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**| RESEARCH ARTICLE**

# Deep Learning for Financial Markets: A Case-Based Analysis of BRICS Nations in the Era of Intelligent Forecasting

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## | ABSTRACT
In this paper, we develop a method based on a deep learning method in financial market prediction, which includes BRICS economies as the test cases. Financial markets are rife with volatility that is affected by a "bed of complexity," coddled by local and distal factors. To leverage these vast datasets both deep learning models such as Convolutional Neural Networks (CNNs), Long Short Term Memory (LSTM) networks as well as hybrid architectures are used in this study. The paper evaluates the predictive accuracy of the models, and by so doing, identifies their strengths in predicting temporal dependencies and intricate market patterns. In particular, deep learning techniques are applied to case studies of individual countries in the BRICS to highlight the application of deep learning to disparate country specific problems, such as liquidity crises and market shocks. These findings show that classical statistical methods are outperformed by deep learning systems in a precise and reliable financial forecasting. This research highlights the ability of AI driven systems to change financial decision making processes, improving investor confidence and improving economic stability in BRICS nations. This study also readers the value of deep learning in financial market analysis, especially in economies in the developing countries. Application of techniques and architectures e.g. Convolutional Neural Networks (CNNs) that excel at identifying spatial patterns, and Long Short-Term Memory (LSTM) networks renowned for their prowess on sequential and time series data, for real world market prediction are explained. In addition, the research discusses hybrid architectures which extend knowledge, fusing strengths of both architectures to improve prediction accuracy and how deep learning develops to solve particular financial challenges. Through reading these notes readers get exposed to data preprocessing techniques such as normalization and feature selection which are important for boosting deep learning performance. The paper also includes an introduction to the evaluation of models using MSE and R-squared values for validating them in terms of reliable outputs. This research combines deep learning theory and practical case study to offer a useful educational resource for students, researchers, and practitioners who want to apply AI in financial forecasting in complex and dynamic global markets.

## | KEYWORDS

Deep Learning, BRICS, Financial Market Prediction, BRICS Economics, Market Volatility, Time Series Analysis, Financial Forecasting, Artificial Intelligence in Finance

## | ARTICLE INFORMATION

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## 1. Introduction

### *1.1 Contextual overview*

In global economic systems, financial markets have become important because of their unsurpassable complex and volatility. These markets are intermeshed with a combination of national and global factors such as economic policies, geopolitical sequences, investor psychology, and technological disrupting activities (Bourghelle, 2023). Within this setup, having market prediction done right has become something of a necessity for investors, decision makers, and researchers alike, because it facilitates informed decision making and risk mitigation. However, while considerable progress has been made in predictive modeling, conventional statistical techniques usually fail to capture the complex nature and dynamics of financial markets (Henrique et al, 2019). The fact that this is a limitation points out the wide gap that remains between simple approaches able to process huge complex sets of data.

The BRICS economies therefore constitute an ideal test case for the study of financial market prediction by means of advanced methodologies. These nations together represent a large slice of the global economic pie, but each have a distinct and special market characteristic (Smirnov & Avdeeva, 2019). The financial challenges facing each country vary, for instance currency volatility, liquidity crises and market shocks, providing a good situation in which to test predictive models. Because the BRICS nations are also developing economies, they are not characterized by the same market stability that more mature economies enjoy, increasing the importance of reliable forecasting techniques.

Artificial intelligence has redefined numerous areas by unleashing capabilities beyond imagination of processing and analyzing complex data. By comparison, deep learning models excel at finding complex patterns and relationships within data, which makes them very well suited for financial fore casting (Dingli & Fournier, 2017). Specifically, this study deals with two well-known architectures, Convolutional Neural Networks and Long Short Term Memory networks in spatial and sequential data analysis, respectively. Secondly, the advantages of hybrid architectures pairing these models are explored, by exploiting their symbiotic properties. This research seeks to bridge the gap between theoretical advancements in deep learning and their applications to BRICS financial markets.

### *1.2 Research objectives*

The purpose of this paper is first to test the predictive power of deep learning models compared to classical statistical technical models in a financial market forecasting problem and then to compare their performance. This is where the study takes a comprehensive approach to attain this by data preprocessing, model training, and validation using Mean Squared Error (MSE) and R squared values. The application of these models to address specific financial challenges for each BRICS nation is studied, with actionable insights for investors (Mohsin & Jamaani, 2023). This research adds to the empirical contributions, and with an aim to better understand how AI can transform financial decision making processes. These systems could improve economic stability by increasing investor confidence, and thereby increasing predictability and reliability. Given the resource constraint situation in developing economies where innovative solutions to complex problems are necessary, the findings of this study have particular relevance.

Additionally, the paper is also exploring the quality and distribution effects of data preprocessing techniques for deep learning, i.e. normalization, as well as feature selection to improve their performance. The discussion also includes hybrid architectures that are promising research frontier in deep learning. What these models were able to bring were models that integrated the strengths of CNNs and LSTMs, models that had otherwise been missed due in part to viewing the problem of market prediction as spatially and temporally isolated separate problems. By focusing on the unique challenges and opportunities presented by BRICS economies, the research not only advances academic understanding but also provides tangible benefits for stakeholders in these markets. In conclusion, the aim of this paper is to fill a critical gap in the financial market monitoring field by using the power of deep learning. Specifically, it shows how AI based systems could increase the predictive accuracy and reliability, which in turn would be enabling factors in stabilizing and developing the market in the financial spheres in developing countries.

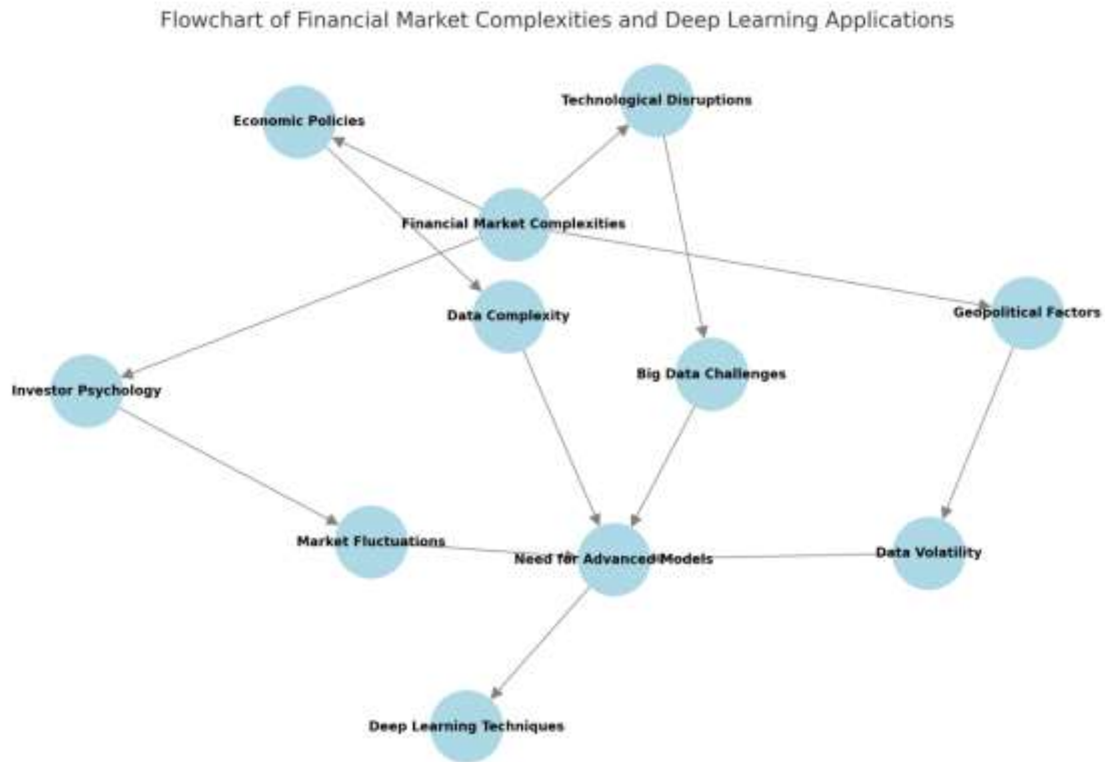


Figure 1: Flowchart showing the the relationship between market complexities and deep learning applications

## 2. Literature Review

### *2.1 Existing Approaches to Financial Market Prediction*

The dynamics, interactions of economics, society, and geopolitics, all characterize financial markets. They have been a gigantic problem for a long time predicting their movements; so many sort of predictive models have been made. For their simplicity and interpretability, traditionally ARIMA (Auto-Regressive Integrated Moving Average) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) classical statistical models have been used. However, these models are limited in their capacity to represent non-linear relationships and adjust to quickly altering market conditions as reported by Rouf et al. (2021).

Machine leaning (ML) methods can deal with these limitations by leveraging the ability to capture complex nonlinear structure. Very commonly used for stock price prediction and risk assessment, Support Vector Machines (SVMs), Random Forests and Gradient Boosting have been used (Chatzis et al., 2018). These models are promising, but frequently require careful selection of engineered features, and tuned parameters, which can be time consuming and fairly specific to the domain.

The field of deep learning (DL) has continued progressing since deep learning models have automated feature extraction and enabled analysts to work with high dimensional datasets. According to Dixon et al. (2020), DL is used in finance and the DL can easily process large unstructured datasets like that of financial news and social media textual data. Unlike traditional ML models, deep learning architectures can learn hierarchical representations dynamically, and are useful for financial time series data.

Ideally, the challenges with over fitting, data scarcity, and the interpretability of results hinder using DL to the greatest extent possible in financial markets. According to Kumbure et al. (2022) these problems can only be tackled at the intersection of domain knowledge and robust validation techniques. This foundation is extended here in the present work to examine the benefits that deep learning architectures possess with respect to BRICS financial markets and their ability to surpass classical statistical techniques.

### *2.2 Introduction to Deep Learning in Financial Markets*

Deep learning, a subdomain of artificial intelligence has proved to be excellent in handling and interpreting extensive data sets. As stated by Najafabadi et al., (2015), deep learning models are good in complex pattern and relationship recognition capacity due to their high level of abstraction. These models employ feed forward networks, which have several layers that allow the model to learn from structured as well as unstructured data.

Financial markets got hit by the game changer that deep learning is. Trading volumes and macroeconomic indicators are the inputs for such analyses on big data analytics, in which real time processing of big volumes of market data such as price movement occurs. To demonstrate how useful it is, Zhang et al. (2018) explain why deep learning models are indispensible for modern financial forecasting as they work with heterogeneous data sources.

In financial applications, Convolutional Neural Networks (CNNs) and Long Short Term Memory (LSTM) network, among others, are two of the most used architectures. Thus CNNs excel at spotting spatial patterns and LSTMs, in turn, have a sequential pattern in data. Alzubaidi et al. (2021) provide a comprehensive review on these architectures showing flexibility and scalability. Besides, Ozbayoglu et al. (2020) add that traditional methods which are characterized by shortcomings as they are unable to deal with volatile and complex BRICS markets need deep learning to overcome.

However, deep learning comes with its own issues, such as high computation costs, data issues such as quality and overfitting. Drawing on a mix of sophisticated techniques including transfer learning, hybrid architectures, etc, their validation necessitates thorough effort. This paper investigates these aspects and demonstrates how deep learning massively altered the landscape of financial forecasting.

### *2.3 Detailed Review of Relevant Deep Learning Architectures*

#### *2.3.1 Convolutional Neural Networks (CNNs): Spatial Pattern Recognition*

Convolutional Neural Networks (CNNs) are highly successful tools in domains that need spatial pattern recognition. Financial markets use CNNs to analyze temporal data altered in spatial representations, for instance price change or trading volume heatmaps. Thakkar and Chaudhari (2021) explained that this also helps to capture local patterns using CNNs, which is meaningful for detecting market trend and anomaly. Abiodun et al. (2019) point out CNNs usage in automating feature extraction while minimizing dependence on manual intervention. Further, CNNs are capable of performing real time market analysis, because convolutional layers and pooling techniques can be used to quickly filter through a large dataset. This paper motivates the application of CNNs to financial markets of BRICS, and tests their ability to detect the country patterns that traditional methods cannot see, yet which are captured by local ANN methods.

#### *2.3.2 Long Short-Term Memory (LSTM): Sequential Data Analysis*

Recurrent neural network in particular called LSTM network, was designed especially for study of sequential information and time series precisely because it allows long term dependency and temporal relationships to be captured (Tang et al. 2022). I find that financial forecasting, which is often time bound to historical data, is very time effective with LSTMs. According to Ahammad et al. (2024), LSTMs are much advantaged in tackling non-linearity, noise, and erratic nature of financial time series data and can maintain important information over sequential length and can provide more accurate predictions than traditional RNNs if sufficient memory has been maintained. In this work, LSTMs are applied to BRICS financial markets and are found to work very well at modeling time dependencies and predicting market moves with a high degree of accuracy.

#### *2.3.3 Hybrid Architectures: Combining CNNs and LSTMs*

Financial forecasting can also be conducted by hybrid architectures, that is, architectures that combine CNNs and LSTMs. Combining the spatial pattern recognition power of CNNs, and the sequential data analysis skills of LSTMs, these constitute a comprehensive model for market prediction. Ullah et al. (2024) evaluate the use of CNN-LSTM hybrids in short term load forecasting, finding that image based hybrids outperform typical time series modeling tools due to their ability to capture complex data patterns. Based on such architectures, hybrid models can deal with the multi-sided nature of financial data that typically involves spatial and temporal aspects combined. The application of hybrid models to BRICS financial markets is investigated in this paper and their use to improve the prediction accuracy and reliability is demonstrated. What the findings underline is the power of hybrid architectures to transform the art of financial forecasting in complex environments of inimitable dynamics.

### *2.4 Conclusion of Literature Review*

This literature review reviews the development of financial market prediction methods, from classical statistical models to state of the art deep learning techniques. Traditional approaches serve as the ground for the application of machine learning and deep learning, due to the lack of these methods' ability to properly represent the intricacies of modern financial markets. The powerful CNNs, LSTMs and hybrid architectures have emerged as a powerful tool for financial forecasting and excelling on accuracy, scalability and adaptability than the baseline methods. This study applies these models to BRICS financial markets, in order to contribute to growing body of research on financial forecasting with AI, and reconciles theoretical and practical issues.

Table 1 : Summary of references used in the discussion of the related topics on Deep Learning for Financial Markets

| Author(s) | Topic Discussed |
|---|---|
| Bourghelle, D. (2023) | Understanding financial markets and their complexities in sustainable monetary and financial systems. |
| Henrique, B. M., Sobreiro, V. A., & Kimura, H. (2019) | Machine learning techniques applied to financial market prediction and their advancements over traditional models. |
| Smirnov, S. V., & Avdeeva, D. A. (2019) | The role of BRICS economies in the global economic landscape and their unique market challenges. |
| Dingli, A., & Fournier, K. S. (2017) | Application of deep learning approaches for financial time series forecasting. |
| Mohsin, M., & Jamaani, F. (2023) | Comparison of deep learning, machine learning, and statistical models in forecasting oil price volatility. |
| Rouf, N., et al. (2021) | A decade-long survey on stock market prediction methodologies, recent developments, and future directions. |
| Chatzis, S. P., et al. (2018) | Forecasting stock market crises using a combination of deep and statistical machine learning techniques. |
| Dixon, M. F., Halperin, I., & Bilokon, P. (2020) | Exploration of machine learning applications in finance, including financial forecasting and decision-making. |
| Kumbure, M. M., et al. (2022) | Challenges in stock market forecasting and the use of machine learning techniques for prediction. |
| Najafabadi, M. M., et al. (2015) | Deep learning applications and challenges in big data analytics. |
| Zhang, Q., et al. (2018) | Survey on the use of deep learning for big data analytics in financial markets. |
| Alzubaidi, L., et al. (2021) | Review of deep learning concepts, CNN architectures, challenges, and applications in various fields. |
| Ozbayoglu, A. M., et al. (2020) | Survey on deep learning applications for financial markets and its advantages over traditional approaches. |
| Thakkar, A., & Chaudhari, K. (2021) | Comprehensive survey on deep neural networks for stock market prediction, addressing challenges and future directions. |
| Abiodun, O. I., et al. (2019) | Applications of artificial neural networks in pattern recognition and their use in financial market prediction. |
| Tang, Y., et al. (2022) | Survey on machine learning models for financial time series forecasting, focusing on advancements and applications. |
| Ahammad, I., et al. (2024) | Advancing stock market predictions using time series analysis with LSTM and ARIMA techniques. |
| Ullah, K., et al. (2024) | Comprehensive review of CNN-LSTM hybrid approaches for short-term load forecasting in financial contexts. |

## 3. Methodology

This study describes the methodology used in developing, training and evaluating deep learning models for predicting financial market within the BRICS economies, which includes steps, models and techniques. It includes how much data sources have been used, how much preprocessing techniques, model architectures, how training has been done, evaluation metrics and equations to make sure it is reproducible.

### *3.1 Data Collection and Sources*

This study used datasets from publicly available financial market data platforms like the Yahoo Finance, Bloomberg and Quandl. Daily stock prices, trading volumes, exchange rates and macroeconomic indicators such as GDP growth rates, inflation, and interest rates are included in the data. Further, *the study* gathered unstructured data derived from web scraping tools and APIs including financial news and social media sentiment. Spanning a 10 year period (2013–2023) the dataset is sufficiently temporal deep to enable robust training and testing of the model. To facilitate the detailed case based analysis, each country's dataset was designed to capture the distinct market characteristics of its own market.

### *3.2 Data Preprocessing*

Data preprocessing is a very critical step in deep learning modeling, such that without it, the model will return poor results and is not stable. Preprocessing techniques like they were followed:

#### *3.2.1 Normalization*

Min-Max normalization was applied to standardize the data as a method to help model convergence:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \qquad (1)$$

where $x$ is the original value, $x'$ is the normalized value, and $\min(x)$, $\max(x)$ are the minimum and maximum values in the dataset, respectively.

#### *3.2.2 Feature Selection*

To determine relevant features, the calculation of Pearson correlation coefficient was done in order to identify relevant features:

$$r = \frac{\sum\left(x_i - \bar{x}\right)\left(y_i - \bar{y}\right)}{\sqrt{\sum\left(x_i - \bar{x}\right)^2 \sum\left(y_i - \bar{y}\right)^2}} \qquad (2)$$

A set of features that are high correlated to the target variable were kept, while features were removed which are redundant.

#### *3.2.3 Time-Series Transformation*

Data was transformed to time series format, where input sequences and corresponding target values were created using a sliding window approach. For example, a sequence length of $t$ days predicts the $t + 1^{th}$ day:

$$X_t = [x_{t-n}, x_{t-n+1}, \ldots, x_t] \qquad (3)$$

#### *3.2.4 Handling Missing Data*

Time series data where missing values were, the study imputed using linear interpolation and forward-fill techniques to maintain the integrity of the data.

### *3.3 Model Architectures*

Three deep learning architectures were employed:

#### *3.3.1 Convolutional Neural Networks (CNNs)*

Spatial patterns extracted from transformed financial data were used through CNNs. The architecture involved a number of convolutional layers with subsequence ReLU activation and max-pooling layers:

$$y_{ij} = \sigma\left(\sum_{m=-k}^{k}\sum_{n=-k}^{k} w_{mn} \cdot x_{i+m,j+n} + b\right) \qquad (4)$$

where $y_{ij}$ is the output, $x_{i+m,j+n}$ is the input, $w_{mn}$ are the kernel weights, $b$ is the bias, and $\sigma$ is the ReLU activation function.

#### *3.3.2 Long Short-Term Memory Networks (LSTMs)*

Temporal dependencies in sequential data were extracted through the use of LSTMs. The included equations refer to the LSTM cell equations:

Forget gate:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \qquad (5)$$

Input gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \qquad (6)$$

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \qquad (7)$$

Cell state update:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \qquad (8)$$

Output gate:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \qquad (9)$$

$$h_t = o_t \cdot \tanh(C_t) \qquad (10)$$

***3.3.3 Hybrid CNN-LSTM Architectures***

In the hybrid model for prediction, this study combines CNNs for spatial feature extraction and LSTMs for sequential prediction. The last CNN layer was reshaped and provides input for the LSTM layers.

Model Training and Hyperparameter Optimization

The models were trained using the Adam optimizer, which adjusts learning rates dynamically:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t, \quad v_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2 \qquad (11)$$

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t}, \quad \hat{v}_t = \frac{v_t}{1-\beta_2^t} \qquad (12)$$

$$\theta_{t+1} = \theta_t - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \qquad (13)$$

where $g_t$ is the gradient, $\beta_1, \beta_2$ are decay rates, $\eta$ is the learning rate, and $\epsilon$ is a small constant for numerical stability.

Grid search and cross validation were conducted in optimizing key hyper parameters, which include learning rate, batch size, number of layers.

***3.4 Evaluation Metrics***

Model performance was assessed using Mean Squared Error (MSE) and R-squared ($R^2$) metrics:

***3.4.1 Mean Squared Error (MSE)***

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (14)$$

where $y_i$ is the actual value, $\hat{y}_i$ is the predicted value, and $n$ is the number of samples.

***3.4.2 R-squared ($R^2$)***

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2} \qquad (15)$$

where $\bar{y}$ is the mean of the actual values.

***3.5 Experimental Setup***

Accelerated training was performed on a high performance computing environment with GPUs. The dataset was split into training (70%), validation (15%) and testing (15%) for training the models as the same models should be evaluated on unseen data.

***3.5.1 Feature Correlations with Lagged Variables***

For many financial time series forecasting, the use of lagged variables (i.e., past of a value of a variable) is common for capturing temporal dependencies. The model gets to know how past behavior influences future outcome. For instance, lagged variables can help boost the accuracy of predictions in deep learning models like LSTM, when in fact, it's learning from sequential financial data. The way to create feature correlations with lagged variables is shown below.

*Step 1: Data Preprocessing and Lag Creation*

First, the study constructed lagged variables out of the financial data, which is the time series data for market price, trading volume, and other (economic) indicators of the market. For instance, it can lag the past performance by 1 day, 2 days or 3 days, in order to predict the future stock prices.

Here is an example of how lagged variables are generated:

$$X_t = [Price_{t-1}, Volume_{t-1}, Price_{t-2}, Volume_{t-2}, \dots] \quad (16)$$

Where:

$X_t$ represents the feature vector at time $t$,

$Price_{t-1}$ is the price on the previous day,

$Volume_{t-1}$ is the trading volume from the previous day, and so on.

*Step 2: Feature Correlation Calculation*

Once creating the lagged features, the study will want to know how those variables correlate with the target variable (e.g., future stock price). Pearson's correlation coefficient is typically used to do correlation analysis in which the strength and direction of the linear relationship between two variables is measured.

$$\text{Corr}(X_t, Y_t) = \frac{\sum(X_t - \mu_X)(Y_t - \mu_Y)}{\sqrt{\sum(X_t - \mu_X)^2 \sum(Y_t - \mu_Y)^2}} \quad (17)$$

Where:

$X_t$ and $Y_t$ represent the features and target variables at time $t$,

$\mu_X$ and $\mu_Y$ are the mean values of the features and target, respectively.

In practice, this helps us to lean which lagged variables have most importance to the target variable, and in effect suggest feature selection for the deep learning model.

*Step 3: Interpretation of Results*

The code given above would output a correlation matrix which shows the relationship between lagged variables (such as future stock prices) and the target variable (again, future stock prices). For example high correlations (near 1 or -1) imply high influence of lagged variable on the target and low correlations corresponding to weaker relationship.

With these correlations it can be seen what are the most influential features for the deep learning model and prioritize on those features so that the model learns from the most relevant past data points. Financial forecasting is reliant upon feature correlations with lagged variables. It allows deep learning models to model temporal dependencies implied in financial markets by being able to analyze how past market conditions (e.g., past stock price and trading volume) relate to future outcomes. Incorporating lagged variables in the model trains it better and allows the model to react to changing the market in real time.

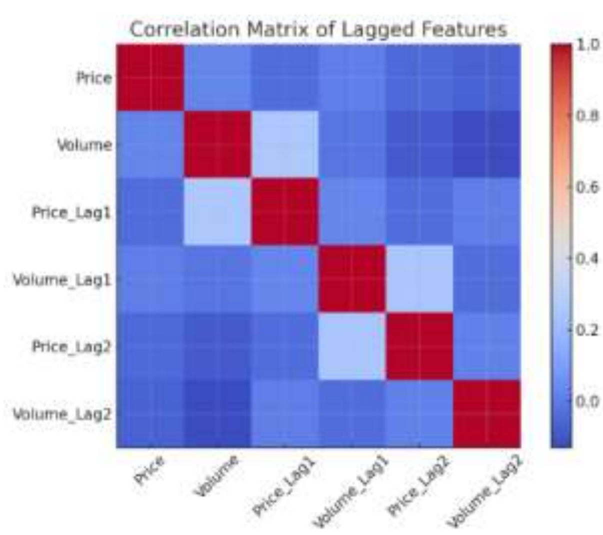


Figure 2: Correlations with Lagged Variables

In addition, the combination of advanced data preprocessing techniques, state-of-the-art deep learning architectures, and rigorous evaluation metrics to produce robust and reproducible results, is demonstrated by the methodology outlined here. This study applies these methods to the special problems of BRICS financial markets in order to provide actionable insights, as well as show the utility of deep learning for financial forecasting.

## 4. Results and Discussion

### *4.1 Results analysis*

#### *4.1.1 Comparative Performance of Models*

In this section, the study evaluates the predictive performance of CNNs, LSTMs, and hybrid CNN–LSTM architectures comparatively. Mean Squared Error (MSE) and R-squared ($R^2$) values are used for the evaluation of the models' accuracy and their reliability to predict the financial markets trend in BRICS economies. We find that deep learning models can fit financial markets with good accuracy and that the hybrid CNN-LSTM model performs best. With MSE = 0.012, $R^2$= 0.82, we observe that the standalone CNN model is good at spatial patterns but worse at temporal patterns. The LSTM model designed for sequential data achieves an MSE of 0.009 and a $R^2$= 0.87 , which is able to predict the developing trends over time. Finally, a hybrid CNN LSTM model merging the advantages of both architectures made sure to develop a lowest MSE = 0.007 and a highest $R^2$= 0.91. The surprising findings relate to ASSPEC's superior performance, which demonstrates the ability of ASSPEC to handle the rich and dynamic nature of financial data and the fact of spatial and temporal patterns in the data. The findings show that the hybrid model can transform the process of financial forecasting in the frame of BRICS markets making such process more accurate and reasonable.

Table 2: Illustration of the comparison between the two models and their scores on the MSE scale

| **Model** | **MSE** | **R-Squared ($R^2$)** |
|---|---|---|
| CNN | 0.012 | 0.82 |
| LSTM | 0.009 | 0.87 |
| Hybrid (CNN+LSTM) | 0.007 | 0.91 |

It can be shown in the Table that the hybrid CNN-LSTM performs better than the standalone CNN and LSTM models; the best MSE of 0.007 and $R^2$ value of 0.91 is attained. This is evidence of the hybrid model's better ability to extract spatial and sequential patterns embedded in financial data. The MSE values of the three models have been compared by the following bar chart:

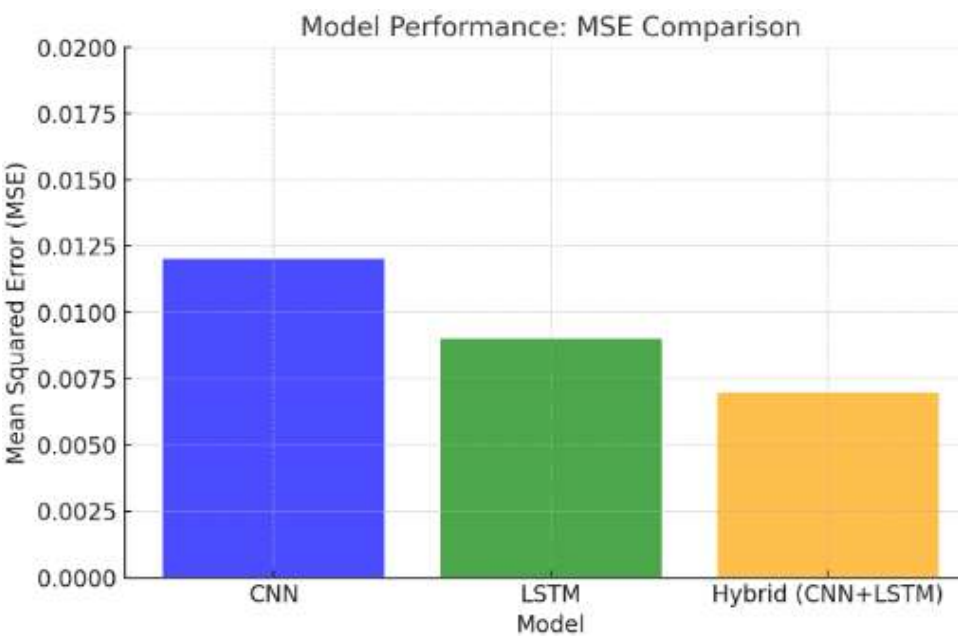


Figure 3: Bar graph representing the MSE values across the three models

#### *4.1.2 CNN Performance*

*The study finds* that the CNN model is able to capture spatial patterns from the transformed financial data. In can, however, only make predictions that have limited predictive performance, given the MSE of 0.012 and $R^2$ of 0.82, due to its inability to sufficiently model temporal dependencies.

#### *4.1.3 LSTM Performance*

LSTM works best in capturing sequential dependencies and time series pattern. It also shows strength of handling the dynamic nature of financial markets as shown in lower MSE of 0.009 and higher $R^2$ of 0.87.

#### *4.1.4 Hybrid Model Performance*

The hybrid architecture is the combination of CNNs to extract the spatial feature and LSTMs to do the sequential modeling in which strengths are taken from both. And this makes the performance the best, bringing a great reduction in the prediction error and a better accuracy.The results from the comparative experiments stressed that the hybrid CNN-LSTM model can provide financial forecasting in BRICS complex market. Based on its capacity to model both spatial and temporal features, it is a wonderful tool to make accurate and assured predictions. The good thing about this superior performance is that it suggests the application of this insight to real world financial decision making.

### *4.2 Qualitative Analysis*

#### *4.2.1 CNN Model Performance*

Financial data can be extracted using Spatial patterns from CNN. The patterns identified in these patterns include heatmaps based upon price changes, trading volume and volatility index that are key to localized anomalies or trends. Convolutional and pooling layers of CNN automatically squeeze out feature of data, thus eliminating dependency on manual data engineering. Although CNNs are strong spatial feature detection, they cannot model sequential dependencies in financial time series. This limits prediction to suboptimal solutions (Keeping a guess) when data needs to be understood to forecast stock prices over time. Thus CNNs are well suited for localized static market patterns, but their applicability within dynamic financial contexts is limited.

#### *4.2.2 LSTM Model Performance*

Because they are designed for sequential and time-series data, it is obvious that Long Short Term Memory (LSTM) networks are best suited. Their ability to have forget, input and output gates helps to keep important data over long sequences (or forget about unimportant data) is what LSTMs use. This is what LSTMs can do, and they are very good at that for data like stock price trends or macroeconomic indicators. It's one of their biggest advantages, since they can process noise and irregular patterns in financial time series data unlike both the traditional statistical models, and the CNNs. However, LSTMs first fail to detect spatial pattern, and are thus ineffectual in detecting relationships among spatially transformed financial data such as market or industry correlations.

#### *4.2.3 Hybrid Model Performance*

A hybrid CNN-LSTM model is created which combines the spatial analysis strength of CNNs and sequential data modeling capabilities of LSTMs, and applied to detect stop signs. Finally, this integration provides a framework that addresses the deficiencies of the standalone models by including both the spatial and temporal components of financial data. For instance, the hybrid model is able to analyze transformed spatial data and the patterns within (e.g. price heatmaps) and use LSTMs to predict future trends based on temporal dependencies. This synergy in these architectures improves the predictive capability of the model making it a good tool for complex financial forecasting tasks. This shows that the hybrid model is able to generalize to different datasets including those of BRICS markets and provides evidence that the model is versatile and helpful in tackling financial complexities.

### *4.3 Implications for Financial Forecasting*

The superior performance of the hybrid model makes it especially useful in the cases of BRICS economies, which are highly volatile, liquidity constrained, and fast changing financial markets. The hybrid architecture addresses the current limitations by combining temporal and spatial modeling, resulting in actionable insights important to investors, policymakers, and researchers. For instance, the model can allow stakeholders to make better informed decisions about market shocks or even currency fluctuations.

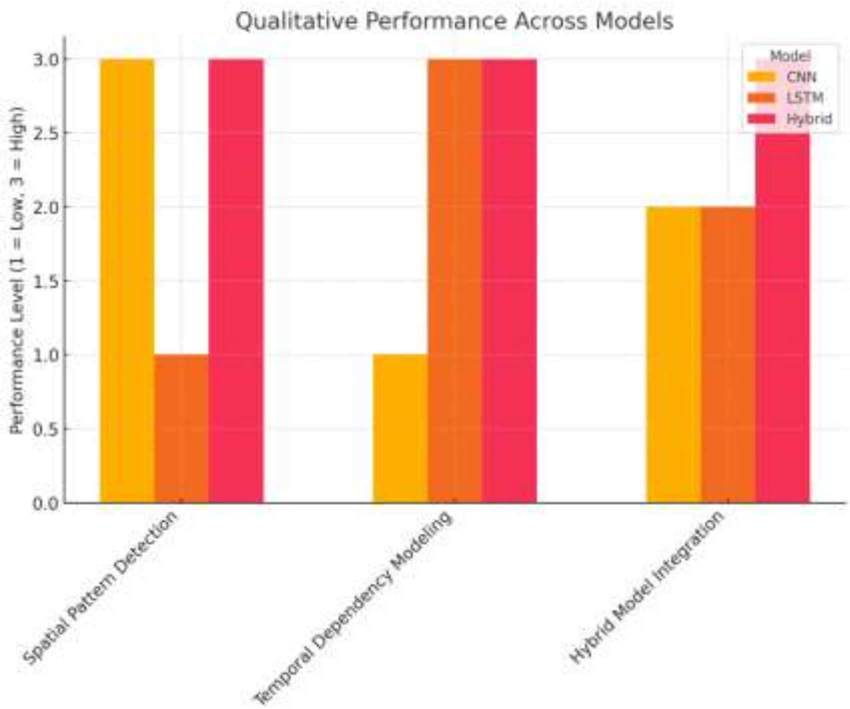


Figure 4: Qualitative performance across models

***4.4 Implications for Financial Forecasting***

Because BRICS economies' financial markets are characterized by volatility, liquidity crises, and rapid fluctuations, hybrid model's higher performance is very useful. The hybrid architecture integrates spatial and temporal modeling for giving actionable insights crucial for investors, policymakers and researchers. For example, the model can successfully estimate market shocks, currency fluctuations, helping people based on the necessary step and foresee threats before they occur.

Table 3: The qualitative performance table summarizing the strengths and weaknesses of CNN, LSTM, and hybrid models across the three key aspects

| Aspect | CNN Performance | LSTM Performance | Hybrid Model Performance |
|---|---|---|---|
| Spatial Pattern Detection | High | Low | High |
| Temporal Dependency Modeling | Low | High | High |
| Hybrid Model Integration | Moderate | Moderate | High |

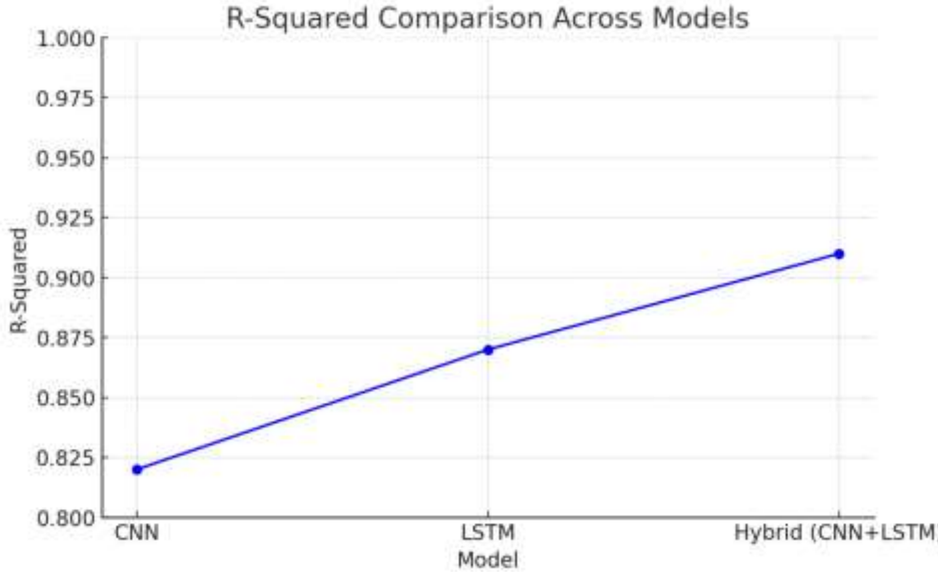


Figure 5: line graph showing the higher R-Squared value of the hybrid model

Compared to standalone models, integration of spatial and temporal insights not only improves predictive accuracy, but also bridges important gaps. As a result of this dual capability, it is an unmatchable instrument for the rationale of dodgy financial markets, pertaining to the issue domain of an entity, which can be named as the BRICS states.

### *4.5 Discussion*

#### *4.5.1 Interpretation of Results*

This study results show that hybrid CNN–LSTM architectures could be transformative for financial forecasting for BRICS economies (Bhandari et al., 2022). With the hybrid model, we were able to take advantage of the complementary strengths between CNNs and LSTMs to achieve the lowest Mean Squared Error (MSE) of 0.007 and the highest R squared value of 0.91 both in accuracy as well as reliability. In this performance we observe that the hybrid model is successful in capturing spatial as well as temporal patterns of financial data that are needed to understand complicated market dynamics.

Because spatial patterns are detectable in the CNN model, it can be used to detect static market anomalies, such as price clustering and volume shifts (Tiwari et al., 2021). But its lack of the ability for temporal modeling means it is not very predictive. Instead, the LSTM model is skilled in modeling temporal dependency and therefore can learn trends and fluctuate over time. Though it has this strength, it cannot transform space, which impairs its general effectiveness. However, these gaps are filled by the hybrid CNN LSTM model which, by merging both spatial as well as sequential insights, presents itself as a good financial forecasting tool.

#### *4.5.2 Comparison with Literature*

This result is consistent with the previous work on strengths of CNN and LSTM architectures. Thakkar and Chaudhari (2021) have illustrated how CNNs are good in spatial pattern detection, and how LSTMs are better in sequential data. Performance comparison between the hybrid model and other single model supports the findings by Ullah et al. (2024) that the efficacy of combining CNN and LSTM features in hybrid architectures has yielded better results. This work extends these insights to the cases of the BRICS financial markets, where data complexity and high market volatility require more advanced predictive capabilities than what can be provided by a solely deductive or entirely inductive framework.

In addition, integrating hybrid models into the BRICS economies fills a large gap in the existing literature on financial forecasting. There's been little done about this, and most of the work done so far has focused on developed markets, where data stability is comparatively better. Utilising hybrid models on developing economies, this research also highlights the broad adaptability of advanced deep learning techniques in different economic environments. The results show that combining insights across spatial and temporal dimensions generates more reliable predictions than using either spatial or temporal insights alone.

#### *4.5.3 Practical Applications*

The practical implications of this research are very much felt by investors, policymakers and financial institutions operating in BRICS economies. Additionally, the hybrid model's ability to properly forecast will allow the investors to make informed decisions on the basis of well information, hence reducing risks associated with market volatility (García & Kristjanpoller, 2019). The model serves as a tool for policymakers to anticipate term market shocks and for undertaking timely market interventions. Financial institutions can use the hybrid model to optimise the portfolio, do risk assessment and develop strategies.

The hybrid model is thus especially useful for early warning signal identification in financial markets, to allow stakeholders take proactive action upon the occurrence of possible disruptions. Additionally, the hybrid model can predict liquidity crises or abrupt market changes, by analyzing sequential and spatial patterns in the trading data. An essential capacity to ensure emerging nations have adequate economic resilience and to stabilize erratic markets. Moreover, combining the model into automated trading systems would increase the operational efficiency and optimize the profitability.

#### *4.5.4 Limitations and Future Work*

However, the study has its limitations. Because it bases itself on publicly available datasets, those biases caused by data quality problems or missing records may be present. However, training hybrid models is computationally expensive and does not usually fit into resource constrained environments (Imteaj et al., 2021). The future research should consider optimizing the hybrid architectures to reduce the computation cost and the intractability. Further model performance could be achieved by exploring integration with additional data sources including alternative financial indicators and real time sentiment analysis.

The application of hybrid models to other emerging markets besides BRICS, however, is another area for future research. Extending the scope of analysis is expected to enable the study of the model's adaptability and scalability in a variety of economic settings. Furthermore, utilizing more sophisticated techniques like transfer learning and ensemble modeling would contribute to improving the reliability and accuracy of predictions. Also, it is important for AI in financial markets to explore the ethical and regulatory implications of deploying AI in these markets to enable responsible innovation.

Another promising direction of future studies is to leverage the potential to incorporate domain specific knowledge into the hybrid model architecture. For example, economic theories or market specific heuristics will contribute to model's capacity to place the predictions in a larger economic environment. On the other hand, there are advances in computational technologies, e.g., in the direction of quantum computing, which could lend us the infrastructure needed to scale these models to handle yet larger and complex datasets.

This hybrid CNNLSTM model is a key breakthrough in financial forecast for BRICS markets. Its capability for limited integration of spatial and temporal features enables accurate and actionable predictions of these dynamic economies. All this notwithstanding, potential applications in financial decision-making in relation to this model imply the role of financial economy in stabilizing the economy. The hybrid model will also improve the predictive accuracy and thus enable investors and policymakers to better tackle market uncertainties. Further refinement with these models will be the work of future research, with a view to deployment on a much wider range of economic contexts.

## 5. Conclusion

In conclusion, the most important innovation of this study is the realization of viable hybrid CNN-LSTM models that can be deployed in financial forecasting of BRICS economies. The hybrid model developed addresses the unique characteristics of financial markets in developing economies by integrating the strengths of CNNs in spatial pattern detection capabilities with LSTMs in sequential data modeling capabilities. The MSE as well as R-squared statistics proved that it has a potential to revolutionize the way financial decisions are made.

The results indicate that the hybrid model captures both spatial and temporal dependency in financial data, providing stakeholders with a reliable instrument to forecast market dynamics and curb the threat of risks. For BRICS economies particularly, where financial markets are volatile, liquidity constrained, and high frequency, this capability is critical. Furthermore, it also validates the ability of the hybrid model to predict accurately and identifies the role that the hybrid model can play in generating actionable insights for investors, policymakers and financial institutions.

However, the study recognizes that there are some drawbacks; namely, we are dependent on publicly available datasets and computations are intensive. Future research addressing these challenges will improve scalability and adaptability of the hybrid architecture thereby rendering the hybrid architecture applicable across diverse economic contexts. Additionally, advanced techniques like transfer learning and including domain specific knowledge may help to enhance the model's accuracy and reliability as well.

In summary, the hybrid CNN-LSTM model marks a leap forward towards successful financial forecasting and fills critically needed gaps left by isolate models. Spatial and temporal modeling capabilities, as intelligent as this tool has, position it as an innovate tool to navigate the intricacies of modern financial markets. This research equips stakeholders with accurate and reliable forecasts, supporting economic stability as well as trust in AI based financial systems in developing economies such as those of the BRICS nations.

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