Sentiment Analysis and Market Forecasting for BRICS Policies Using Machine Learning and LLM Model

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Abstract

The global financial markets are highly susceptible to economic and political policy changes, particularly those taken by the BRICS member nations (Brazil, Russia, India, China, and South Africa). With such a powerful economic bloc, policy changes by BRICS can have potential impacts on world stock indices and major industrial sectors. There is no comprehensive method of evaluating these impacts in a timely manner currently. This study aims to examine the impact of policies implemented by BRICS on world stock markets through the combination of Sentiment Analysis and Time Series Forecasting methods. By using Large Language Models (LLM) in combination with various machine learning algorithms, this research will determine the alignment of investor sentiment related to BRICS policies with the dynamics seen in stock market volatility. Moreover, this research seeks to determine the most impacted industries and offer key empirical insights for policymakers and investors. With an artificial intelligence-based approach, the study seeks to enhance knowledge on the impact of BRICS policies on the behavior of the world financial markets.

Keywords : Machine Learning, BRICS, Market, LLM

1 Introduction

Sentiment analysis and its application in the stock market context have been a topic of significant research since the early 2010s. Advances in technology have caused a shift from conventional machine learning approaches to deep learning models and multimodal analysis that leverage heterogeneous data sources. Over the past decades, the rapid development of internet-based media channels, such as social media and news websites, has facilitated an unprecedented and comprehensive exploration of global public opinion, policymaking, and stock market movements. On these sites, investors, analysts, and stakeholders repeatedly voice their opinions and reactions to economic policy, creating a real-time flow of information that can be harvested and analyzed systematically with the help of sentiment analysis tools. Recent progress in machine learning (ML) and deep learning (DL) technologies has further boosted the performance of sentiment analysis systems. While conventional models like Naïve Bayes, Support Vector Machines (SVM), and Random Forest exhibit certain efficiencies in terms of carrying out sentiment classification tasks, they fail to capture the intricate linguistic patterns and contextual implications that prevail. Deep learning models, however, like Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and Transformer-based models (e.g., BERT, GPT-3, FinBERT), have been very successful at recognizing intricate patterns and contextual relationships in text data. These models are particularly well-adapted to analyzing social media posts and news headlines, which are often characterized by ambiguity, irony, and a high degree of emotional expressions..

2 Level of Analysis

The Sentiment Analysis's main aim is to evaluate textual information and establish its polarity, which exists in the form of positive, negative, or neutral. From the start of this century, Sentiment Analysis has grown tremendously. Various approaches have been suggested, from word preprocessing and embedding methods to sophisticated big data models that have been created, experimented on, and suggested. Several methods are present under the umbrella of sentiment analysis, ranging from traditional machine learning techniques to deep learning frameworks, lexicon-based methods, and ensemble models. Apart from this, a concise overview of the challenges associated with sentiment analysis, along with solutions, is also presented.(Maada et al., 2022)

Sentiment analysis, which is also referred to as opinion mining or emotional artificial intelligence, is a collection of analytical methods aimed at extracting and determining information like sentiments, opinions, and attitudes present in textual data. It employs techniques on loan from the fields of natural language processing, text analysis, and computational linguistics. Results from this analysis can be utilized as a means for gauging customer satisfaction with a product, in addition to forecasting specific behavior, including the results of an election.(Maada et al., 2022)

3 Sentiment Analysis Method

In this section, we will discuss several methods that will be used for the sentiment analysis process. The methods that will be applied consist of two categories, namely machine learning and deep learning.

3.1 Machine Learning Approach

Various machine learning algorithms have been used for sentiment analysis, each with its pros and cons:

a. Naive Bayes is a probabilistic classification method founded on Bayes' theorem, which demonstrates strong performance in text classification because of its efficiency and simplicity.

b. Support Vector Machines is a supervised learning framework that seeks the optimal hyperplane to separate classes in a feature space with resilience to high-dimensional spaces.

c. Random Forest: This is an ensemble learning methodology where many decision trees are created, and their results are combined to improve the performance of classification tasks while reducing the danger of overfitting.

d. Neural Networks: Neural models take their inspiration from the functioning of the human brain; thus, neural networks have the ability to learn extremely complicated patterns within data. Derivatives of deep learning, like Convolutional Neural Networks and Long Short-Term Memory networks, have been found quite suitable for sentiment analysis tasks.

A comparative study by (Kolchyna et al., 2015) demonstrated the superiority of machine learning methods, especially SVM and Naive Bayes classifiers over lexicon-based approaches when performing sentiment classification tasks.

3.2 Deep Learning

Deep learning employs a hierarchical representation with regard to the hidden layers of a neural network. Traditional machine learning approaches, however, involve the manual extraction and specification of features or employ feature selection techniques. Deep learning architectures, nevertheless, facilitate automatic learning and feature extraction, thereby enhancing accuracy and performance. The classifier model's hyper-parameters are also automatically assessed in most cases.(Dang et al., 2020)

3.2.1 LLM

Conventional methods have employed Convolutional Neural Networks (CNN) for spatiotemporal feature extraction and Long Short-Term Memory (LSTM) Networks for identifying temporal dependencies with minimal incorporation of external text-based data. Large Language Models (LLM) are precisely meant to glean deep insights from unstructured text-based data, enriching the numerical data derived from spatiotemporal analysis by incorporating the relevant contextual and sentiment analysis. For example, LLM can be used to extract the sentiment of financial news releases to determine market mood and how it might influence share prices. The combination of spatial, temporal, and text data enables a more complete view of market action, so investors can make more informed decisions.(Chakraborty & Basu, n.d.)

3.2.2 LTSM

Large Time Series Models (LTSMs) that are based on universal transformers and use an autoregressive prediction approach are expressly designed to improve Time Series Forecasting Models (TSFs). Training LTSMs on heterogeneous time series data presents unique challenges, including differences in frequency, dimensionality, and the varied patterns presented across the dataset. Recent studies have concentrated on evaluating a variety of design options aimed at improving both the training efficiency and generalization of LTSMs. (Chuang et al., 2024)

3.2.3 FinBERT & BERT

BERT (Bidirectional Encoder Representations from Transformers) is a pre-trained BERT based on a bidirectional Transformer model trained on a large corpus of text with masked language modeling and next sentence prediction tasks to learn word relationships in context. BERT in this study is used to understand complex linguistic patterns in policy reports and financial reports of BRICS nations. FinBERT, the finance domain BERT, is trained using a financial corpus and therefore most appropriate for financial sentiment analysis. Such models are most appropriate in financial reports and policy documents analysis since they are able to capture complex linguistic patterns and vocabulary and therefore best capture sentiment and recognize key market-driving information.

Leverage the contextual understanding of BERT and financial domain understanding of FinBERT, this study tries to advance knowledge of policy sentiment's impact on BRICS financial markets.

Formula (Transformer Architecture):

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V(a)$$

Where:
Q = Query matrix
K = Key matrix
V = Value matrix
d_k = Dimensionality of keys

3.2.4 CNN & LSTM Hybrid Methods

The integration of Convolutional Neural Networks (CNNs) and Long Short-Term Memory Networks (LSTMs) enables us to extract local features through CNNs and recognize long-term dependencies through LSTMs. Such a joint method is suitable for sentiment analysis on social media text, for which syntactic structures along with sequential patterns matter.
Formulas:
CNN Layer Output:

$$h_i = f(W \cdot x_{i:i+k-1} + b) \qquad (b)$$

Convolutional Neural Network (CNN) Formula
Explanation:

h_i: The output feature after applying the convolution operation (Feature Map).

W: The weight matrix of the convolution kernel (or filter).

$x_{i:i+k-1}$: A sliding window of the input data. In text processing, this might be a sequence of consecutive words or characters.

k: The size of the convolution kernel, i.e., the length of the input segment being processed each time.

b: Bias term, which is often used to enhance the flexibility of the model.

f: Activation function such as ReLU, tanh, or sigmoid, used to introduce non-linearity.

LSTM Cell Formulas

Long Short-Term Memory (LSTM) is a type of Recurrent Neural Network (RNN) architecture designed to effectively capture long-term dependencies.

LSTM Cell:

$$h_t = o_t \times tanh(c_t) \qquad (c)$$

h_t: The hidden state at the current time step, representing the memory content of the current input.

o_t: The output gate value, controlling how much of the cell state c_t should be exposed to the next layer.

$tanh(c_t)$: Non-linear transformation of the cell state c_t with a range of [-1, 1].

In Table 2, will present a comparison of various sentiment analysis methods along with the advantages and disadvantages of each method.(Mao et al., 2024)

Table 2. Comparison of Sentiment Analysis Methods

Technique	Advantages	Disadvantages
SVM	• The most well-known Sentiment Analysis algorithms • have the ability to achieve good levels of accuracy when applied to large data sets.	• Model tuning is time consuming and challenging. • Long training processes are required to manage large datasets.
Naïve Bayes	• Easy implementation. • The amount of training data required is relatively less.	• Assuming that the features are independent • a zero-frequency problem may arise.

	• Both data and time required for training are less when compared to other methods.	• This is limited by the imbalance in the data categories.
KNN	• Non-linear decision boundaries can be formulated. • Without explicit training, data can be added over time.	• More datasets and dimensions will result in more complex predictions. • In addition, all features are given equal weight.
LTSM	• Superior compared to RNN. • Capable of capturing long-term dependencies.	• Very complex model. • Long training duration.

4 Related Work

In recent times, many researchers have conducted research on sentiment analysis of public reactions by utilizing machine learning technology. This study compares various machine learning techniques, including Naïve Bayes, Support Vector Machine (SVM), and Random Forest, in the context of sentiment analysis. The results show that the Random Forest method has the highest accuracy rate in analyzing product review datasets. However, the main drawback of this method lies in its limitations in handling complex sentence contexts. (Wawer & Chudziak, 2025)

Deep learning approaches, such as Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and transformer-based models, including Bidirectional Encoder Representations from Transformers (BERT), are used in sentiment analysis. The main findings of this study indicate that transformer-based models have shown the best performance; however, they require higher computational power compared to conventional models.(Mo et al., 2025)

The use of Large Language Models (LLM) such as GPT-3 and BERT for sentiment analysis has shown advantages in capturing context. However, these models still face challenges in identifying explicit irony or sarcasm.(Kocaman et al., 2025)

The performance of BERT and LSTM models in sentiment analysis on the Twitter dataset shows significant results. Based on the experimental results, BERT shows a higher level of accuracy compared to LSTM in understanding the complexity of natural language.(Xx et al., n.d.)

For more detailed information, please refer to Table 1 which shows related work that has been done, which uses sentiment analysis on public reactions with the application of machine learning.

Table 2. Related Work Sentiment Analysis with Machine Learning

Topic	**Mechanism**	**Strength**	**Limitation**	**Prospective Scenario**	**Ref**

Sentiment Analysis Using ML Technique	NB, SVM, RF	High accuracy with RF	Poor handling of complex contexts	Using transformer models like BERT for better context understanding	(Wawer & Chudziak, 2025)
Deep Learning for Sentiment Analysis : A Survey	CNN, LSTM, BERT	High performance with BERT	Requires high computing	Optimizing models with parameter pruning and quantization	(Mo et al., 2025)
Hybrid Approach for Sentiment Analysis	ML + DL	Improved accuracy	Need complex tuning	Using autoML or hyperparameter optimization	(Haldar et al., 2025)
Leveraging Pre-trained LLMs for Sentiment Analysis	GPT-3, BERT	Capture context better	Difficulty in sarcasm	Using a custom dataset to detect sarcasm and irony	(Kocaman et al., 2025)
Sentiment Analysis on Twitter Data	BERT, LSTM	BERT is more accurate	LSTM loses in understanding complex languages	Using an ensemble model between BERT and LSTM	(Lu et al., 2025)
ML vs Transformer Based Models	SVM, RF, BERT	Transformers excel in syntax and semantics	SVM is efficient for small data	Applying distillation model to make transformer lighter	(Chen et al., 2022)
Multimodal Sentiment Analysis	CNN, BERT	The combination of text and images is more accurate	It takes a lot of data and computing	Using transfer learning techniques for multimodal learning	(Zaslavsky et al., 2025)
Aspect-Based Sentiment Analysis	LSTM, Transformer	More specific in aspects	Difficult to handle synonyms	Leveraging lexical-based embedding to better capture synonyms	(Amin et al., 2025)
Real-time Sentiment Analysis	ML, LLMs	Efficient for fast processing	Latency on large datasets	Using stream processing or edge computing techniques	(Lippi & Plebani, 2025)
Fine-tuning LLMs for Sentiment Analysis	GPT-3, BERT	Improve accuracy	Requires a lot of data	Using few-shot learning or zero-shot learning	(Kritika, n.d.)
Financial Sentiment Analysis	Transformer	Effective for financial texts	Difficult to handle jargon	Adding domain-specific embedding for the financial sector	(Schlund et al., n.d.; Zuo et al., 2025)
Cross-Domain	Transfer Learning	Better generalization	Need a lot of data	Using domain adaptation	(Haque et al., 2022)

Sentiment Analysis				techniques such as adversarial learning	
Low-Resources Sentiment Analysis with LLMs	LLMs	Can be used for rare languages	Adaptation is still needed	Using multilingual transformers and transfer learning	(Xx et al., n.d.)
Emotion-Based Sentiment Analysis	CNN, LSTM	Detecting emotions better	Ambiguity in emotions	Added prosody (voice intonation) analysis to improve accuracy	(Daniel et al., 2025)
Few-Shot Learning in LLMs for Sentiment Analysis	Few-shot LLM	Can work with little data	Less stable on varying data	Using meta-learning to improve stability	(Daniel et al., 2025)

In Table 2, which relates to previous research, and by considering the advantages and disadvantages of each study, it can be concluded that the development of sentiment analysis based on public reactions can be carried out by applying machine learning and deep learning techniques based on Large Language Models (LLM). Here are some reasons underlying this conclusion:

a. LLM Model Optimization: Pruning and quantization techniques can be used to optimize and make LLM models efficient.

b. Better Contextualization: These models can be improved using multiple datasets that deal with sarcasm, irony, and figurative language.

c. Multimodal Sentiment Analysis: Integration of text, audio, and visual inputs for sentiment analysis can improve accuracy, especially in video reviews or visually oriented social media.

d. Cross-Domain Adaptation: These models are able to process datasets from different domains more effectively without requiring a large amount of additional data through the use of transfer learning and domain adaptation.

e. Real-Time Sentiment Analysis: With the help of stream processing, edge computing, and distributed architecture, sentiment analysis can be performed in real-time with low latency.

b) Conclusion

Against the background of the changing digital age, sentiment analysis of BRICS policies has ever more become crucial in appreciating public opinion and its influence on global geopolitical and economic relations. In this paper, researchers talk about how machine learning-based approaches and large language models (LLMs) can be used to maximize both accuracy and efficiency in mining public opinion data on BRICS policies. Through the employment of Natural Language Processing (NLP) methods, the models are capable of automatically detecting patterns of sentiment, thereby facilitating the understanding of the public attitude regarding policies adopted by BRICS nations.

The application of this sentiment analysis system is of high potential in assisting policymakers in making more fact-based decisions.

By integrating machine learning techniques and large language models, this system is able to speed up the analysis of sentiments from diverse digital sources, such as social media and news outlets.

Moreover, this research offers guidelines for future studies on enhancing the model's interpretability, thereby enabling the analytical findings to be more transparent and helpful to all parties involved.

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