z is the linear combination of the independent variables and their coefficients.

$$z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \tag{2}$$

where β_0 represents the intercept, $\beta_1, \beta_2, \cdots, \beta_n$ are the coefficients corresponding to the independent variables $X_1, X_2, \cdots, X_n$, respectively, [43]. This algorithm can be used when the dependent variable is binary and analyzes the data after employing discretization of the continuous variables. The MB is a sub-classification module of meta algorithm, it can do classification and regression depending on the base learner. Similar to Naïve Bayes, it is used when the variables are binary class, missing class values, nominal classes or numeric classes. The CVR is also subclassification module of the meta algorithm. It is binarized and one regression model is built for each class value. It is used when the variable binary class, missing class values, and nominal class. In addition, the DT is a sub-classification module of the rules algorithm, whereas the DS is a sub-classification module of the tree algorithm. The DT is usually used in conjunction with a boosting algorithm. The goal of DT is to create a model that estimates the value of a target variable based on several input variables. The DT is used when the variables are binary class, missing class values, nominal class, or numeric class. Meanwhile, DS does regression based on mean-squared error, and missing is treated as a separate value. It is used when the variables are binary class, missing class values, nominal class, or numeric class. The J48 is also a sub-classification module of the tree algorithm and it uses the rules of the C4.5 algorithm. Similar to DS and J48, the RT is also a sub-classification module of the tree algorithm. It performs no pruning. It also has an option to allow estimation of class probabilities. They are capable use of using different data types. NB, SL, CVR, and J48 manage binary and nominal datasets with missing values, whereas MB, DT, DS, and RT manage binary, and nominal numerical data sets with missing values.

3.2.1 Classifier Performance Measures

Classifier performance is measured by using the accuracy of correctly classified instances, mean absolute error (MAE), root mean square error (RMSE), and various performance metrics such as precision, recall, F-statistic, ROC Area, and confusion matrix. The confusion matrix presents a visualization of the classification performance based on a table that contains columns representing the instances in a predicted class and rows representing the instances in an actual class. Classification accuracy refers to the ratio of correct predictions to the total number of predictions made. It is calculated as the percentage of correctly predicted instances over the total number of instances. In literature, 80% is assumed as the threshold point, [44]. If it is close to 100% the accuracy rate is an overwhelming situation to say that the data are perfectly classified. Another criterion is the kappa statistic, which measures the agreement between observed and expected classification outcomes. It varies from -1 to +1, [45]. The kappa statistic value can be interpreted as follows: values ≤ 0 as indicating no agreement and 0.01-0.20 as none to slight, 0.21-0.40 as fair, 0.41- 0.60 as moderate, 0.61-0.80 as substantial, and 0.81-1.00 as almost perfect agreement, [46]. ROC curve is another performance measure. It measures the overall performance of the classifier according to the area under the curve. It can be used to compare two or more class performances. The area under the curve is the highest and the best classifier. The range of values for the area under the curve changes from 0 to 1. 1 indicates the classifier is perfect. A ROC curve can be used to select a threshold for a classifier that maximizes the true positives while minimizing the false positives, [47]. Precision quantifies the number of correct positive predictions made whereas recall quantifies the number of incorrect positive predictions made from all positive predictions that could have been made. Maximizing precision will minimize the number of false positives, whereas maximizing the recall will minimize the number of false negatives. Like precision and recall, a poor F-Measure score is 0.0 and a best or perfect F-Measure score is 1.0, [47].

3.3 BRICS Countries

The BRICS countries have a significant role in the world economy and they are the most powerful and fastest-growing emerging markets, [48]. The BRICS countries stand as significant recipients of global investment streams and are major consumers of commodities worldwide, [1]. According to World Bank data, the BRICS countries have different demographic and economic structures. Table 2 illustrates some demographic and economic indicators in 2022 for BRICS countries and the world, [5].

Table 2. Demographic and economic indicators of BRICS countries and the World in 2022

Country	Population	Population growth (annual %)	Surface area (sq. km)	GDP (current US$)	GDP growth (annual %)
Brazil	215,313,498	0.460	8,515,770	1,920,095,779,022.73	2.901
Russia	59,893,885	0.074	17,098,250	2,240,422,427,458.58	-2.070
India	1,417,173,173	0.680	3,287,260	3,416,645,826,052.87	7.240
China	1,412,175,000	-0.013	9,562,910	17,963,171,479,205.30	2.989
South Africa	144,236,933	0.841	1,219,090	405,270,850,099.38	1.910
World	7,950,946,800	0.794	140,486,936.909	101,325,686,724.63	3.087
BRICS to World (%)	40.86%		28.25%		

In terms of population size, China and India lead with vast populations of approximately 1.5 billion each, while Brazil, Russia, and South Africa have smaller populations (Table 2). Population growth rates differ among these countries. South Africa has the highest growth rate at 0.841% and India has the second highest growth rate at 0.680%. Brazil's growth rate is modest at 0.46%, and Russia's is much lower at 0.074%. Meanwhile, China experiences a slight decline with a growth rate of -0.013%, [49]. In terms of land area, Russia is the largest, followed by China, Brazil, India, and South Africa, [50]. Economically, China leads with the highest GDP of approximately $17.96 trillion US dollars, followed by India at $3.4 trillion US dollars. Brazil and Russia lag behind with $2.24 trillion US dollars and $1.92 trillion US dollars, respectively. South Africa has the smallest GDP at $405 billion US dollars. Among the BRICS countries, Russia is the only country with a negative GDP growth rate, primarily due to sanctions following its invasion of Ukraine in February 2022, [50]. India boasts the highest growth rate at 7.24%, followed by China, Brazil, and South Africa at 2.99%, 2.90%, and 1.91%, respectively. Globally, the population is nearly 7.95 billion with an annual population growth rate of 0.79% and a total area of approximately 140 million square kilometers. The global GDP stands at about $101.33 trillion USD, with a growth rate of 3.087%. In terms of demographic composition, the BRICS countries cover 28.25% of the world's land area and account for over 40% of the global population, [5]. The BRICS countries show diverse economic and socio-political structures, each with distinct natural resources. Their economies depend on factors such as industrialization, commodities, trade openness, exports, and imports. These lead to distinct growth drivers for each country, [12]. For instance, Brazil has rich natural resources, such as iron ore, soybeans, and oil. It is a major exporter of agricultural products, minerals, and manufactured goods, [12]. Russia also has rich natural sources, particularly crude oil and gas, [12]. It exports mainly oil, gas, various commodities, metals, and military equipment. India has cheap laborlabor and exports commodities, like textiles, chemicals, machinery, and software services. Similarly, China benefits from a large labor pool and is a leading exporter of electronics, machinery, textiles, and other goods. South Africa has diverse resources, like gold, platinum, and diamonds, along with strengths in agriculture and tourism. It exports agricultural products, as well as gold, platinum, and diamonds, [12], [17].

3.4 Stock Price Volatilities of BRICS Countries

The stock market is a mirror of the economy and wellness of a country. The dynamic of stock price volatility depends on many factors, such as exchange rates, oil prices export and import volatilities, trading, and assets. Risk is another factor highly influential on stock price volatility. In highly risky situations, domestic or foreign investors do not invest which leads to a volatility decrease.

For this study, annual SPV data of BRICS countries in US dollars were received from the World Bank and OECD Data from 1994 to 2022. To account for volatility variations among countries and missing data for some countries before 2000, the data were standardized to percentages, with the year 2000 serving as the reference point for aggregation. Figure 1 illustrates the SPV of BRICS countries from 2000 to 2021. In 2000, due to aggregation, the SPV of BRICS countries showed the unique economic conditions and market responses in each country.

The SPV of BRICS countries demonstrated fluctuations during the study period from 2000 to 2021 due to three economic and financial crises, the 2007-2009 global financial crisis, the 2014-2016 crisis, and the 2019-2020 COVID-19 pandemic crisis. The economic structure and stock markets of countries face significant impacts from global economic disturbances and financial market instability. These disruptions lead to fluctuations in various sectors, such as declines in SPV and production, increases in unemployment and inflation. The SPV of BRICS countries has also been affected by these crises. The SPV of Brazil started at 100% in 2000, decreased to 79.72% in 2001, and fluctuated moderately until a peak of 118.89% in 2009. This is coming from the effects of the global crisis. After 2009, the SPV of Brazil generally declined until 2018 and then slightly increased to 82.95% in 2021. During this period, political scandals (Operation Car Wash), and unemployment increases affected seriously its economy. The SPV of Russia shows a more volatile pattern. It increased to a peak of 193.59% in 2004, then dropped significantly after 2008. It reached 49.12% in 2010 and stabilized in the 30-60% range afterward. The war between Russia and Georgia, economic sanctions due to in 2014 annexation of Crimea, and the ongoing Russia-Ukrainian war drastically affected Russia's economy and SPV. As a big commodity exporter, oil price decreases also affected its economy seriously. The SPV of India shows a similar trend to Russia until 2016, then increased until 2020. It had a pick value 184.91% in 2004. Between 2005 and 2011, India's SPV showed a general declining trend, stabilizing around 66-68% then it has a pick at 121.62% in 2020. From 2000 to 2004 ease China's SPV showed a gradual decrease, then increased to the pick value of 147.74% in 2009. It fluctuated between 62-106% after 2015. From 2000 to 2004, South Africa's SPV remained stable with minor fluctuations, then reached a low of 70.46% in 2005. It displayed moderate volatility until 2009 and peaked at 175.88% and 119.95% in 2009 and 2020, respectively. It generally stabilized around 70-120% after 2009. These trends highlight how each country's unique economic, political, and market conditions influence their SPV.

Fig. 1: Stock price volatility percent at constant 2000 prices, [5]

4 Findings and Discussion

The following subsections present detailed outcomes from eight classification techniques via WEKA.

4.1 Naïve Bayes

The initial classification technique employed is the Naïve Bayes (NB), utilizing the full training dataset for evaluation. Table 3 displays the results of NB for BRICS countries. The accuracy of correctly classified instances for BRICS countries ranged from 67.86% to 89.28%. India shows the highest accuracy, followed by South Africa, Russia, China, and Brazil in descending order. The Kappa statistic, which measures the agreement between observed and expected classification results, shows that India's classification has the highest agreement at 0.7813, followed by South Africa at 0.7083. Russia has a moderate agreement at 0.6%, whereas China and Brazil demonstrate low agreements at 0.43% and 0.27%, respectively. Additional performance metrics include the mean absolute error (MAE) and root mean squared error (RMSE). These metrics measure the average deviation of predicted values from actual values in classification, with lower values indicating better classifier performance. India and South Africa show lower MAE and RMSE compared to the other countries. The true positive (TP) rate and false positive (FP) rate provide information about the sensitivity and specificity of the classification model.

Table 3. Classification results of Naïve Bayes

Metrics	BRICS Countries				
	Brazil	Russia	India	China	South Africa
CCI[a] (%)	19 (67.86)	24 (80.00)	25 (89.28)	21 (75.00)	24 (85.71)
ICI[b] (%)	9 (32.14)	6 (20.00)	3 (10.71)	7 (25.00)	4 (14.29)
Kappa statistic	0.2759	0.6000	0.7813	0.4302	0.7083
MAE[c]	0.3289	0.2297	0.121	0.2712	0.1815
RMSE[d]	0.5131	0.4015	0.2731	0.4542	0.3702
TP[e] Rate (P[f]-N[g])	0.250-1.000	0.733-0.867	0.769-1.000	0.455-0.941	0.875-0.833
FP[h] Rate (P[f]-N[g])	0.000-0.750	0.133-0.267	0.000-0.231	0.059-0.545	0.167-0.125
Precision (P[f]-N[g])	1.000-0.640	0.846-0.765	1.000-0.833	0.833-0.727	0.875-0.833
Recall (P[f]-N[g])	0.400-0.780	0.786-0.813	0.870-0.909	0.455-0.941	0.875-0.833
F-Measure (P[f]-N[g])	0.400-0.400	0.605-0.605	0.801-0.801	0.588-0.821	0.708-0.708
ROC Area (P[e]-N[f])	0.419-0.804	0.796-0.813	0.847-0.956	0.566-0.859	0.851-0.860

[a]CCI:Correctly classified instances, [b]ICI: Incorrectly classified instances, [c] MAE: Mean absolute error, [d]RMSE: Root mean squared error, [e]TP: True positive, [h]FP: False positive: increase in SPV, [g]N: decrease in SPV

In Table 3, TP and FP rates were presented for Positive (P) and Negative (N) SPV data. India, South Africa, and Russia have high-levellevels of TP rates for Positive and Negative SPV data. The performance of the classifier is evaluated using metrics such as Precision, Recall, F-measure, and ROC Area, which measure correctness and completeness. A high precision suggests fewer false positives, while a high recall indicates fewer false negatives. The F-Measure shows a balance between precision and recall, and a high ROC Area signifies good classifier performance.In comparing these metrics, India shows the highest performance, followed by South Africa and Russia. The performance of NB is less satisfactory for China and Brazil. The classifier effectively classifies SPVs of India, South Africa, and Russia, while classifying SPV of China moderately. Brazil shows the lowest correctly classified instances and generally underperforms in comparison to the other countries.

4.2 Simple Logistic

The Simple Logistic (SL) is the second classification technique that uses the full training data. Table 4 shows the results of SL across BRICS countries. In terms of correctly classified instances, South Africa demonstrates a high accuracy of 96.43%, and closely Russia follows with 93.99% accuracy. For Brazil, the classifier achieved a good accuracy of 85.71%. Meanwhile, India and China exhibit moderate accuracies of 78.57% and 67.86%, respectively.

Table 4. Classification results of Simple logistic

Metrics	BRICS Countries				
	Brazil	Russia	India	China	South Africa
CCI[a] (%)	24 (85.71)	28 (93.99)	22 (78.57)	19 (67.86)	27 (96.43)
ICI[b] (%)	4 (14.29)	2 (6.67)	6 (21.43)	9 (32.14)	1 (3.57)
Kappa statistic	0.7021	0.8667	0.5602	0.2921	0.9278
MAE[c]	0.2617	0.2727	0.3524	0.4210	0.1493
RMSE[d]	0.3254	0.3286	0.3914	0.4533	0.2129
TP[e] Rate (P[f]-N[g])	0.750-0.938	1.000-0.867	0.933-0.615	0.455-0.824	0.938-1.000
FP[h] Rate (P[f]-N[g])	0.063-0.250	0.133-0.000	0.385-0.067	0.176-0.545	0.000-0.063
Precision (P[f]-N[g])	0.900-0.833	0.882-1.000	0.737-0.889	0.625-0.700	1.000-0.923
Recall (P[f]-N[g])	0.750-0.938	1.000-0.867	0.933-0.615	0.455-0.824	0.938-1.000
F-Measure (P[f]-N[g])	0.818-0.882	0.938-0.929	0.824-0.727	0.526-0.757	0.968-0.960
ROC Area (P[e]-N[f])	0.934-0.798	0.721-0.911	0.893-0.815	0.748-0.631	0.961-0.985

[a]CCI:Correctly classified instances, [b]ICI: Incorrectly classified instances, [c] MAE: Mean absolute error, [d]RMSE: Root mean squared error, [e]TP: True positive, [h]FP: False positive: increase in SPV, [g]N: decrease in SPV

Similar to accuracies, Kappa statistic is high for South Africa and Russia. Brazil and India show moderate Kappa statistics, while Kappa statistics for China are comparatively low. The TP rate and FP rate for South Africa and Russia are excellent in distinguishing positive and negative instances. Brazil and India also show good TP and FP rates, but China demonstrates low TP and FP rates. The performance metrics for SL range from strong to weak across the countries in the following order: South Africa, Russia, Brazil, India, and China. Based on the results in Table 4, South Africa stands out as the best-performing country, followed by Russia and Brazil. The SL generated two sets of equations based on the output: one for positive SPV values and another for negative SPV values. The main difference between these sets is in the signs of the coefficients of the indicators. The following logistic equations were achieved for positive values of SPV.

$$z_{Brazil} = -0.22 + 0.01X4 + 0.02X6 - 0.1\boldsymbol{X7} + 0.07X9 + 5.41\boldsymbol{X17} - 0.01X18 + 0.19\boldsymbol{X19} - 0.06\boldsymbol{X21} - 8.13X23 + 0.03X27 \quad (3)$$

$$z_{Russia} = -5.25 + 0.31\boldsymbol{X7} + 4.99X12 - 0.19X13 - 0.05X14 - 0.03X15 + 1.65X16 - 0.01\boldsymbol{X21} + 0.02X25 \quad (4)$$

$$z_{China} = -1.42 + 0.44X9 \quad (5)$$

$$z_{India} = -14.3 + 0.03X6 - 2.52\boldsymbol{X7} + 0.9X14 + 0.33X16 + 7.48\boldsymbol{X17} + 0.55\boldsymbol{X19} + 0.08X22 + 0.01X25 \quad (6)$$

$$z_{South\ Africa} = -28.37 + 0.01X4 - 0.32\boldsymbol{X7} + 2.75\boldsymbol{X17} + 0.24\boldsymbol{X19} + 0.01X20 + 0.07\boldsymbol{X21} - 3.07X23 - 0.01X24 - 0.02X26 \quad (7)$$

According to the logistic equations (3)-(7), Bank capital to total assets percent (X7) emerges as a common indicator for BRICS countries, with the exception of China. Bank capital to total assets percent (X7) has a positive effect on Russia but a negative effect on Brazil, India, and South Africa. Additionally, Non-life insurance premium volume to GDP percent (X17) and Pension fund assets to GDP percent (X19) are shared indicators for Brazil, India, and South Africa. Both of the indicators positively impact these three countries. For Brazil, the most influential indicators, whether positive or negative, include Non-life insurance premium volume to GDP percent (X17) and Remittance inflows to GDP percent (X23), Nominal Effective Exchange Rate

(X4), Pension fund assets to GDP percent (X19), and Bank capital to total assets percent (X7). In Russia, the key indicators are Gross portfolio debt liabilities to GDP percent (X12), Bank capital to total assets percent (X7), Gross portfolio equity liabilities to GDP Percent (X13), and Mutual fund assets to GDP percent (X16). India's key indicators include Non-life insurance premium volume to GDP percent (X17), Bank capital to total assets percent (X7), Insurance company assets to GDP percent (X14), Pension fund assets to GDP percent (X19), and Mutual fund assets to GDP percent (X16). Lastly, for South Africa, the primary indicators are Non-life insurance premium volume to GDP percent (X17), Remittance inflows to GDP percent (X23), Bank capital to total assets percent (X7), and External loans and deposits of reporting banks vis a vis the nonbanking sectors percent of domestic bank deposits (X9).

The results indicate that key indicators vary across the countries. The variations in indicators depend on the political and socio-economic structures of the countries, as well as ongoing expected and unexpected global events like the Russia-Ukraine war and the COVID-19 pandemic. These events have altered the profile of indicators influencing the SPV. The results of SL indicate that no common indicators were identified across all BRICS countries. Consequently, this finding rejects the hypothesis H1: “There are common indicators that significantly influence the SPV of BRICS countries.”

4.3 Meta Bagging

The Meta Bagging (MB) utilized the full training dataset for evaluation. Table 5 presents the classification results of MB across BRICS countries.

According to the classification results of MB, the correctly classified instances (CCI) range from 78.57% to 92.86% accuracies. South Africa showed the highest value of CCI, while Brazil and China demonstrated the lowest values. India and Russia fall in between. The Kappa statistic is highest for South Africa (0.8511) and lowest for China (0.5435).

Although MAE and RMSE are lowest for South Africa, suggesting better overall model performance, they are very close to South Africa for the other BRICS countries. When considering TP and FP rates, South Africa achieves the highest value while Brazil and China show a wider range. This indicates higher sensitivity and a higher FP rate. India and Russia show good performances. Although precision, recall, F-measure, and ROC area vary across the countries, they generally perform well. South Africa achieves the highest values compared to the other countries, followed by India, Russia, China, and Brazil. Based on the classification results of MB in Table 5, South Africa demonstrates strong classification results, followed by India, Russia, China, and Brazil. Therefore, the results show that MB classified the SPV data for BRICS countries effectively.

Table 5. Classification results of Meta Bagging

Metrics	BRICS Countries				
	Brazil	Russia	India	China	South Africa
CCI[a] (%)	22 (78.57)	25 (83.33)	24 (85.71)	22 (78.57)	26 (92.86)
ICI[b] (%)	6 (21.43)	5 (16.67)	4 (14.29)	6 (21.43)	2 (7.14)
Kappa statistic	0.5435	0.6667	0.7098	0.5359	0.8511
MAE[c]	0.3777	0.3951	0.3423	0.3822	0.3187
RMSE[d]	0.4000	0.4092	0.3659	0.4000	0.3375
TP[e] Rate (P[f]-N[g])	0.538-0.938	0.933-0.733	0.933-0.769	0.636-0.882	1.000-0.833
FP[h] Rate (P[f]-N[g])	0.063-0.417	0.267-0.067	0.231-0.067	0.118-0.364	0.167-0.000
Precision (P[f]-N[g])	0.875-0.750	0.778-0.917	0.824-0.909	0.778-0.789	0.889-1.000
Recall (P[f]-N[g])	0.583-0.938	0.933-0.733	0.933-0.769	0.636-0.882	1.000-0.833
F-Measure (P[f]-N[g])	0.700-0.833	0.848-0.815	0.875-0.833	0.700-0.833	0.941-0.909
ROC Area (P[e]-N[f])	0.871-0.831	0.924-0.810	0.945-0.848	0.866-0.898	0.996-0.941

[a]CCI:Correctly classified instances, [b]ICI: Incorrectly classified instances, [c] MAE: Mean absolute error, [d]RMSE: Root mean squared error, [e]TP: True positive, [h]FP: False positive: increase in SPV, [g]N: decrease in SPV

4.4 Classification via Regression

The fourth classification technique is Classification via Regression (CVR). Full training data and M5 pruned model tree were used for evaluation. Table 6 illustrates the classification results of CVR.

In terms of CCI, India and South Africa achieved the highest percentages with both 85.71% accuracy. Russia and Brazil follow with 80% and 75% accuracy, respectively. China has the lowest CCI (71.43%). Kappa statistic shows that India has the highest agreement between observed and expected accuracy with 0.7068. South Africa and Russia follow India with the Kappa statistic values of 0.6957 and 0.600, respectively. However, the Kappa statistics for Brazil (0.4615) and China (0.3600) are very low, which indicates a low agreement between observed and expected accuracy. MAE and RMSE are the lowest for South Africa and low for India, which implies better overall performance, compared to the other BRICS countries. When considering the TP rate and FP rates, South Africa, India, and Russia demonstrate higher rates, whereas Brazil and China display lower rates. In terms of the performance metrics, South Africa shows the highest values, closely followed by India. China shows the lowest values in these metrics. When considering the classification performance of CVR, it shows varied performances for BRICS countries.

Table 6. Classification results of Classification via Regression

Performance Metrics	BRICS Countries				
	Brazil	Russia	India	China	South Africa
CCI[a] (%)	21 (75.00)	24 (80.00)	24 (85.71)	20 (71.43)	24 (85.71)
ICI[b] (%)	7 (25.00)	6 (20.00)	4 (14.29)	8 (28.57)	4 (14.29)
Kappa statistic	0.4615	0.6000	0.7068	0.3600	0.6957
MAE[c]	0.3827	0.4101	0.3369	0.3543	0.2801
RMSE[d]	0.4157	0.4262	0.3970	0.4169	0.3154
TP[e] Rate (P[f]-N[g])	0.500-0.938	0.800-0.800	1.000-0.692	0.455-0.882	1.000-0.667
FP[h] Rate (P[f]-N[g])	0.063-0.500	0.200-0.200	0.308-0.000	0.118-0.545	0.333-0.000
Precision (P[f]-N[g])	0.857-0.714	0.800-0.800	0.789-1.000	0.714-0.714	0.800-1.000
Recall (P[f]-N[g])	0.500-0.938	0.800-0.800	1.000-0.692	0.455-0.882	1.000-0.667
F-Measure (P[f]-N[g])	0.632-0.811	0.800-0.800	0.882-0.818	0.556-0.789	0.889-0.800
ROC Area (P[e]-N[f])	0.925-0.664	0.697-0.907	0.779-0.782	0.699-0.809	0.778-0.998

[a]CCI:Correctly classified instances, [b]ICI: Incorrectly classified instances, [c] MAE: Mean absolute error, [d]RMSE: Root mean squared error, [e]TP: True positive, [h]FP: False positive: increase in SPV, [g]N: decrease in SPV

4.5 Decision Table

The fifth classification technique employed is the Decision Table (DT). It uses both the full training data and the M5 pruned model tree for evaluation. Table 7 illustrates the classification results of DT.

Russia and South Africa show the highest percentage of CCI, with accuracies of 80% and 78.57%, respectively. Brazil's accuracy is the lowest (60.71%), while China's and India's fall in between. The Kappa statistic ranges from 0.4011 to 0.6000, indicating fair to low agreement between observed and expected accuracy. Russia has the highest Kappa statistic, whereas China has the lowest. MAE and RMSE metrics show the average magnitude of errors for all. Russia has the lowest values, indicating good performance, whereas Brazil has the highest.

In terms of TP rate and FP rate, China demonstrates the best performance, followed by Russia and India. Precision, recall, and F measures for positive and negative instances demonstrate unbalanced performances. While Brazil and Russia show high performance in positive instances, India, China, and South Africa show high performance in negative instances. ROC area values for the BRICS countries vary. When considering the positive and negative instances Russia, China, and India demonstrate strong discriminatory abilities, while Brazil and South Africa display weaker performance. Comparing the classification of DT with other classification techniques, it appears that other techniques outperform the DT. Although the results of the DT vary across countries, Russia and India demonstrate better classification results compared to other BRICS countries.

Table 7. Classification results of Decision Table

Metrics	BRICS Countries				
	Brazil	Russia	India	China	South Africa
CCI[a] (%)	17 (60.71)	24 (80.00)	20 (71.43)	21 (75.00)	22 (78.57)
ICI[b] (%)	11 (39.29)	6 (20.00)	8 (28.57)	7 (25.00)	6 (21.43)
Kappa statistic	0.4852	0.6000	0.4011	0.5149	0.5333
MAE[c]	0.4852	0.3326	0.4266	0.3697	0.3536
RMSE[d]	0.4921	0.3913	0.4472	0.4161	0.4013
TP[e] Rate (P[f]-N[g])	0.083-1.000	0.600-1.000	1.000-0.385	0.909-0.647	1.000-0.500
FP[h] Rate (P[f]-N[g])	0.000-0.917	0.000-0.400	0.615-0.000	0.353-0.091	0.500-0.000
Precision (P[f]-N[g])	1.000-0.593	1.000-0.714	0.652-1.000	0.625-0.917	0.727-1.000
Recall (P[f]-N[g])	0.083-1.000	0.600-1.000	1.000-0.385	0.909-0.647	1.000-0.500
F-Measure (P[f]-N[g])	0.154-0.744	0.750-0.833	0.789-0.556	0.741-0.759	0.842-0.667
ROC Area (P[e]-N[f])	0.252-0.838	0.612-0.917	0.823-0.532	0.819-0.685	0.265-0.895

[a]CCI:Correctly classified instances, [b]ICI: Incorrectly classified instances, [c] MAE: Mean absolute error, [d]RMSE: Root mean squared error, [e]TP: True positive, [h]FP: False positive: increase in SPV, [g]N: decrease in SPV

4.6 Decision Stump

Decision Stump (DS) is the sixth classification technique which uses both the full training data and the M5 pruned model tree for evaluation. Table 8 shows the results of DS across BRICS countries.

The results in Table 8 show that Russia achieves the highest accuracy of 80%, followed closely by South Africa at 78.57%. Brazil, India, and China all have the same accuracy of 75%. The Kappa statistic indicates moderate to low agreement between observed and expected accuracy, ranging between 0.4615 and 0.6002. Among the BRICS countries, Russia demonstrates the highest Kappa statistic, whereas Brazil shows the lowest. The MAE and the RMSE show the average magnitude error. Russia has the smallest value, and Brazil has the highest value. When considering TP Rate and FP Rate for positive and negative instances, Russia and China show high rates. However, there is an unbalanced gap between the TP rate and FP rate for Brazil, India, and South Africa. Precision, Recall, and F-Measure demonstrate reasonable performance. Russia, Brazil, and China show better performances in these metrics than India and South Africa. ROC Area values vary across the countries. South Africa and Russia show better classification ability than the other countries for both positive and negative instances. In terms of the classification ability of the DS, Russia and South Africa were categorized with high performance compared to the other countries. However, when compared with previous classification techniques, other techniques exhibit better performances than DS, similar to the findings with DT.

Table 8. Classification results of Decision Stump

Metrics	BRICS Countries				
	Brazil	Russia	India	China	South Africa
CCI[a] (%)	21 (75.00)	24 (80.00)	21 (75.00)	21 (75.00)	22 (78.57)
ICI[b] (%)	7 (25.00)	6 (20.00)	7 (25.00)	7 (25.00)	6 (21.43)
Kappa statistic	0.4615	0.6000	0.4787	0.5000	0.5333
MAE[c]	0.3612	0.2974	0.3274	0.3422	0.3117
RMSE[d]	0.4250	0.3856	0.4046	0.4137	0.3948
TP[e] Rate (P[f]-N[g])	0.500-0.938	0.867-0.733	1.000-0.462	0.818-0.706	1.000-0.500
FP[h] Rate (P[f]-N[g])	0.063-0.500	0.267-0.133	0.538-0.000	0.294-0.182	0.500-0.000
Precision (P[f]-N[g])	0.857-0.714	0.765-0.846	0.682-1.000	0.643-0.857	0.727-1.000
Recall (P[f]-N[g])	0.500-0.938	0.867-0.733	1.000-0.462	0.818-0.706	1.000-0.500
F-Measure (P[f]-N[g])	0.632-0.811	0.813-0.786	0.811-0.632	0.720-0.774	0.842-0.667
ROC Area (P[e]-N[f])	0.888-0.279	0.434-0.930	0.395-0.889	0.364-0.925	0.912-0.605

[a]CCI:Correctly classified instances, [b]ICI: Incorrectly classified instances, [c] MAE: Mean absolute error, [d]RMSE: Root mean squared error, [e]TP: True positive, [h]FP: False positive: increase in SPV, [g]N: decrease in SPV

4.7 J48

The seventh classification technique is the J48 which utilizes full training data for evaluation. Table 9 presents the results of the J48 across BRICS countries.

According to the findings in Table 9, the CCI ranges between 92.86% and 75%. India leads with the highest percentage, performing well at 92.86%, followed by Brazil at 89.29%. China and Russia follow with accuracies of 82.14% and 80%, respectively. South Africa demonstrates the lowest CCI at 75%. The Kappa statistic displays very good agreement for India, followed by Brazil. While China and Russia show moderate agreement levels, South Africa shows the least agreement between observed and expected accuracy. The MAE and the RMSE indicate the average magnitude of errors. India and Brazil show the better performance, followed by China and Russia. India, Brazil, and Russia demonstrate very high TP Rate and FP Rate, while China also shows good rates. However, South Africa shows the lowestperformance in these metrics. In terms of Precision, Recall, and F-Measure metrics, the performance rankings from highest to lowest are as follows: India, Brazil, China, Russia, and South Africa. Additionally, the ROC Area metric indicates strong performance across the countries. India and Brazil show the highest ROC Areas, followed by China, Russia, and South Africa.

Table 9. Classification results of Decision Stump

Metrics	BRICS Countries				
	Brazil	Russia	India	China	South Africa
CCI[a] (%)	25 (89.29)	24 (80.00)	26 (92.86)	23 (82.14)	21 (75.00)
ICI[b] (%)	3 (10.71)	6 (20.00)	2 (7.14)	5 (17.86)	7 (25.00)
Kappa statistic	0.7835	0.6000	0.8549	0.6196	0.4731
MAE[c]	0.1934	0.3541	0.2317	0.2980	0.2555
RMSE[d]	0.3033	0.3885	0.2952	0.3671	0.4815
TP[e] Rate (P[f]-N[g])	0.917-0.875	0.800-0.800	1.000-0.846	0.727-0.882	0.875-0.583
FP[h] Rate (P[f]-N[g])	0.125-0.083	0.200-0.200	0.154-0.000	0.118-0.273	0.417-0.125
Precision (P[f]-N[g])	0.846-0.933	0.800-0.800	0.882-1.000	0.800-0.833	0.737-0.778
Recall (P[f]-N[g])	0.917-0.875	0.800-0.800	1.000-0.846	0.727-0.882	0.875-0.583
F-Measure (P[f]-N[g])	0.880-0.903	0.800-0.800	0.938-0.917	0.376-0.857	0.800-0.667
ROC Area (P[e]-N[f])	0.914-0.887	0.750-0.903	0.953-0.880	0.821-0.882	0.827-0.629

[a]CCI:Correctly classified instances, [b]ICI: Incorrectly classified instances, [c] MAE: Mean absolute error, [d]RMSE: Root mean squared error, [e]TP: True positive, [h]FP: False positive: increase in SPV, [g]N: decrease in SPV

Based on the performance metrics of BRICS countries obtained by J48 as shown in Table 9, this classification technique demonstrated impressive performance compared to the previous classification techniques. According to the outputs of J48, the key indicators affecting SPV vary for the countries. In Brazil, Financial system deposits to GDP percent (X10), Gross portfolio debt liabilities to GDP percent (X12), and Non-life insurance premium volume to GDP percent (X17) are influential. For Russia, Gross portfolio debt liabilities to GDP percent (X12), Pension fund assets to GDP percent (X19), and Stock market turnover ratio percent (X27) play significant roles. For India, Gross portfolio equity liabilities to GDP percent (X13) and Non-life insurance premium volume to GDP percent (X17) are influential. The SPV of China is impacted by External loans and deposits of reporting banks vis a vis the nonbanking sectors' percent of domestic bank deposits (X9) and Mutual fund assets to GDP percent (X16). Lastly, the Nominal Effective Exchange Rate (X4), Liquid liabilities to GDP percent (X15), Provisions to nonperforming loans percent (X22), and Stock market capitalization to GDP percent (X24) influence the SPV of South Africa.

4.8 Random Tree

Random Tree (RT) is the eighth classification technique employed in this study. RT uses the full training data for evaluation. Table 10 displays the classification results of RT for BRICS countries.

According to the classification results in Table 10, Brazil, Russia, China, and South Africa achieve perfect percentages of CCI, indicating perfect accuracy. Conversely, India shows a lower percentage of 71.4%, with 8 instances incorrectly classified. The Kappa statistics show perfect agreement between observed and expected accuracy for all BRICS countries, except India. India shows fair agreement. The MAE and the RMSE metrics are very low for South Africa, Brazil, Russia, and China. This indicates that they have an approximately perfect performance. However, these metrics are higher for India. Similarly, TP Rate and FP Rate show perfect true positive rates and no false positive rates for all countries except India. Precision, Recall, and F-Measure metrics indicate a strong balance between precision and recall for most countries, whereas India demonstrates low values. ROC Area values are excellent for all countries except India.

Based on the results in Table 10, the RT appears to be a powerful classifier for the SPV of BRICS countries compared with the previous classification techniques. The outputs from the RT show significant indicators affecting the SPV of BRICS countries. In Brazil, the indicators such as Exports Merchandise Customs current US dollars millions not seasonally adjusted (X1), GDP at market prices current US dollars millions of seasonally adjusted (X2), Nominal Effective Exchange Rate (X4), Total Reserves (X5), Central bank assets to GDP percent (X8), External loans and deposits of reporting banks a vis the nonbanking sectors percent of domestic bank deposits (X9) and Stock market turnover ratio percent (X27) demonstrate influence. Similarly, in Russia, the influential indicators include Exports Merchandise Customs current US dollars millions, not seas adj (X1), GDP at market prices current US dollars millions of seasonally adjusted (X2), Nominal Effective Exchange Rate (X4), Total Reserves (X5), Real Effective Exchange Rate (X6) and Private credit by deposit money banks and other financial institutions to GDP percent (X20). For China, the indicators affecting SPV are Exports Merchandise Customs current US dollars millions not seas adj (X1), Imports Merchandise Customs current Us dollars millions not seasonally adjusted (X3), Central bank assets to GDP percent (X8), Financial system deposits to GDP percent (X10), Liquid liabilities to GDP percent (X15) and Stock market return percent year on year (X25). In the case of India, Non-life insurance premium volume to GDP percent (X17) influences SPV, while for South Africa, the influential indicators are Liquid liabilities to GDP percent (X15), Remittance inflows to GDP percent (X23), and Stock market total value traded to GDP percent (X26).

Table 10. Classification results of Random Tree

Metrics	BRICS countries				
	Brazil	Russia	India	China	South Africa
CCI[a] (%)	28 (100.00)	30 (100.00)	20 (71.40)	28 (100.00)	28 (100.00)
ICI[b] (%)	0 (0.00)	0 (0.00)	8 (28.57)	0 (0.00)	0 (0.00)
Kappa statistic	1.0000	1.0000	0.4074	1.0000	1.0000
MAE[c]	0.0251	0.0434	0.4071	0.2036	0.0000
RMSE[d]	0.0768	0.1104	0.4463	0.2202	0.0000
TP[e] Rate (P[f]-N[g])	1.000-1.000	1.000-1.000	0.462-0.933	1.000-1.000	1.000-1.000
FP[h] Rate (P[f]-N[g])	0.000-0.000	0.000-0.000	0.067-0.538	0.000-0.000	0.000-0.000
Precision (P[f]-N[g])	1.000-1.000	1.000-1.000	0.857-0.667	1.000-1.000	1.000-1.000
Recall (P[f]-N[g])	1.000-1.000	1.000-1.000	0.462-0.933	1.000-1.000	1.000-1.000
F-Measure (P[f]-N[g])	1.000-1.000	1.000-1.000	0.600-0.778	1.000-1.000	1.000-1.000
ROC Area (P[e]-N[f])	1.000-0.998	1.000-1.000	0.580-0.804	1.000-1.000	1.000-1.000

[a]CCI:Correctly classified instances, [b]ICI: Incorrectly classified instances, [c] MAE: Mean absolute error, [d]RMSE: Root mean squared error, [e]TP: True positive, [h]FP: False positive: increase in SPV, [g]N: decrease in SPV

4.9 Comparison

Kappa statistics, accuracy, and RMSE are used to compare the classification techniques. To identify an effective classification technique for BRICS countries, these metrics serve as the basis for comparison.

Table 11. Comparison of classification techniques

2000-2021 data				
Country	Technique	Accuracy[a] (%)	Kappa statistic	RMSE[b]
Brazil	NB	67.86%	0.2759	0.5131
	SL	85.71%	0.7021	0.3254
	MB	78.57%	0.5435	0.4000
	CVR	75.00%	0.4615	0.4157
	DT	60.71%	0.4852	0.4921
	DS	75.00%	0.4615	0.4250
	J48	89.29%	0.7835	0.3033
	RT	100.00%	1.0000	0.0251
Russia	NB	80.00%	0.6000	0.4015
	SL	93.99%	0.8667	0.3286
	MB	83.33%	0.6667	0.4092
	CVR	80.00%	0.6000	0.4262
	DT	80.00%	0.6000	0.3913
	DS	80.00%	0.6000	0.3856
	J48	80.00%	0.6000	0.3885
	RT	100.00%	1.0000	0.1104
India	NB	89.28%	0.7813	0.2731
	SL	78.57%	0.5602	0.3414
	MB	85.71%	0.7098	0.3659
	CVR	85.71%	0.7068	0.3970
	DT	71.43%	0.4011	0.4472
	DS	75.00%	0.4787	0.4046
	J48	96.86%	0.8549	0.2952
	RT	71.40%	0.4074	0.4461
China	NB	75.00%	0.4302	0.4542
	SL	67.86%	0.2921	0.4533
	MB	78.57%	0.5359	0.4000
	CVR	71.43%	0.3600	0.4169
	DT	75.00%	0.5149	0.3697
	DS	75.00%	0.5000	0.4137
	J48	82.14%	0.6196	0.3671
	RT	100.00%	1.0000	0.2202
South Africa	NB	85.71%	0.7083	0.3702
	SL	96.43%	0.9278	0.2129
	MB	92.86%	0.8511	0.3375
	CVR	85.71%	0.6957	0.3154
	DT	78.57%	0.5333	0.4013
	DS	78.57%	0.5333	0.3948
	J48	75.00%	0.4731	0.4815
	RT	100.00%	1.0000	0.0000

[b]*RMSE: Root mean squared error,*

Table 11 shows an overview of these evaluation metrics. The top-performing and the second-best performing classification techniques were highlighted in blue and orange, respectively. When accuracy exceeds 80%, the classification technique demonstrates strong data classification. Approaching or achieving 100% accuracy indicates nearly perfect classification. Similarly, A Kappa statistic nearing 1 displays strong agreement between observed and expected classification results. The RMSE measures the average deviation of predicted values from actual values in classification, and a low value is expected for optimal classifier performance. Based on the evaluation criteria, for Brazil, RT shows the perfect accuracy, then J48 follows it with the accuracy of 89.29%. SL also performs well, achieving 85.71% accuracy. In Russia, RT demonstrates perfect performance with 100% accuracy, followed by SL with 93.99% accuracy. For India, J48 leads with a high accuracy of 96.86%, followed by NB with an accuracy of 89.28%. In the case of China, RT achieves perfect accuracy, while J48 follows with 82.14% accuracy.

Lastly, for South Africa, RT demonstrates the perfect accuracy and SL follows RT with 96.43% accuracy. The results indicate varying effectiveness of classification techniques across countries. While RT achieves perfect classification for Brazil, Russia, China, and South Africa, J48 performs best for India with an accuracy of 96.86%. There is no common classification technique, therefore hypothesis H2: “A common classification technique effectively classifies the data of BRICS countries.” is rejected.

5 Conclusion

The results of eight classification techniques reveal that there is no common classification technique categorizing the SPVs of BRICS countries. Among these techniques, RT provided promising results and perfectly categorized the SPV of BRICS countries except India which was effectively classified by J48. When ranking the classifiers based on their performance from high to low, the order is RT, J48, SL, MB, and CVR. This variability can be attributed to the diverse economic, social, and political structures of the countries. For instance, Brazil has been dealing with high inflation, political fluctuations, and slow industrialization. The ongoing war between Russia and Ukraine led Russia to be the most sanctioned country in the world, which is impacting its economy, GDP growth, and stock market. Meanwhile, South Africa faces challenges, such as high inflation, unemployment, reduced trade and fluctuation in financial flows, and increasing public expenditure, [51].

By analyzing the outcomes of the top three effective classification techniques, RT, J48, and SL, the pivotal indicators significantly impacting the SPVs of BRICS countries were identified. While no common indicator was identified, “Exports Merchandise Customs current US dollars millions not seasonally adjusted” (X1) is prominent for Brazil, Russia, and China based on the outputs of RT. Additionally, “GDP at market prices current US dollars millions seasonally adjusted” (X2) has an impact on the SPVs of Brazil and Russia, while “Central bank assets to GDP percent” (X8) is common to the SPV of Brazil and China. “Liquid liabilities to GDP percent” (X15) and “Stock market return percent, year on year” (X25) are common indicators for China and South Africa. In addition to the commonly shared indicators, several others play significant roles in individual countries' SPV.

In Brazil, key indicators include “External loans and deposits of reporting banks vis a vis the nonbanking sectors percent of domestic bank deposits" (X9) and "Stock market turnover ratio percent" (X27). Russia's key indicators include "Nominal Effective Exchange Rate" (X4), "Real Effective Exchange Rate" (X6) and "Private credit by deposit money banks and other financial institutions to GDP percent" (X20). For China, the important indicators are "Imports Merchandise Customs current US dollars millions not seasonally adjusted" (X3) and "Financial system deposits to GDP percent" (X10). Lastly, for South Africa, the key indicators are "Remittance inflows to GDP percent" (X23) and "Stock market total value traded to GDP percent" (X26). The J48 revealed fewer common indicators influencing the SPV compared to the RT. "Gross portfolio debt liabilities to GDP percent" (X12) is common for Brazil and Russia, while "Non-life insurance premium volume to GDP percent" (X17) is common for Brazil and India. The remaining influential indices vary for each country. For India, "Non-life insurance premium volume to GDP percent" (X17) is consistent with both RT and J48 results. Regarding the outputs of the SL, "Bank capital to total assets percent" (X7) is a shared indicator for all countries except China.

Trade, import, and export play important roles in the economies of BRICS countries. Brazil and Russia are net oil exporters, while China, South Africa, and India are net oil importers. Fluctuations in oil prices significantly affect the economic balance and currency. The classification outcomes from RT indicate that nominal and real exchange rates have an impact on Brazil's and Russia's SPV which contributes to the literature [14], [51], [52], [53].

This paper has several limitations. Firstly, due to the unavailability of daily, monthly, or quarterly data for some countries, annual data were used for analysis. Secondly, missing values were observed in the datasets from 1994 to 2022. To address this issue annual data from 2000 to 2021 were used for analysis. To maintain the integrity of the original data during the analysis process, random variables or means were not assigned to the missing values.

Although there is no standardized technique for classifying the SPV data of BRICS countries and no common indicators have been identified, the findings will assist investors and policymakers in understanding market conditions, especially during periods of fluctuation, and managing stock market dynamics.

5.1 Future Research and Recommendations

The inclusion of new five members, Egypt, Ethiopia, Iran, Saudi Arabia, and the United Arab Emirates (UAE), effective from January 1st, 2024, BRICS countries are likely to attract many scholars' attention in the future. According to 2022 World Bank Data, with this extension, the new population of BRICS countries became 45.50% of the world population and their land area represents 32.61% of the world's land area. In the "Situation Report", it was stated that BRICS countries with the new members represent 28.1% of the global economy and the expanded group holds more than 43% of global oil production, [7].

Future research could enhance comparisons by including additional indicators, such as oil prices, trade volatility, and unemployment. Utilizing the high frequency data is strongly recommended for further studies. Replicating this study with an expanded set of BRICS countries could provide valuable insights. Additionally, alternative methods such as ARCH/ GARCH models, multiple regression, and structural analysis could be employed and their results could be compared.

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