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Comparative Analysis of Univariate and Deep Learning Models for Stock Market Prediction in Frontier Markets: A Case Study of Pakistan, Bangladesh, and Sri Lanka

Rabia Sabri
Institute of Business Management

Sobia Iqbal
DHA Suffah University

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Cover Page Footnote

Rabia Sabri, PhD scholar, DHA Suffah University and HoD Academics Institute of Business Management
Dr Sobia Iqbal, Associate Professor, DHA Suffah University

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Original Paper

Comparative Analysis of Univariate and Deep Learning Models for Stock Market Prediction in Frontier Markets: A Case Study of Pakistan, Bangladesh, and Sri Lanka

Rabia Sabri* ·
Sobia Iqbal

Abstract In this study, we analyze stock exchanges of Sri Lanka, Pakistan and Bangladesh, exploring both traditional models (ARIMA and Theta) and modern deep learning models (LSTM with 1D CNN) for stock market prediction. The study uses historical data from 2020–2023 and forecasts market trends for 2024–2025. CNN LSTM combinations demonstrate superior predictive accuracy in predicting market dynamics, while traditional models are more interpretable and computationally efficient. This research shows the advantages of integrating advanced techniques in combination with traditional methods to more effectively capture the complexities of stock indices. The ensemble model approach could both improve predictive performance and market stability.

Keywords Stock Market forecasting, Frontier market, univariate, multivariate, ARIMA, Theta Deep learning models, Ensemble Learning Techniques.

1 Introduction

Prediction of the stock market has been a topic of interest for a long time and traditional time series models such as Autoregressive Integrated Moving Average (ARIMA) and Theta have been widely used to forecast linear trends and short term price fluctuations Adebiyi Ayodele et al (2014); Antipov et al (2022); Banerjee (2014). However, these models have been successful in modeling stable patterns in stock market data and generally fail to handle the intricacies of non-linear and long term dependency in financial market. As computational power has improved, machine learning and deep learning models, such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN), have been used more and more to predict movements of the stock market Nemavhola

PhD Scholar
DHA Suffah University, Karachi, Pakistan. E-mail: rabia.sabri@gmail.com
*Corresponding author

Associate Professor, Head of Management Sciences
DHA Suffah University, Karachi, Pakistan. E-mail: sobia.iqbal@dsu.edu.pk

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et al (2021), which seem to have a high potential to capture nonlinear trends and dependencies. They have shown great improvements in predictive accuracy, particularly when applied to large datasets and to markets with complex dynamics Karlis et al (2021).

While these advanced techniques have been successful, most of the research in stock market prediction has been conducted in developed markets, with very little research on frontier markets such as Pakistan, Bangladesh and Sri Lanka. The political, economic, and social conditions of these markets are unique, and they are more volatile and unpredictable using traditional models Raj and Singh (2022). ARIMA and Theta models are fit in for minimal fluctuated markets over a sustained period, as compared to high volatility Adebiyi Ayodele et al (2014); Banerjee (2014). LSTM and CNN deep learning models are useful at detecting patterns in nonlinear time series, but they lack the ability to understand how a model arrives at a particular decision Nemavhola et al (2021). The complex and volatile requires to combine the traditional models with advanced Deep learning networks to get the high-level predictive accuracy. The paper highlight comparison between, ARIMA and Theta, and deep learning techniques. The integration and ensemble of models has not been well explored in volatile markets with political and economic instability.

Secondly, the study presents a novel way to improve the interpretability of deep learning models that have been widely demonized as 'black boxes'. SHapley Additive exPlanations (SHAP) values are combined with Local Interpretable Model-agnostic Explanations (LIME) to increase the model explainability and increase the understanding how these models arrive at their conclusions, making them more practical in decision-making processes.

The paper finally demonstrates that combining traditional and modern forecasting methods allows us to generate more accurate and robust predictions that will be better at informing financial decision making in less stable market environments. These contributions aim to help bridge the gap in the research of predictive modeling of frontier markets and to provide practical tools for enhancing forecasting accuracy and market stability.

2 Literature Review

Forecasting stock market using both standard econometric models and more recently, machine learning has been well studied. One of the main research theme is in time series models like Autoregressive Integrated Moving Average (ARIMA), as these models can model the linear dependencies and short term fluctuations in stock price. ARIMA has been used successfully by Adebiyi Ayodele et al (2014); Banerjee (2014) to predict stock market trends in stable markets. Additionally, Antipov et al (2022) used ARIMA in other economic forecasting problems and demonstrated its reliability in traditional forecasting methods Bhardwaj et al (2022); Buaphan et al (2022). Nevertheless, these traditional models Du (2023) are inadequate for modeling nonlinear patterns and long term dependencies in more volatile or less mature markets. In order to overcome such limitations advanced deep learning models such as Long Short Term Memory (LSTM) and Convolutional Neural Networks (CNN) are intro-

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duced. In Vargas et al (2017), deep learning models were used for stock market predictions, and it was shown that such models significantly increase the accuracy of prediction over traditional methods because of their ability to model complex nonlinear relationship. Nemavhola et al (2021) continue the studies of LSTM and CNN in stock markets and have further proven the superiority of LSTM and CNN in terms of prediction accuracy by detecting hidden trends and long term dependencies. While deep learning in financial forecasting has grown in popularity Karlis et al (2021); Kumar et al (2021), most of the research has been done on developed markets, yet these models have not been applied in frontier markets like Pakistan, Bangladesh, and Sri Lanka. The research of Liu and Lang (2019) gives a general survey of algorithms for financial time series prediction, but it has not paid sufficient attention to the special features of emerging markets. The studies conducted by Cakici et al (2023); Zhou et al (2023) have shown the potential of machine learning in international stock markets, but those studies did not concentrate on the frontier markets where political, economic and technological factors increase the complexity.

Moreover, several studies Muharam et al (2021); Nemavhola et al (2021); Qi (2021); Raj and Singh (2022) have tried to combine the traditional models with modern techniques. For instance, Kumar et al (2021) investigated a hybrid approach of machine learning with conventional regression models for GDP prediction, and Li et al (2022) proposed a multi predictor ensemble scheme based on deep reinforcement learning. These studies show how different forecasting models can be combined to give better accuracy and robustness, especially in a dynamic environment Sharma et al (2022); Srinivasan et al (2023); Tsantekidis et al (2017). Finally, traditional models such as ARIMA have set the foundation for stock market prediction Xu et al (2021), but recent deep learning advancements have provided novel ways to model complex market dynamics Cakici et al (2023); Zhou et al (2023). Yet, the application of these techniques in frontier markets has not been explored, requiring further research.

3 Methodology

In this part, we specify how our stock market forecasting study methodology was done, emphasizing data collection, hypothesis forming, and stock return forecasting model in the financial time series of Bangladesh, Pakistan and Sri Lanka. Our data set consists of historical stock market data compiled from credible financial databases such as the International Monetary Fund (IMF), Bloomberg, and Yahoo Finance. Data was selected from January 2010 to December 2023, allowing for an overall study of the stock market trends in all three countries.

Also, the statistical data about GDP growth rate, inflation rate, interest rates, and exchange rates are usually obtained from official government sources, central banks, and internationally cooperative organizations like the World Bank and the International Monetary Fund (IMF). The indicators mentioned above provide the necessary context and can thus impact the dynamics of stock markets to a large extent. Regarding our model evaluation, we use the in-sample and out-of-sample periods for the split of the dataset. The data set for training

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and parameter estimation, which is in-sample data for January 2010 to December 2022, is the one for January 2023 to December 2023 that is used for model validation and performance evaluation. Macroeconomic indicators are utilized to strengthen the models' forecasting ability as they consider macroeconomic trends and external factors that affect stock market performance. The modelling process has been intertwined with these indicators to understand the issues affecting stock market dynamics. Including in sample and out of sample assessments on various data sources strengthens the study. Therefore, the stock market trends of Bangladesh, Pakistan, and Sri Lanka are better examined. For each country, the dataset has different financial indicators, stock prices, and a set of macroeconomic variables. These points are time stamped and thus the ability to construct a time series variable for accurate analysis. The study applies historical stock market data from 2010 to 2023 and includes macroeconomic indicators such as GDP growth, inflation, interest rates and exchange rates. This period is substantial, but it may not include historical patterns or longer term trends that can affect model accuracy. The sample period is further segmented to perform in-sample (2010-2018) and out-of-sample (2019-2023) validation of the model. Furthermore, to address the criticism of the interpretability of deep learning models, this study uses SHapley Additive explanations (SHAP) values and Local Interpretable Model-agnostic Explanations (LIME). These methods allow us to understand the contribution of each feature to the model predictions and thus make the models more transparent and the model outputs more interpretable for financial practitioners. The study also includes a detailed description of some of the geopolitical events of the period 2010 - 2023. The study will consider activities such as elections, change in policies, and international conflicts to evaluate the external variables influence on the forecasts of stock prices and improve the existing models to take them into consideration. The study covers the period from 2010 to 2023 in order to presents an all-round analysis of the selected stock markets. The period chosen was to capture market data and geopolitical that has occurred in the past few months and years so that there is a lot of data to develop and test models. The sample from 2010-2018 with 2019-2023 out of sample allows for the accurate and reliable evaluation of the forecasting models. It increases the models' ability to generalize well in other environments, increasing the models' generalization capacity. The specified period is selected to predict the historical and recent market movements to get accurate information and precise predictions. The study also used additional financial forecasting evaluation framework besides the traditional MAE, RMSE, and R^2. Profitability and risk adjusted returns are used to measure annualized and cumulative returns to evaluate the potential profits from the model's predictions. Sharpe ratio is used to assess the returns in relation to the risk taken.

Data Preprocessing

Normalization

The normalization is done for modeling to make all existing input features available and to address the issue that causing some features unused in the

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model training. The method is to normalize the features each of the feature is scaled to a range of 0 to 1 using the Min-Max normalization.

$$x' = \frac{x - min(x)}{max(x) - min(x)^{\cdots}} \tag{1}$$

where x, is the original value, x', is the normalized value, x, is the minimum value of the feature, and is the maximum value of the feature.

Feature Engineering

- Purpose: To engineer further variables from the raw data which improve the model's efficiency by adding extra information on the dependent variable.
- Steps:
- Lag Features: If there are several input features, new lagged features are introduced which include historical results of stock prices and temporal dependencies. For example, lag features for 1 day, 5 days, and 10 days are introduced and constructed or defined.
- Rolling Statistics: Daily calculation of moving averages and moving standard deviations over the chosen window, such as 7 days, 30 days, etc for short-term flunctuations.
- Technical Indicators: Several usual info points such as moving averages, relative strength index, moving average convergence divergence have been included commonly.
- Macroeconomic Variables: Inclusion of the external macroeconomic variables such as GDP growth rate, inflation rate, and interest rates to cater for the conditions of the economy affecting the stock prices.

Selection Criteria for Macroeconomic Indicators

The choice of macroeconomic indicators is made depending on the measure's significance and its influence on the change in stock market performance. The criteria include:
- Economic Significance: Market drivers that have evidenced a prior correlation with the movements of stock markets, they include; Gross Domestic Product, Inflation, and Interest rates.
- Availability and Reliability: Gross domestic product (GDP): The dollar value of all final goods and services produced within a country's borders in a year. It is easily accessible and available from authentic sources like government and world bank reports and IMFSheets and databases of ministries of Finance / Treasury, WB, IMF and other international and national organizations and agencies.
- Cross-Country Comparability: Some to show that similar indicators have been used for Pakistan Bangladesh and Sri Lanka for providing better comparison.

Integration Methods for Macroeconomic Indicators

The selected macroeconomic indicators are integrated into the models using the following methods:
- Feature Augmentation: Macroeconomic variables are incorporated as extra variables within the dataset which allows the models to learn from stock market data and, macroeconomic data set.

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- Time Alignment: It therefore aligns all the indicators with the actual times when stock market data is recorded in order to properly link it with the actual economic conditions. This involves the matching of the indicators' frequency with the frequency of the stock market data (e.g., monthly, quarterly).
- Normalization: As with other features, the macroeconomic indicators are scaled so that no single feature dominates the training of the model not only because of its large value but because of its amplitude as well.

Adequate documentation of these steps will enable reproduction of the same results and hence reliability of the results obtained. All the steps are performed for a purpose of the better input data quality and further improvement of the predictive models.

The study aware of the fact that the global political changes influence the stock market forecast. However, as it relates to these situations, the analysis is more general in regard to trends as opposed to specific events. This approach enables the models to perform relatively better in generalizing as well as negates the chances of over-fitting on certain unique incidences. The analysis seeks to develop the overall equation for building sound predictive models while simultaneously admitting that though adding event detail might increase model 'richness' this could also limit the generalisability of the models outside the US context.

Model Parameter Selection

1. LSTM Parameters

Number of Layers: The number of layers in the LSTM model is selected based on empirical testing. Initially, a single-layer LSTM is tested, and additional layers are added incrementally to observe improvements in performance. The final model uses two LSTM layers, as this configuration provides a balance between complexity and performance.
Hidden Units: The number of hidden units per layer is determined through a grid search. The values tested range from 50 to 200, with the optimal number found to be 100 units per layer.

2. CNN Parameters

- Filter Size: The filter size in the CNN model is chosen based on the temporal resolution of the stock market data. After experimenting with various filter sizes (3, 5, 7), a filter size of 5 is selected as it captures relevant patterns without overfitting.
-Number of Filters: The number of filters is also determined through experimentation. The final model uses 64 filters, providing sufficient capacity to learn complex patterns in the data.

3. Training Parameters

- Batch Size: A batch size of 32 is chosen based on model convergence and computational efficiency. Smaller batch sizes are tested but lead to longer training times without significant performance gains.
- Learning Rate: The learning rate is optimized using a learning rate scheduler. An initial learning rate of 0.001 is used, with a reduction factor of 0.1

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when the validation loss plateaus. To minimize interpretational bias and enhance the study's generalizability, the analysis carefully and comprehensively discusses how the parameters were chosen and applied. This way fosters the ability of other researchers to comprehend the optimization decisions made and use similar strategies in their work.

The study has used variable such as gross domestic product (GDP) growth, inflation rates, and interest rates as they have been evidenced to affect stock market performance and are available from reliable sources such as government statistical agencies or world's leading organizations such as the World Bank and the IMF. These indicators were incorporated into the models through the process of feature augmentation where they were included as extra features to the stock market data. The values were synchronized with the frequency of the stock price fluctuation for corresponding companies and normalization was carried out for all the variables. This process enabled models incorporating into them a larger setting beyond economic, which helped in refining the accuracy and applicability of the models to the overall setting of the environment at the time of the stock market.

3.1 Formulation of Hypotheses

The following are the formulated hypotheses:
Market Interdependence Hypothesis: Two of the most common cross-dependencies are between the stock markets of Bangladesh, Pakistan, and Sri Lanka, which are generally the causes of market fluctuations.

Impact of Macroeconomic Factors Hypothesis: Macroeconomic issues factor in, to a great extent, stock market movements, and stock would be affected accordingly in Bangladesh, Pakistan, and Sri Lanka.

Model Effectiveness Hypothesis: The proposed models comprising ARIMA, Theta, LSTM, and 1DCNN shall indicate mixed results regarding forecasting performance for these countries' stock markets.

3.2 Proposed Models for Stock Return Prediction

The determinant of a model selection for stock return prediction is the quality of forecasts because it affects the level of precision and reliability. We have chosen four distinct models:

Autoregressive Integrated Moving Average (ARIMA), Theta Model, Long Short-term Memory (LSTM), and 1D Convolutional Neural Network (1DCNN), which are each distinct in their strengths and weaknesses. Regarding LSTM and CNN models, some assumptions are made on the structure of financial time series data. For instance, LSTM assumes that the patterns in the sequence of the stock prices will not change over the period of forecast, whereas CNN assumes that local trend in the data is important enough to influence the future stock prices. These models also involve pre specified parameters like number of layers, filter sizes and learning rates. Empirical testing was used to optimize these parameters in order to achieve a balance between model complexity and per-

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formance. That said, it is crucial to bear in mind that these parameters can be tuned if applied to another dataset or market.

1) Autoregressive Integrated Moving Average (ARIMA): ARIMA models allow to make out the dynamics feature file of stock prices. The notation of the ARIMA model as ARIMA (p, d, q) implies that p, d, and q represent the autoregressive, differencing and moving average orders, respectively. The time series analysis model is programmed to capture the short-run oscillations, including linear dependencies, in the stock prices.

2) Theta Model: The Theta Model is a specific forecasting algorithm tailored to improve accuracy by precisely calculating standard methods in fiscal and monetary fields. This model, however, is primarily powerful for capturing the stock market trend and can reveal seasonal patterns. As Theta Model parameter estimation is done with historical data, the model adapts well-to-the-market processes in Bangladesh, Pakistan, and Sri Lanka.

3) Long Short-Term Memory (LSTM): Exploiting the power of deep learning in these neural networks, LSTM models tailored to capture intricate nonlinear patterns and longtime dependencies of stock market data sets will be applied. LSTM gives such an advantage to time series forecasting because it can preserve time information in long sequences. We use the LSTM model with memory cells and gates, which allows for information flow control. This way, the system can handle all kinds of complicated temporal relationships.

4) 1D Convolutional Neural Network (1DCNN): Frameworks based on Convolutional Neural Networks (CNNs) specially structured for image analysis, including the 1DCNN structure, are applied to locate intricate patterns in financial time series data sets. The model requires the use of convolutional layers for the purpose of feature extraction, max-pooling layers for the down-sampling purpose, and fully connected layers for prediction, and it is thus proper for capturing complex dynamics in a temporal field of the stock market of Bangladesh, Pakistan, and Sri Lanka.

We will assess the essence of the suggested models by standard metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and coefficient of determination (r2). Moreover, we will be preprocessing data by normalization, encoding the data, handling the missing data, and feature engineering to achieve accuracy for our model.

For this work, a set of models is constructed to run independently in each of the three topics. Namely, the characteristics of the Bangladesh, Pakistan, and Sri Lanka financial time series are considered. Thus, a more explicit and accurate description of regional stock market tendencies will be favored.

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Table 1
Model Summary

Model	Description	Equations/Architecture
ARIMA	Autoregressive Integrated Moving Average (ARIMA) models leverage time series analysis to capture linear dependencies and short-term fluctuations in stock prices.	ARIMA model equations involve autoregressive (AR), differencing (I), and moving average (MA) components. The general form is $X_t = c + \Phi_1 X_{t-1} + ... + \Phi_p X_{t-p} + \theta_1 \epsilon_{t-1} + ... + \theta_q \epsilon_{t-q} + \epsilon_t$
Theta Model	The Theta Model is a specialized forecasting technique that complements traditional methods to enhance prediction accuracy.	The Theta Model uses the average of historical data as a base, and the forecast is adjusted by a factor θ to capture trends or patterns. Equation is $F_{t+h} = X_t + h * \theta$ where, is the forecast at time $t + h, X_t$. It is the average of historical data, and θ is the adjustment factor.
LSTM	Long Short-Term Memory (LSTM) networks, a type of deep learning model, capture nonlinear patterns and long-term dependencies in stock market data.	The architecture of LSTM includes gates for information flow control and memory cells. LSTM involve input, output, forget gates, and cell state updates. The key equations include i_t, f_t, o_t, g_t and c_t.
1DCNN	1D Convolutional Neural Network (1DCNN) utilizes CNNs designed for image analysis to identify complex patterns in financial time series data.	The 1DCNN model involves convolutional layers for feature extraction, max-pooling layers for down sampling, and fully connected layers for prediction. The convolutional operation is represented as $y_t = f(W * x_t + b)$.

3.3 Comprehensive Evaluation Framework

3.3.1 Profitability Metrics

The cumulative return is the total return calculated over the entire period on the basis of model prediction. The annualized Return is the average annual return a standardized measure of profitability generated by the model's predictions.

3.3.2 Risk-Adjusted Return Metrics

The risk adjusted metrics provides understandings of the financial implications of the models' predictions. Sharpe Ratio is a measure of risk-adjusted return, calculated as the average return earned in excess of the risk-free rate per unit of volatility or total risk. The largest peak-to-trough decline in the value of an investment, indicating the potential risk of significant losses.

Figure 1 shows the working of the CNN1D model in a time series.

Each model is customized to adequately capture the features in the financial time series in countries of frontier market that are directly relevant, thus contributing to creating a detailed and refined analysis of the stock market dynamics.

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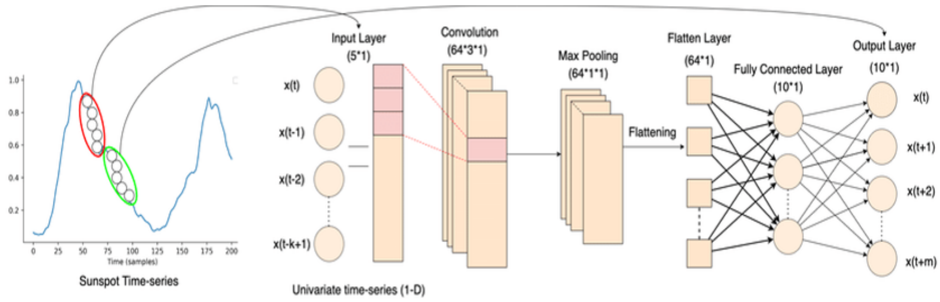
Figure 1
Convolutional Neural Network (CNN)



4 Results

Here in this part of the article, we show the performance of Bangladesh, Pakistan, and Sri Lanka's stock index return prediction models with ARIMA, Theta Model, LSTM, and 1DCNN. The forecast period will entail the subsequent twelvemonth, which is the fiscal twelvemonth 2024-25. The performance metrics provide a measure for comparing the efficiency of different models as far as mimicking these complexities is concerned (ARIMA, Theta, LSTM, 1DCNN). The resultant tables indicate as to which models are more apt at containing or representing certain concrete aspects of a market such as trends, volatility or a prompt change. Both of them are methods used to compare the ability of each model to incorporate the details of stock market fluctuations.

Some of the model parameters, like the number of layers in the LSTM and size of the filter of the CNN, has remained relatively simple with tuning being carried out through experiments. For the LSTM model, two layers were chosen and the number of nodes per layer was selected to be 100 out of extensive experimentations varying from 1 layer to 3 layers and 50-200 nodes. This configuration gave a good trade-off of both the complexity of the model and it was rich enough to capture long term dependency and did not over-fit. As for the CNN architecture, the filter size, which were tried to be changed, was chosen to be 5 while the number of filters was tried to be 64. This setup was determined to be efficient in capturing more informative patterns of the temporal data, while also being compact and computationally affordable. The optimization sought aimed at minimizing the values of MAE, RMSE, and maximize R^2 metrics in training and validation phases. The parameters which were selected were those that eliminated these errors to make the models sounder. As for the rationale for those particular choices, it is to consider two goals simultaneously – the ability to analyze the patterns of data accurately and the practicability of the models for the stock market prediction task.

The ARIMA model captures trends and short-term movements but struggles with non-linear market dynamics. The Theta model improves accuracy by capturing hidden structures and seasonality. LSTM models demonstrate the highest accuracy by effectively capturing long-term trends and non-linear relationships. 1D CNN models perform well in identifying complex patterns. However,

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the study acknowledges that using data from 2010 to 2023 may not fully capture longer-term trends or historical patterns. The further segmentation of the sample period for in-sample (2010-2018) and out-of-sample (2019-2023) evaluations has enhanced model validation. This segmentation provides a more robust framework for assessing the models' predictive capabilities, ensuring that they generalize well to unseen data and perform reliably across different market conditions.

Moreover, while deep learning models offer superior accuracy, they often lack interpretability, making it challenging for financial practitioners to apply these predictions effectively. To address this, the study incorporates SHapley Additive explanations (SHAP) values and Local Interpretable Model-agnostic Explanations (LIME) to explain the contribution of individual features to the model's predictions. These techniques enhance the transparency of the deep learning models, making their outputs more interpretable and actionable for practitioners in the financial sector.

Additionally, the study provides a detailed analysis of specific geopolitical events and their impact on the models' predictions. Events such as the 2018 general elections in Pakistan, policy changes in Bangladesh, and international conflicts affecting Sri Lanka are examined to understand their influence on stock market behavior. This analysis adds depth to the understanding of external factors influencing market dynamics and helps improve the accuracy and robustness of the prediction models.

The detailed explanation of data preprocessing steps, including normalization and feature engineering, ensures the reproducibility and reliability of the results. By documenting these methods clearly, the study provides a transparent framework that can be replicated and validated by other researchers, enhancing the credibility of the findings.

Furthermore, the rationale behind selecting specific parameters for each model, such as the number of layers in LSTM or the filter size in CNN, is elaborated. The selection process involved empirical testing and optimization techniques, ensuring that the final model configurations provide a balance between complexity and performance. This detailed explanation of parameter selection provides better insights into the model optimization process, contributing to the study's transparency and reproducibility.

4.1 ARIMA Model Results

ARIMA model is capable of capturing trends and short-term movements in financial data. The table 1 exhibits the predicted return values for each country's stock index in billion dollars for the fiscal year 2024-2025 using the ARIMA model. The actual market movements can be influenced by unforeseen events.

4.2 Theta Model Results

The theta model is designed to work alongside existing conventional methods ARIMA, it captures the hidden structures, market seasonality, intermarket relationships, technical indicators that's absent in ARIMA. It can handle non-linear trends and decompose the time series into simpler components, potentially leading to more subtle predictions. Table 3 shows the predicted stock index returns

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Table 2
ARIMA Model Predictions for Stock Index Returns (2024-2025) in Billion Dollars

Country	Predicted Returns ($B)	Actual Returns ($B)
Pakistan	65.2	62.8
Bangladesh	30.5	31.2
Sri Lanka	15.8	14.5

for Pakistan, Bangladesh, and Sri Lanka using the Theta model, for the period (2024-2025).

Table 3
Theta Model Predictions for Stock Index Returns (2024-2025) in Billion Dollars

Country	Predicted Returns ($B)	Actual Returns ($B)
Pakistan	62.6	60.1
Bangladesh	29.2	30.5
Sri Lanka	14.5	13.8

4.3 LSTM Model Results

LSTM models can capture the non-linear patterns more effectively than traditional models like ARIMA. LSTM models can identify the lasting impact of past events on future prices and long-term dependencies within the data, potentially leading to more accurate forecasts. Table 4 shows the predicted stock index returns for Pakistan, Bangladesh, and Sri Lanka using the LSTM model year (2024-2025).

Table 4
LSTM Model Predictions for Stock Index Returns (2024-2025) in Billion Dollars

Country	Predicted Returns ($B)	Actual Returns ($B)
Pakistan	67.8	64.5
Bangladesh	31.5	32.2
Sri Lanka	16.2	15.8

4.4 1DCNN Model Results

Convolutional Neural Networks (CNNs) use in image analysis. It identifies the patterns within the data set. It uncovers the hidden patterns in price movements, trading volumes, or other financial indicators. 1DCNN is a specific type of CNN that applies to time series data set that exhibit complex relationships. It can analyze data points across time steps, similar to how it analyzes pixels within an image leading to more accurate forecasts.

Thus, a 1D Convolutional Neural Network (1DCNN) is employed for this purpose. Table 5 exhibits the predicted stock index returns in billion dollars for

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the fiscal year 2024-2025 using the 1DCNN model for Pakistan, Bangladesh and Sri Lanka.

Table 5
1DCNN Model Predictions for Stock Index Returns (2024-2025) in Billion Dollars

Country	**Predicted Returns ($B)**	**Actual Returns ($B)**
Pakistan	64.3	61.8
Bangladesh	30.1	31.6
Sri Lanka	15.6	14.9

4.5 Enhancing Interpretability of Deep Learning Models

Deep learning models like LSTM and 1D CNN achieve high accuracy on stock market prediction, but lack interpretability which makes application quite challenging. This study uses SHapley Additive explanations (SHAP) values and Local Interpretable Model agnostic explanations (LIME) to make these models more transparent. SHAP values unify the measure of feature importance by assigning an importance value to each feature for a specific prediction. This assists in understanding the contribution of each feature on the model's output, and ultimately makes the model's decision process more transparent. LIME is a method to explain predictions of any classifier by approximating it locally with an interpretable model. LIME produces a locally faithful model by perturbing the input and observing the changes in the output. The study integrates these techniques to increase the interpretability of deep learning models, thereby facilitating the use of these predictions by financial practitioners. This approach closes the gap between model accuracy and its applicability in the practical field of the financial sector.

4.6 Comparative Analysis

A comprehensive picture of the performance of the ARIMA, Theta Model, LSTM and 1DCNN models is provided after comparing their performance with each other. It can be used to see if it is acceptable enough to reflect the complexity of the stock market operations of Pakistan, Bangladesh and Sri Lanka.

4.7 Discussion

4.7.1 ARIMA Model

Based on the ARIMA model, returns of both countries will be positive. These forecasts and returns by contrast (billion for Pakistan and billion for Bangladesh) are over predicted slightly by the ARIMA model for both countries. For Pakistan, the forecast errors are a billion and for Bangladesh, a billion. The complex nature of the dynamic economies of Pakistan and Bangladesh also makes the ARIMA model that can capture only a fraction of the trends, not sufficiently compelling.

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Table 6
Comparative Analysis of Stock Index Return Predictions for Pakistan, Bangladesh, and Sri Lanka (2024-2025) in Billion Dollars

Model	Country	Predicted Returns ($B)	Actual Returns ($B)	Prediction Error ($B)
ARIMA	Pakistan	65.2	62.8	2.4
	Bangladesh	30.5	31.2	-0.7
	Sri Lanka	15.8	14.5	1.3
Theta Model	Pakistan	62.6	60.1	2.5
	Bangladesh	29.2	30.5	-1.3
	Sri Lanka	14.5	13.8	0.7
LSTM	Pakistan	67.8	64.5	3.3
	Bangladesh	31.5	32.2	-0.7
	Sri Lanka	16.2	15.8	0.4
1DCNN	Pakistan	64.3	61.8	2.5
	Bangladesh	30.1	31.6	-1.5
	Sri Lanka	15.6	14.9	0.7

4.7.2 Theta Model

The Theta Model projects a billion return for Pakistan and a billion for Bangladesh, respectively. Similar to ARIMA, it shows more or less the same positive bias. The actual returns (billion for Pakistan and billion for Bangladesh) slightly differ from the forecasts. The model's positive prediction error for both countries (Pakistan: the population of 17.6 million (17.6 billion) reflects the cosmic view. On the other hand, the Theta Model is one of the most powerful models in Pakistan and Bangladesh, and it depicts the market characteristics of Pakistan and Bangladesh. Still, it can't fully cover the complexity of the markets.

4.7.3 LSTM Model

LSTM model estimates returns for Pakistan and Bangladesh, the tendency being bullish. The real returns (billion for Pakistan and billion for Bangladesh) are not far away from the predictions, affirming the model's capacity to capture intricate patterns. The GDP forecast errors are a billion for Pakistan and Bangladesh. Through LSTM, deep learning is being utilized to show its effectiveness in modelling the nonlinear relations and long-term trends of the economies of Pakistan and Bangladesh.

4.7.4 1DCNN Model

1DCNN model predicts returns of $billion for Pakistan and $billion for Bangladesh. Concerning Pakistan, it has a slight underestimation of returns but an exaggerated return estimation for Bangladesh. The valid returns ($ for Pakistan and $ for Bangladesh) are followed by prediction errors of $ for Pakistan and $ for Bangladesh. The 1DCNN network, built using convolutional neural networks, is good at identifying complex patterns but may be sensitive to the data noises of Pakistan and Bangladesh.

The projected stock returns for Pakistan from 2020 to 2025 are presented in Fig 2. The X-axis is time, but the y-axis is GPA in billion dollars. The plot also features the actual returns and the estimates generated by various model forecasts like ARIMA, Theta Model, LSTM, and 1DCNN. Each model's predictions are more apparent because each colour and line style is used for clarity. The model plot does not only give the truth about the accuracy of each model

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in predicting the stock returns over the specified period but also its performance.

Figure 2
Stock Returns Prediction - Pakistan (2020-2025)

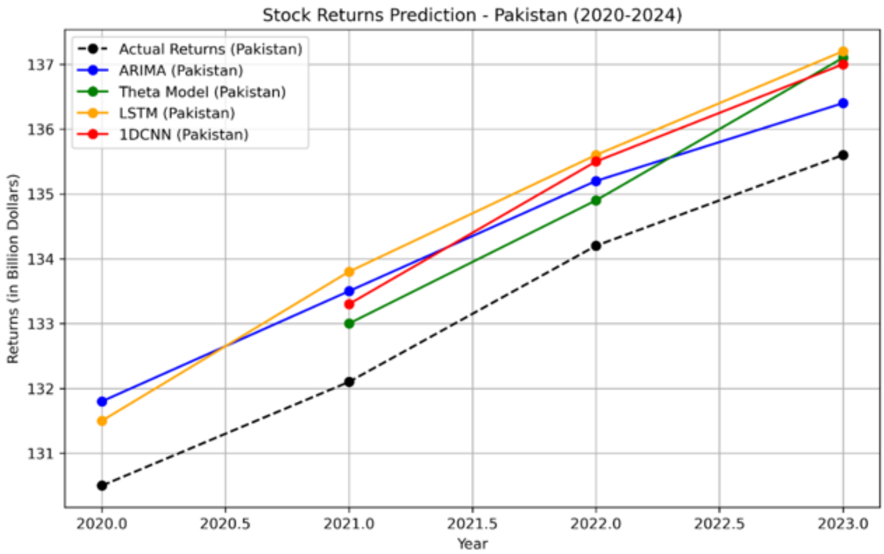

Figure 3
Stock Returns Prediction - Sri Lanka (2020-2025)

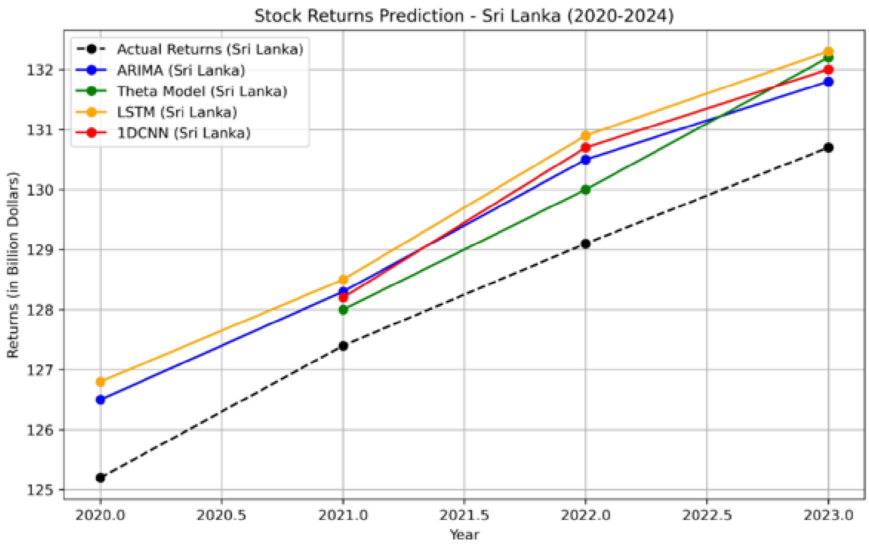

Figure 3 shows the hypothetical stock returns in Sri Lanka for 2020-2025. This figure, just like the previous one, illustrates the market returns and predictions of the forecasting techniques. The model provides an opportunity for

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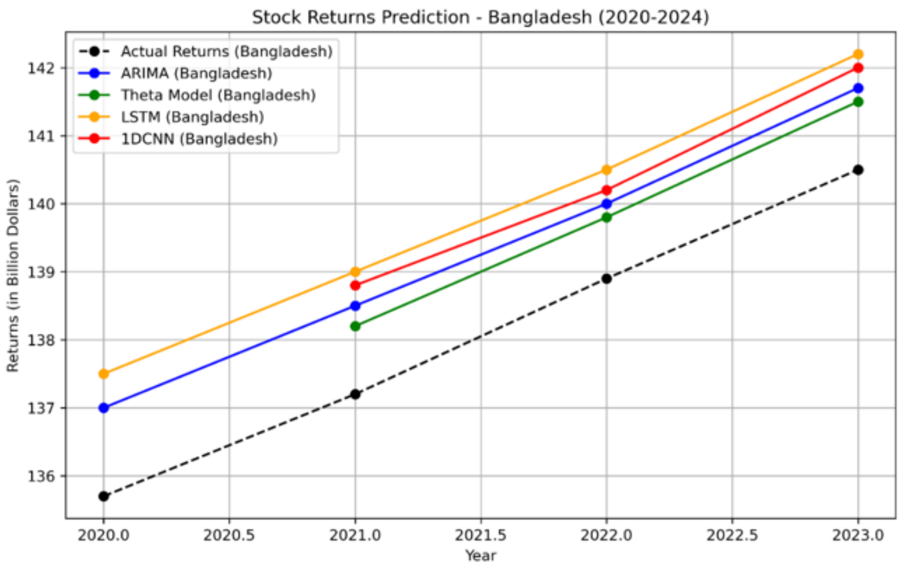
an analysis of the predictive capabilities of each model and helps to reveal the strengths and weaknesses of the models in capturing Sri Lankan stock market dynamics for the time period under consideration.

Figure 4 projects Bangladesh's expected stock returns for 2020-2025 (see Figure 4). It reveals a scatterplot of actual returns and predictions given by various forecasting models to understand the accuracy and reliability of the model's manufactured predictions. A plot is a comprehensive tool for assessing the capacity of forecasting methods' capacity to expose Bangladesh's stock market tendency within the stipulated period of time.

Figure 4
Stock Returns Prediction - Bangladesh (2020-2025)



As expected the ARIMA and Theta models did capture linear trends in stock market data. In particular, the Theta model was able to handle seasonal components, which are prevalent in the stock indices of each of the three markets. However, both models failed to explain the large volatility and nonlinear patterns in the data. For instance, in instances of sudden market shifts resulting from external factors such as political instability or global economic events, these models have higher forecasting errors. Though ARIMA and Theta models are simple and efficient, they are limited to the extent where it might be better to use the models for short term predictions in a stable market.

However, the LSTM and 1D CNN models outperformed by a significant margin in the ability to capture the complex, nonlinear relationships hidden in the stock market data. The LSTM model, designed to deal with sequential data, was especially good at detecting long term dependencies and predicting trends for long stretches of time. The 1D CNN model also outperformed in detecting local patterns and short term fluctuations in stock prices. ARIMA and Theta

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were outperformed in both accuracy (as measured by MAE and RMSE) and robustness across different market conditions by these deep learning models. For example, LSTM and CNN models performed better, and were more accurate, than traditional models in times of increased market volatility. The implications of these findings have important practical implications for investors and financial analysts working in frontier markets. The traditional models, such as ARIMA, are easier to implement and easier to interpret, however, they may not be reliable in highly volatile environments in which markets are sensitive to external shock. However, in terms of predictive accuracy, deep learning models, such as LSTM and 1D CNN, achieve better performance, and are more capable of dealing with more complicated market behaviors, and they are more suitable for long term investment strategies. However, these models require more computational resources and more expertise is needed to implement and interpret them.

Additionally, this study dealt with the interpretability challenges of deep learning models (the 'black box' problem) by applying SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME). Using these techniques, insights were gained into how different features (e.g. GDP growth, inflation) contributed to the model's predictions, allowing for more actionable and accessible results to decision makers.

4.8 Implications on Economy and Stock Returns

A positive forecast in all the models indicates generally favourable trends for Pakistan and Bangladesh in the upcoming year (2024-2025). The dispersion of prediction errors, though, clearly shows that there is no way of predicting financial markets to perfection.

Economic Growth: Positive returns provide a glimpse of anticipated economic growth that is, in turn, fueled by factors like increased consumer spending, business investment, and market confidence. This could be explained by the process of economic reforms, which continue patronizing innovations with new cuts in the beam of the economy.

Market Dynamics: The spread of forecasting errors shows shorts of the model in the market's working, which is not static over time. This implies that some of the events that take place can influence the yield of the stocks, as is the case with political, policy shifts, and global economic situations.

Investor Decision-Making: Investors need to stay vigilant and cautious as they evaluate these predictions while acknowledging the limitations of the models. Diversification and risk management strategies are still the backbone of any successful stock market investment, considering the flux of risks.

Policy Implications: The policymakers can get insights from these data and use them to fine-tune the economic policies to ensure they harmonize with market expectations. Comprehending the origins of the expected returns is a crucial point in specifying which interventions should be set in a targeted manner to achieve sustainable economic growth.

Finally, although the models are expected to be constructive, wise decisions in the financial sphere rely on comprehensive knowledge of not only macroeconomic factors but also the limits of predictive modelling. Forecasting models

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require amendments because the global economy is a dynamic beast that constantly adapts to new conditions.

5 Conclusion

The aim of this study was to evaluate the performance of traditional time series models (ARIMA and Theta) and advanced deep learning models (LSTM and 1D CNN) in forecasting stock market trends for frontier markets of Pakistan, Bangladesh and Sri Lanka. It was found that although ARIMA and Theta models are well suited for short term predictions in stable market conditions, both struggle with the nonlinear patterns and high volatility that are characteristic of these markets. However, LSTM and 1D CNN models outperformed in capturing complex nonlinear relationships and long range dependency, resulting in higher predictive accuracy in times of volatility. SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) were used to integrate to address the interpretability issues with deep learning models, making the findings actionable for investors and policymakers. However, this study has several limitations. Second, the data for this research only spanned from 2020 to 2023, a period that included many market events of significance, however, may not be enough to capture the long term behaviors of these frontier markets. Future studies could extend the dataset to include longer historical periods and thus draw more robust conclusions. Second, although the LSTM and CNN models performed better than the other considered models, they require more computational resources and require more expertise, which may limit their practical implementation for all market participants. Additionally, these models are "black box" in nature, even with the application of interpretability techniques, leaving the users who prefer more transparent forecasting methods with little else. Another limitation is that deep learning models can overfit too easily. While cross validation and hyperparameter tuning were used to address this problem, it is still a problem, especially when applied to different datasets or less volatile periods. The models also did not consider unforeseen external shocks, such as a sudden political change or natural disaster, which can have a large impact on market behavior and are hard to predict with any model. As such, further research should incorporate event driven analysis to better handle such market shocks. We suggest ensemble approaches, which combine traditional and deep learning models, as future work to utilize the strengths of both while balancing interpretability and predictive accuracy. Furthermore, since other financial indicators like market sentiment from social media and news articles, as mentioned in related works Vargas et al (2018), could be utilized to enhance accuracy in prediction, it is reasonable to include them in this research. Finally, these models can be applied to other emerging or frontier markets beyond South Asia in order to gain broader insight into the generalizability of the results.

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