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Reassessing Rolling Window effects in the Era of Machine Learning: Evidence from ARIMA and LSTM Models for Stock Index Forecasting

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Abstract
Under the theories of the Efficient Market Hypothesis (EMH) and Adaptive Market Hypothesis (AMH), the study aims to evaluate and compare the forecasting accuracy of three competing models, viz., ARIMA (recursive), ARIMA (rolling), and LSTM, across three international stock market indices from India, the US, and China using the Diebold-Mariano (DM) test. To simulate real-world forecasting conditions and ensure a comparison between the LSTM and ARIMA models, the Rolling-Window Forecasting method is employed. The methodological innovation of rolling window forecasting not only aligns ARIMA (rolling) with LSTM in terms of level playing field but, crucially, delivers significantly superior forecasting accuracy. Although LSTM excels at capturing both the nonlinear and linear nature of data compared with ARIMA, the forecasting accuracy of ARIMA (rolling) is significantly better than that of LSTM and ARIMA (recursive) as per DM test. However, the forecasting accuracy of LSTM is significantly better than that of ARIMA (recursive) as per DM test. The three models for each of the three indices are also evaluated on the basis of five measures-MAE, MSE, RMSE, MAPE, R^2. On all five measures, ARIMA (rolling) has less forecasting errors than LSTM and ARIMA (recursive), and, like the extant literature, LSTM has fewer forecasting errors than ARIMA (recursive).

Keywords: Adaptive Market Hypothesis; Efficient Market Hypothesis; Deep Learning; LSTM; Neural networks; Rolling Forecasting,

1. Introduction

Forecasting financial time-series data is a pivotal aspect of economic and market analyses, serving as a critical tool for investors, analysts, and policymakers to make data-driven decisions. Sound investment decisions, efficient asset allocation, effective risk management, and corporate strategic planning can be based on accurate forecasting of stock indices. For macroeconomic stability, effective policy support, and prevention of economic shocks (such as the 2008 crisis) accurate forecasting is an absolute necessity. However, research on forecasting faces the theoretical hurdles of the Efficient Market Hypothesis (EMH) and interdisciplinary challenges in statistics, mathematics, machine/deep learning, economics, finance, and behavioral sciences. The inherent volatility, nonlinearity, and complexity of financial markets pose significant challenges in developing accurate and robust predictive models. Although forecasting is highly challenging, it is equally rewarding, both intellectually and in terms of the benefits it accrues. The Adaptive market hypothesis allows stock market forecasting due to real-world inefficiencies (Lo, 2004). New technological advancements and tools, such as machine learning, deep learning, and artificial neural networks, allow for better capturing of volatility, non-linearity, and financial market complexity to build smarter and adaptive models for forecasting.
Unlike inherently limited forecasting (passive) under the Efficient Market Hypothesis (Timmermann & Granger, 2004), the Adaptive Market Hypothesis provides space for active forecasting in the stock market (Lo, 2004). The recursive and rolling forecasting methods have been used to highlight and capture the contrast between EMH and AMH, respectively. Over time, statistical and econometric techniques have evolved and have been used to enable the robust prediction of financial time-series data. Owing to the simplicity, interpretability, and applicability of the ARIMA technique to many economic and financial datasets, it has become a standard

for forecasting (Nau, 2020). Among the new techniques of Deep Learning and Machine Learning, the Long Short-Term Memory (LSTM) has become an important technique for forecasting in the stock market with the advancement of computational capability. (Ozdemir et al., 2021). ARIMA and LSTM, both the techniques show tremendous potential in addressing the time-series forecasting issues.

The objectives of this study are twofold: First, to utilize the statistical and econometric ARIMA models (viz., ARIMA (rolling) and ARIMA (recursive)) and the Deep Learning LSTM model to forecast the three major global stock indices viz., the Nifty Fifty Index (Nifty) (India), Standard & Poor 500 Index (SPX) (USA), and Shanghai Stock Exchange Composite Index (SHCOMP) (China) and evaluate their forecasting accuracy. Second, to compare and test the performances of three time-series forecasting models, viz., both ARIMA models (recursive & rolling) and the LSTM model, by using the Diebold-Mariano (DM) test. By evaluating and comparing these models on a very long range of time-series data sets that incorporate varied market conditions, this study aims to provide insights into the relative strengths and limitations of the three forecasting models, contribute to the growing body of research on financial time-series forecasting, and enhance decision-making in stock trading strategies.

The paper is organized as follows. In Section 2, we provide a concise review of the existing research relating to ARIMA and LSTM techniques in forecasting. A description of the data and proposed method is provided in Section 3. The result and discussion of the data analysis are presented in Section 4, while the conclusions and suggestions for future research are presented in Section 5.

2. Theoretical Framework

Research on stock market forecasting centers on two key theories: the Efficient Market Hypothesis (EMH) and the Adaptive Market Hypothesis (AMH). The EMH argues that asset prices quickly absorb all available information, making it challenging to consistently forecast market movements or achieve above-average returns (Fama, 1970). The EMH forecasting focuses on risk modelling rather than price prediction, as markets are assumed to be efficient. However, the EMH aids passive forecasting, that is, predicting long-term expected returns based on historical averages under the assumption of informational efficiency, and not short-term price movements (Vuković et al., 2024). Unlike the evolving and dynamic market efficiency as per the AMH, the EMH assumes the market efficiency as "a steady-state limit of a population with constant environmental conditions" (Lo, 2004). Instead of timing the market, EMH argues for a long-term strategy for investment in the market. In a stable economic environment, the stock market becomes efficient, and EMH serves as a reasonably good approximation of reality (Lo and Zhang, 2024). The steady-state, long-term efficiency and stability in the market could be operationalized through recursive forecasting methods. The recursive forecasting methods are effective when the data-generating process (economic and environmental conditions) is stable. The recursive prediction method is more consistent with the EMH, which uses the model's own forecasted values as input for future predictions under the assumption that the underlying data-generating process (economic environmental conditions) remains stable over time i.e., the parameters of the model trained on past data remain the same going forward. The ARIMA (recursive) forecasting model, involving the ARIMA technique with a recursive prediction method, is used to forecast the three major global stock indices in this study.

In contrast, the AMH proposes that financial markets adapt over time as investors adjust their behavior in response to evolving conditions and new information, occasionally leading to inefficiencies that can be exploited for forecasting (Lo, 2004). This dynamic perspective recognizes that markets may exhibit predictable patterns at specific times and are not always completely efficient (Vuong et al. 2022). Asset prices will fluctuate in response to any new information. The need for flexible and dynamic forecasting methods and techniques that can change with the market is highlighted by the stock market's dynamic and ever-changing behavior. These contrasting views between the EMH and AMH highlight the complexity of financial time series, and the approach towards forecasting will also change. The rolling-window forecasting model, a dynamic and adaptive process, has become a practical approach to reflect the dynamic and changing nature of the stock market under the AMH. (Lo, 2004; Sing & Singh, 2024). The ARIMA(rolling) forecasting model, which combines the ARIMA technique with the rolling window prediction method, is used to forecast the three major global stock indices in this study.

Several forecasting techniques have evolved to study stock market forecasting. Statistical and econometric techniques, including the ARIMA, are applied in time-series forecasting because they are simple to implement, easy to understand, and can capture stationary and linear data (Nau, 2020). Despite the strength of ARIMA, the technique turns out to be weak in modeling the nonlinear structure and dynamic patterns that underlie financial markets (Sheth & Shah, 2023).

Recent research has increasingly looked into machine learning (ML) and deep learning (DL) techniques, which are excellent at modeling complex temporal relationships and nonlinear dependencies in sequential datasets, as a way to overcome the shortcomings of econometric and statistical models. According to Hochreiter and Schmidhuber (1997), Gers et al. (2000), and Brownlee (2018), LSTM networks—a subset of Recurrent Neural Networks (RNNs)—have proven to be particularly effective at handling sequential data with high variability and capturing long-range dependencies. Numerous forecasting studies have demonstrated that machine learning and deep learning techniques can outperform statistical and econometric techniques in terms of predictive performance on financial time-series data.

Extensive research has been conducted on ARIMA and LSTM-machine learning and deep learning techniques for stock market index forecasting. Because the financial time-series data is stochastic, nonlinear, and volatile, forecasting market indices is intrinsically difficult. The statistical and econometric techniques like Auto Regressive Integrated Moving Average (ARIMA) and modern Deep Learning techniques like Long Short-Term Memory (LSTM) networks, are widely used in this domain. The main studies that look at and contrast the effectiveness of LSTM and ARIMA in stock market forecasting are summarized in this review.
Box and Jenkins (1970) laid the foundation for ARIMA modeling by showcasing its efficacy in simulating linear stationary time-series or series that can be rendered stationary through differencing. Hochreiter and Schmidhuber (1997), introduced LSTM, a Recurrent Neural Network (RNN) variation intended for long-term dependency learning. Since then, LSTM has become more and more popular in financial forecasting due to its capacity to model non-linearities and retain data over long periods of time. Di Persio and Honchar (2019) compared a number of machine learning and deep learning approaches, using RNN, LSTM, and GRU for Google stock forecasting. They found out that LSTM was more effective than the other methods used in the study.

The effectiveness of LSTM (Long Short-Term Memory) and ARIMA (Auto Regressive Integrated Moving Average) models for predicting future trends in a variety of fields has been the subject of numerous empirical investigations. The goal of this ongoing study is to ascertain which model—or combination of models—offers better predictive power in various scenarios. The performance of ARIMA and LSTM in various time-series datasets is examined in recent works by Yang & Wang (2024), Xia (2024), and Kırelli (2024). Likewise, research by Kuang (2023), Tong et al. (2023), and Yavasani & Wang (2023) also explores similar approaches. The expanding body of research contrasting these two well-known forecasting techniques is further supported by additional contributions from Bagul et al. (2022) and Xiao et al. (2022). Li (2024) examined the performance of ARIMA and LSTM in companies in the healthcare, e-commerce, gaming, and AI sectors and concluded that ARIMA performed better in terms of forecast closing stock prices over the previous few years. and had a lower mean squared error (MSE).

A number of recent studies (Baughman et al., 2018; Rana et al., 2019; Chatterjee et al., 2021; Pothuganti, 2021) have emphasized LSTM's ability to model complex financial behavior. Yang and Wang (2024) stated that whenever they compared the predictive accuracy of the LSTM and ARIMA models, LSTM performed better in comparison to ARIMA. Although both models identified the general trend direction, Yang and Wang (2024) found that LSTM produced more accurate forecasts than ARIMA in predicting the stock prices of NVIDIA. Zhang (2023) also confirmed the superior performance of LSTM in stock prediction. Using a rolling forecast approach, Namini et al. (2018) demonstrated that LSTM significantly decreased RMSE in comparison to ARIMA, and that performance gains in LSTM plateaued after a specific number of training epochs. Kara, Acar, and Dirican (2021) also found LSTM to outperform ARIMA on the Istanbul Stock Exchange in terms of RMSE and MAE. Xiao et al. (2022) used multiple performance metrics (MAE, MSE, and RMSE) across various stocks and argued that LSTM has better forecasting performance than ARIMA.

However, on the basis of just model evaluation performance metrics (viz., MAE, MSE, RMSE, etc.,), some of the studies proclaimed different results for different techniques, which muddied the water. Kirelli (2024), while forecasting Oracle's stock, found that LSTM produced lower error values (MSE, MAE, RMSE), but ARIMA was more accurate in percentage error terms (MAPE) and trend direction.

However, some of the studies argued that a particular technique is better under specific circumstances. A comparative study by Taslim and Munwantara (2024) on fluctuating time-series prediction revealed that ARIMA was more accurate than LSTM for a larger dataset, as evaluated using the RMSE. This outcome challenges the common belief that LSTM models generally perform better with more data points. In contrast, when tested on a smaller dataset of 60 points in the same study, LSTM outperformed ARIMA in terms of accuracy. Others have also shown that ARIMA continues to be competitive in short-horizon forecasting, particularly when the data are primarily linear (Adebiyi et al., 2014), despite the fact that numerous studies (Yang & Wang, 2024; Liu & Lai, 2024; Kuang, 2023) indicate that LSTM generally performs better than ARIMA, especially when capturing complex nonlinear and long-horizon patterns.

While comparing the predictive performance of ARIMA and LSTM models on the different time horizons, Choudhury et al.(2020), Zhang et al. (2018), Choy et al. (2021), and Singh et al. (2022) concluded that ARIMA was efficient for short-horizon forecasting, the LSTM model performed better to capture the long-horizon patterns due to its capacity to model sophisticated temporal dependencies. Albeladi et al. (2023), on the other hand, established that ARIMA performed better compared to LSTM on model evaluation standard error metrics (viz., MAE, MSE, RMSE, MAPE, R^2). Lahboub and Binali (2024) discovered that ARIMA equalled LSTM in long-horizon forecasting of ETFs. This reflects ARIMA's appropriateness for capturing immediate market movement and LSTM's appropriateness for capturing long-horizon trends. Nti, Adekoya, and Weyori (2020) clarified that ARIMA works effectively for stationary, linear data but stops working with nonlinear patterns. In contrast, Nelson, Pereira, and de Oliveira (2017) discovered that LSTM captures nonlinear dynamics in the Brazilian stock market index better. The LSTM model is better suited in volatile scenarios than ARIMA, as justified by Huck (2009) and Fischer & Krauss (2018). Adebiyi et al. (2014) and Patel et al. (2015) noted ARIMA's struggle with abrupt market shifts and high volatility, whereas recurrent models such as LSTM proved more resilient. In another study, Yavasani and Wang (2023) found that while ARIMA struggled with volatile trends, LSTM better handled dynamic financial patterns.

Although several studies have compared ARIMA and LSTM models for stock price forecasting, a notable methodological gap remains in the methods of these comparisons. Specifically, the extant literature often contrasts the ARIMA (recursive) model with the LSTM model, whereas LSTM, by its very nature, is a rolling-window forecasting technique, resulting in an unequal basis for comparison.
Some of the studies compared the models under different circumstances, contexts, and environments. Additionally, the list of model evaluation techniques (such as MAE, MAPE, MSE, RMSE, R^2) are not common among all the reviewed studies, which may have resulted in different results regarding the forecasting accuracy of different models. Moreover, rarely any research study has rigorously assessed and tested the forecasting accuracy of these models against each other using robust statistical techniques such as the DM test.

The study addresses a key methodological bias often present in comparisons favoring LSTM models by innovatively extending the ARIMA framework to incorporate **rolling window forecasting**. To address these gaps, this study conducts a systematic comparison of ARIMA (recursive), ARIMA (rolling), and LSTM forecasting models on three global stock market indices of the top three economies of the world (viz., Nifty Fifty Index (Nifty) (India), Standard & Poor 500 Index (SPX) (USA), and Shanghai Stock Exchange Composite Index (SHCOMP) (China)) through a comprehensive list of model evaluation techniques, viz., MAE, MSE, RMSE, MAPE, and R^2. To incorporate all kinds of circumstances, contexts, and environments, the forecasting models are trained and developed on a very long range of time-series datasets. Additionally, this study tests the predictive performance of these three forecasting models against each other using the Diebold-Mariano (DM) test to statistically validate the differences in forecasting accuracy.

Null hypothesis of the study

(i) ARIMA (rolling) and ARIMA (recursive) models do not show a statistically significant difference in forecasting accuracy across the three stock market indices under study.
(ii) ARIMA (recursive) and LSTM models do not show a statistically significant difference in forecasting accuracy across the three stock market indices under study.
(iii) ARIMA (rolling) and LSTM models do not show a statistically significant difference in forecasting accuracy across the three stock market indices under study.

3. Material and Methods

The closing price data of three selected stock market indices, viz., Nifty Fifty Index (Nifty) (India), Standard & Poor 500 Index (SPX) (USA), and Shanghai Stock Exchange Composite Index (SHCOMP) (China), spanning from January 1, 2000 to December 31, 2024, covering 24 years, are sourced from Bloomberg. The log of the daily closing price of these indices is calculated for further analysis. In ARIMA models, a total of 80% of the financial time series data from each of three indices are used for training, while the remaining 20% are used to evaluate the models accuracy and precision. In the LSTM technique, the look-back data of 60 previous data points are taken out to predict the next data point; the remaining data in each of the three indices are divided into 80% training and 20% testing data. Table 1 shows the distribution of data points for each index dataset under both techniques.

Table-1 No. of Time series Data-points for Training and Testing

Name of the Index	Ticker	Total No. of Data Points	ARIMA		LSTM		
			Training Data (80%)	Test Data (20%)	Look Back	Training Data (80%)	Test Data (20%)
Nifty 50 Index	Nifty	6217	4973	1244	60	4925	1232
S & P 500 Index	SPX	6289	5031	1258	60	4983	1246
Shanghai Stock Exchange Composite Index	SHCOMP	6058	4846	1212	60	4798	1200

3.1 *Recursive Forecasting Method*

In the recursive forecasting method, the predictions extend over multiple future time-steps at one go. While the model is trained and developed on historical data until time (t), future predictions at future time-steps (t+1, t+2, t+3,...) are generated recursively, where forecasted values are fed back into the model as if they were actual observations. Once the model forecasts the first future value, it uses that prediction as input to estimate the next one, and so on. This approach assumes that the underlying model or data-generating process remains stable over time- a notion more consistent with EMH.

3.2 *Rolling-Window Forecasting Method:*

In the Rolling or Rolling-window forecasting method, the model predicts one step (t+1) at a time, relying solely on actual historical observations up to the time point (t). While the model is trained on historical data up to time (t), it is used to forecast one step ahead (t+1) using actual past data. For each subsequent prediction, the true observed value at time (t+1) is used for predicting the value at time (t+2) and so on. As a result of this rolling-window mechanism, forecasted values cannot be used as inputs.

3.3 *ARIMA*

ARIMA is a statistical model used to forecast and analyze time series. In ARIMA model, 'AR' stands for autoregression, which evaluates an observation's dependence on its previous values (p); 'I' stands for integrated, a method for generating stationarity by varying observations across distinct intervals (d); and 'MA' stands for moving average, an approach that evaluates whether observations are affected by the residual errors derived from applying a simple moving average to lagged observations (q). A model such as this is usually designated as ARIMA (p,d,q). In the ARIMA (rolling), the model predicts future values one step at a time, relying solely on actual historical observations up to the current time point. While in the ARIMA (recursive), predictions extend over multiple future time steps, where forecasted values are fed back into the model as if they were actual observations.

The general mathematical structure of an ARIMA (p, d, q) model is given by:

$$\hat{y}_{t+h} = f(\hat{y}_{t+h-1}, \hat{y}_{t+h-2}, \ldots\ldots \hat{e}_{t+h-1}, \hat{e}_{t+h-2}, \ldots\ldots) \quad (1)$$

- h indicates the forecast horizon (number of steps ahead- In rolling method, one step at a time, and in recursive, multiple steps at the same time),
- $\hat{y}$ is the forecasted value at time t+h,
- e_t is the residual errors.

The log of the closing prices of the three indices is calculated. On the training data of such log closing prices of these indices, the ARIMA technique has been applied under both the methods for developing ARIMA models viz., ARIMA (recursive) model and ARIMA (rolling) model, for each of the indices. During the testing phase, the parameters and equations of both trained ARIMA (i.e., the p, d, q) models are applied on testing data of each index to calculate the forecasted values. The forecasted values of both models are evaluated on actual testing data and DM tested against other models for each index.

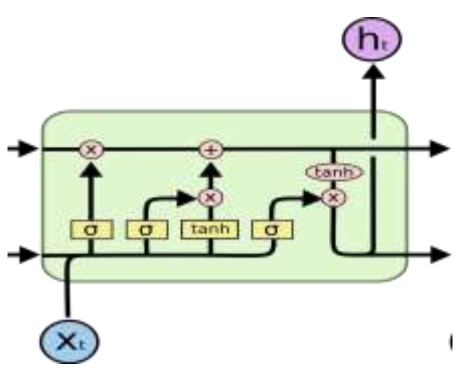
3.4 *LSTM*

Long Short Term Memory (LSTM) is a specialized variant of Recurrent Neural Networks (RNNs) and belongs to the RNNs family. LSTM is capable of long-term dependencies, unlike RNNs, and, thus, removes one of the limitations of RNNs and works better than RNNs in some of the problems. However, RNN, a specialized type of Artificial Neural Networks, is developed to handle sequential data and has the architecture of neural networks. As a branch of Machine learning (ML), the Deep Learning (DL) models work with the Artificial Neural Networks with multiple layers of neurons to deal with the large datasets.

The Neural Networks are developed as algorithms to imitate and replicate the human brain neural networks. The Artificial Neural Network consists of one or more layers of interconnected nodes. These layers could be arranged as an input layer, one or more hidden layers, and an output layer. Every node on each layer is connected to all nodes in the subsequent layer. By adding many hidden layers, the depth of the network can be increased and that's why it's called Deep Learning. Each node takes weighted input values, adds a bias term, applies non-linear activation function and produces its output. This output transforms from the one layer of nodes to the next layers of nodes of the network and so on till the final output comes through the output layer.

The Recurrent Neural Networks (RNNs) is quite useful in the Time Series Analysis as the "recurrent" nature of the neural networks that use the previous information from the earlier sequence of data such as y_{t-1}, y_{t-2}, etc., to process the current data of y_t and predict the future data y_{t+1}. The internal memory of RNNs hold previous information of the earlier sequence. However, RNN has a problem of vanishing gradient i.e., the earliest information from earliest sequences are getting lost while new information is added into the process. The LSTM uses the internal memory like RNNs but removes the vanishing gradient problem by using long-term dependencies more effectively i.e., using earliest information too. The LSTM technique of Machine/Deep Learning approach is by its very nature a rolling-window method.

In the LSTM, the information in the internal memory is stored in cell state and information is used as per condition. The LSTM uses the following Gate Mechanism to control the flow of the information into the processing system.



1. Input gate- it controls how new information is added to the cell state. It combines a sigmoid function as given in equation 2 which suggests which values to update and how.
2. Forget gate- it controls which information from the cell state would be discarded or retained as per the equation 3.
3. Candidate Cell state (c_t)- It represents a potential new version of the memory that combines output of input gate to form the updated cell state (c_t) as per equation 4.
4. Output gate- it controls which information from the cell state will be the output as per equation 5.
5. x_t is the input vector
6. h_t is the output vector as given in equation 6.
7. W and b are weights and bayes values.

$$i_t = \sigma(W_i\,[h_{t-1}, x_t] + b_i) \quad (2)$$

$$f_t = \sigma(W_f\,[h_{t-1}, x_t] + b_f) \quad (3)$$

$$c_t = \tanh(W_c\,[h_{t-1}, x_t] + b_c) \quad (4)$$

$$o_t = sigma(W_o\,[h_{t-1}, x_t] + b_o) \quad (5)$$

$$h_t = sigma * tanh(c_t) \quad (6)$$

The LSTM is quite useful and effective in problems involving sequential data. Apart from speech recognition, the LSTM is quite effective in learning, predicting and providing solutions to the tasks related to Time Series Analysis.
During the training phase of the LSTM, the weights and biases are calculated at first and, then, adjusted to minimize the error between actual values and predicted values, which could be called the LSTM model. The same LSTM model is applied on the values of both training and testing data to calculate the predicted values for both training data and testing data. Consequently, the LSTM model's forecasted values of testing data are evaluated against actual testing data values and the LSTM model is DM tested against other models (viz., ARIMA (recursive) and ARIMA (rolling)) on forecasting accuracy for all the three indices in the study.

3.5 *Model Evaluation:*

The forecasting model accuracy was evaluated using the following five measures.
1. Mean absolute Error (MAE): It refers to the mean of the absolute values between actual values and predicted values as per the following equation 7.

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}| \tag{7}$$

2. Mean Squared Error (MSE):It refers to the mean of the sum of squares of difference between the predicted ($\hat{y}$) and actual (y_i) values as per the following equation 8.

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y})^2 \tag{8}$$

3. Root Mean Squared Error (RMSE): It refers to the square root of the mean squared error (MSE) as per the following equation 9.

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y})^2} \tag{9}$$

4. Mean absolute Percentage Error (MAPE): It refers to the mean of the absolute percentage between the predicted and actual values as per the following equation 10.

$$\text{MSPE} = \frac{1}{N}\sum_{i=1}^{N} \frac{|y_i - \hat{y}|}{y_i} \tag{10}$$

5. R^2- : The R^2 is known as the coefficient of determination and measures how well a model explains the variance in the actual data.

$$R^2 = 1 - \frac{\sum (y_i - \hat{y})2}{\sum (y_i - \underline{y})2} \tag{11}$$

If $R^2 = 1$, Perfect Prediction. If $R^2 = 0$, the model is as good as simply predicting the mean.
If $R^2 < 0$, model is worse than just using the mean of the data

3.6 *Diebold-Mariano (DM) test:*

The DM test is a statistical test that compares the predictive accuracy of two forecasting models. It helps in determining which one of two predictive models is significantly better than another in terms of forecasting accuracy as follows:
1. Forecasting Errors of each forecasting models viz., Model 1 and Model 2:
Forecast error (Error) = Actual Value - Predicted Value
2. Loss Differential: The Loss Differential is calculated using Mean Absolute Error in this paper. However, it can also be calculated using Mean Squared Error.
Loss Differential = $|Error_1|$ - $|Error_2|$
3. Mean Loss differential: The mean loss differential (d_{mean}) is the average of the loss differential values:
$d_{mean} = \frac{1}{N}\sum_{i=1}^{N} Loss\ Differential_i$ where N is the number of observations.
4. Variance of Loss Differential: The variance of the loss differential (d_{var}) takes into account the autocorrelation within the series of loss differentials:
d_{var} = sum of Autocorrelations
Autocorrelation accounts for dependencies in the error series over time
5. Diebold-Mariano (DM) Statistics: DM statistics is calculated as

$$\text{DM Statistics} = \frac{dmean}{\sqrt{\frac{dvar}{N}}}$$

6. Under the assumption that $\mu = 0$ (the null hypothesis), DM follows a Standard Normal Distribution. DM ~ N(0,1)
7. If the p value of the DM Statistics is significant, the Positive DM statistics suggests that Model 2 is significantly better and Negative DM statistics suggests that Model 1 is significantly better.

The research study trains and develops three models viz., ARIMA (recursive), ARIMA (rolling), and LSTM to predict the log of daily closing prices of three key indices: Nifty Fifty Index (Nifty) (India), Standard & Poor 500 Index (SPX) (USA), and Shanghai Stock Exchange Composite Index (SHCOMP) (China) for testing phase, evaluates these models against actual values through model evaluation measures, and compares these models against each other on their forecasting accuracy through DM tests.

Specifically, the study explores the application of Auto Regressive Integrated Moving Average (ARIMA) and the Deep Learning-based Long Short-Term Memory (LSTM) technique for forecasting of stock indices. Unlike the statistical forecasting technique that requires manual intervention for model selection and parameter tuning, advanced methods (viz., LSTM) use automated processes such as hyperparameter optimization (Petropoulos, et al., 2022). The automation allows the scalability of the models which could be applied in case of large datasets. Python programming is used to apply the Recursive and Rolling-window forecasting method with ARIMA technique as well as to automate the ARIMA model development, which provides a level-playing field to ARIMA technique. Python programming facilitates the automation of model selection and parameter tuning as well as scalability in ARIMA through the auto_arima function within the pmdarima library. The model development through training on three stock market indices datasets using three techniques, forecasting on the testing datasets, model evaluation on testing dataset and forecasted dataset, and testing the forecasting accuracy of each model against each other as per DM test are done using Python programming.

4. Results and Discussion

The results of the comparative analysis of ARIMA (recursive & rolling) and LSTM models' evaluations in forecasting stock market indices are shown in table 2. The ARIMA (recursive) models consistently underperform across all error metrics, with high Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) values, indicating its inability to adapt to evolving market conditions. R-squared (R^2) scores are found to be small or negative proving its inefficiency in explaining market variance. On the other hand, the ARIMA (rolling) models demonstrate superior predictive accuracy, drastically reducing MAE, MSE, RMSE and MAPE across all indices. The minimal forecasting errors and high R^2 values (~0.99), making it the most effective approach for financial time-series forecasting in this case.

The LSTM models perform better than ARIMA (recursive) models across all error metrics for all three indices. While comparing LSTM models with ARIMA (rolling) models, all LSTM models provide slightly higher errors for all three indices suggesting that although Deep Learning models capture complex patterns and nonlinear dependencies, they cannot exceed the forecasting accuracy of ARIMA (rolling) models. Despite this, LSTM models achieve competitive R^2 scores (0.94-0.99), proving its ability to model intricate relationships in stock market data

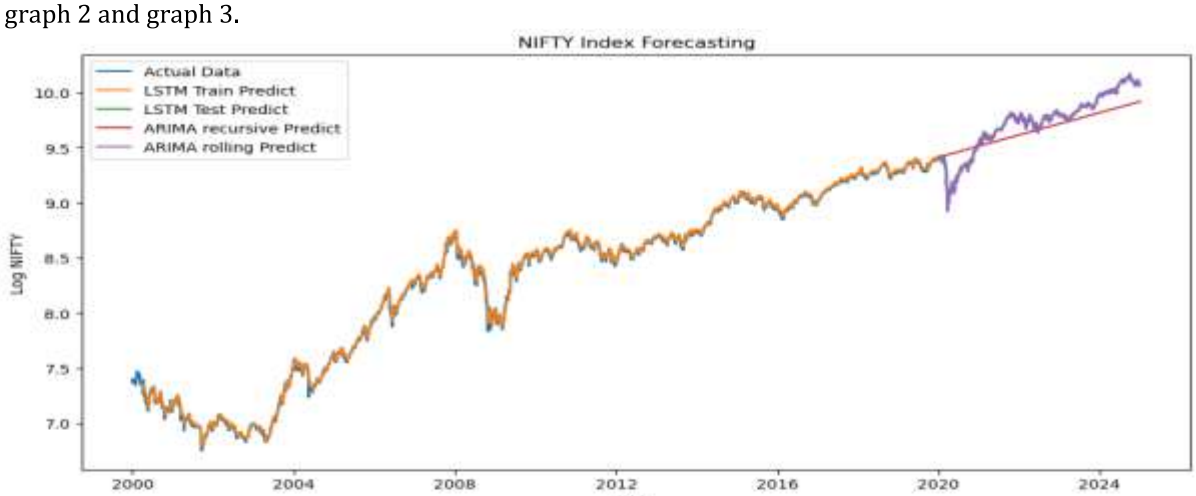
Table-2 Comparison of ARIMA (recursive & rolling) and LSTM (rolling) models in forecasting stock market indices

Model Evaluation	**Models**	**Nifty 50 Index (India)**	**S & P 500 Index (USA)**	**Shanghai Stock Exchange Composite Index (SHCOMP)**
	ARIMA (p,d,q)	**(2,1,0)**	**(0,1,5)**	**(2,1,3)**
MAE	ARIMA (recursive)	0.124	0.182	0.0951
	ARIMA (rolling)	0.007	0.008	0.0076
	LSTM	0.013	0.030	0.0138
MSE	ARIMA (recursive)	0.0216	0.045	0.0122

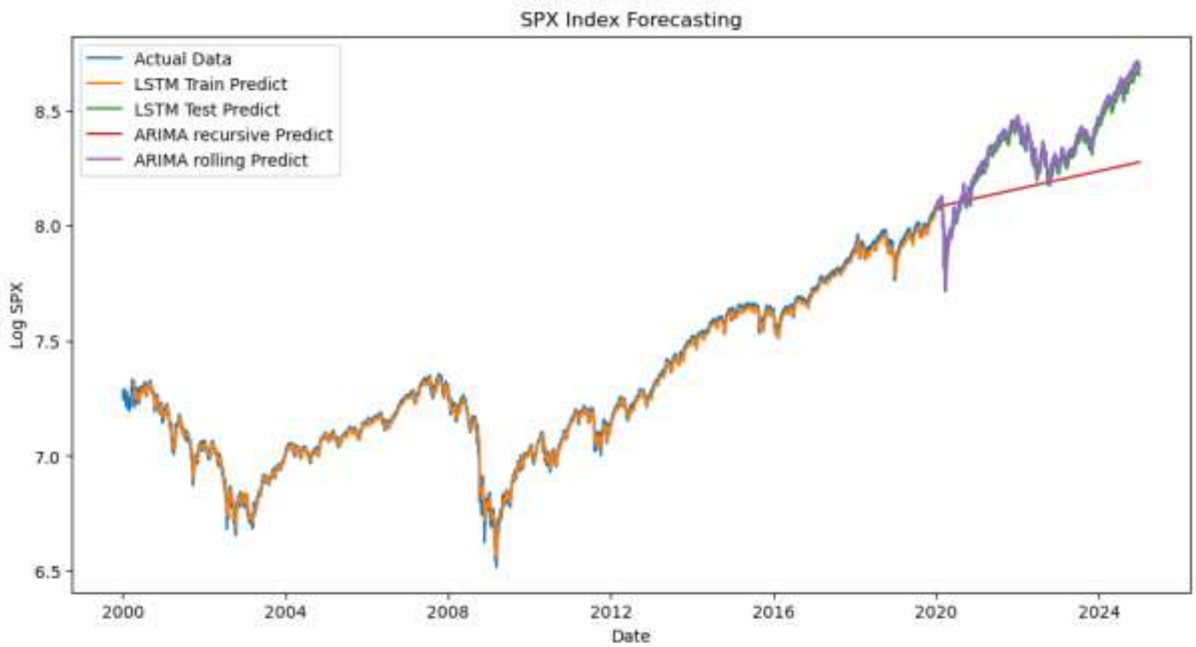
	ARIMA (rolling)	0.0001	0.00018	0.00011
	LSTM	0.0004	0.00121	0.00031
RMSE	ARIMA (recursive)	0.147	0.213	0.110
	ARIMA (rolling)	0.012	0.013	0.010
	LSTM	0.020	0.034	0.017
MAPE	ARIMA (recursive)	1.28%	2.16%	1.18%
	ARIMA (rolling)	0.08%	0.10%	0.09%
	LSTM	0.14%	0.36%	0.17%
R-squared	ARIMA (recursive)	0.67	-0.36	-1.27
	ARIMA (rolling)	0.99	0.99	0.97
	LSTM	0.99	0.96	0.94

This analysis highlights the importance of dynamic forecasting models under Adaptive Market Hypothesis and shows that ARIMA (rolling) and LSTM outperforms ARIMA (recursive) on all model evaluation parameters for all three global stock market indices. Even in adaptive and dynamic forecasting models, ARIMA (rolling), a statistical and econometric technique, outperforms LSTM, a Machine/Deep Learning technique.

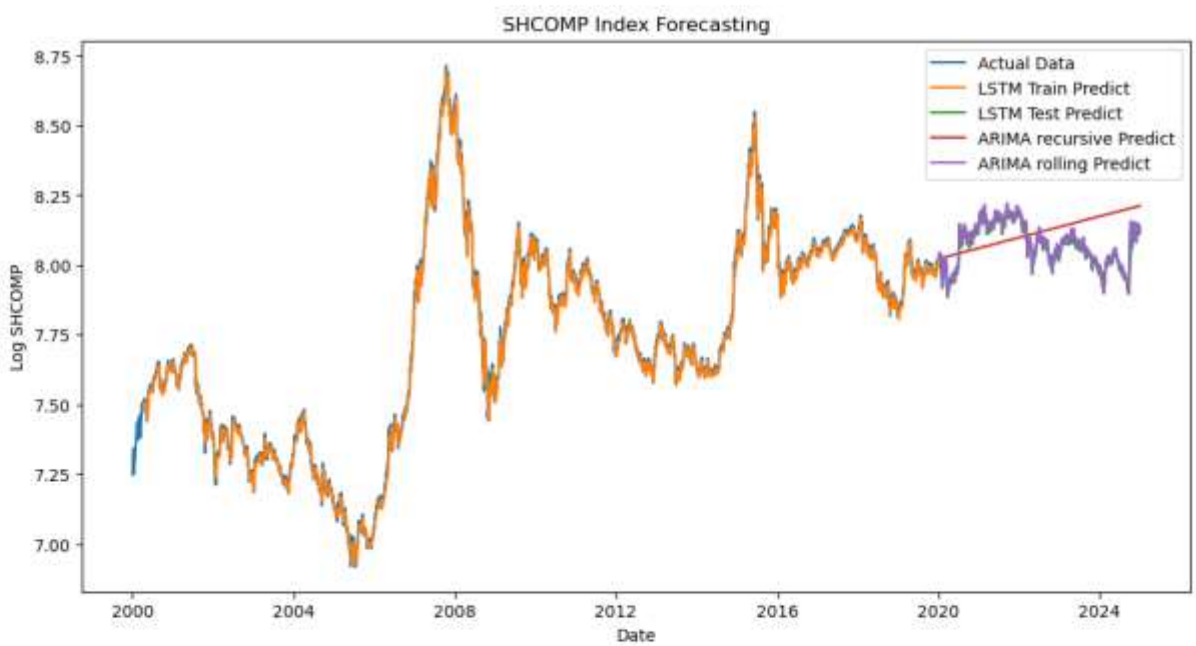
The graph 1 compares predicted NIFTY index values (log-transformed) from three forecasting models against the actual historical NIFTY data (2000–2024) to assess how closely each model's forecast approximate actual NIFTY movement over time. The LSTM predictions (forecasted training data is shown by orange line and forecasted testing data is shown by green lines) aligns tightly with the actual data curve shown by graph 1. The ARIMA (rolling) predictions (purple line) almost perfectly overlaps with actual training data, particularly during testing phase (~2020–2024) where it closely shadows actual NIFTY movements by maintaining consistency and keeping pace with short-term fluctuations. The ARIMA (recursive) diverges notably from actual NIFTY starting around 2020 shown by the red line. It underestimates the NIFTY index decline or growth, failing to capture the steep COVID decline or post-COVID market rally. The similar trend can also be seen within the Standard & Poor 500 Index (SPX) (USA), and Shanghai Stock Exchange Composite Index (SHCOMP) (China) in graph 2 and graph 3.



Graph-1 Nifty 50 Index-Nifty



Graph-2- S & P 500 Index- SPX



Graph-3 Shanghai Stock Exchange Composite Index-SHCOMP

Table 3 presents the results of the Diebold-Mariano (DM) tests, which assesses & statistically tests forecasting accuracy among three models—ARIMA (rolling), ARIMA (recursive), and LSTM—across three major stock indices: Nifty Fifty Index (Nifty) (India), Standard & Poor 500 Index (SPX) (USA), and Shanghai Stock Exchange Composite Index (SHCOMP) (China). The test determines whether the forecasting accuracy of competing models differs significantly or not. In all the comparisons amongst models, the p-value is 0.0000, which confirms that the forecasting accuracy of LSTM, ARIMA (recursive) and ARIMA (rolling) models are significantly different from one another in each of the indices.

A comparison between ARIMA (rolling) models and ARIMA (recursive) models reveals consistently negative DM statistics (e.g., -28.4796 for Nifty 50, -34.6703 for S&P 500, -28.4720 for SHCOMP). This demonstrates that ARIMA (rolling) models significantly outperforms ARIMA (recursive) models across all indices on forecasting accuracy. When ARIMA (recursive) models and LSTM models are compared, positive DM statistics (e.g., 28.4162 for Nifty 50, 34.0893 for S&P 500, 27.9587 for SHCOMP) indicate that LSTM models exhibits superior and statistically significant forecasting accuracy than ARIMA (recursive) models. Interestingly, ARIMA (rolling) models significantly surpass LSTM models in predictive accuracy across all indices, as evidenced by negative DM statistics (e.g., -8.2085 for Nifty 50, -31.4539 for S&P 500, -11.9113 for SHCOMP). While ARIMA (rolling) and LSTM models significantly outperform ARIMA (recursive) models, ARIMA (rolling) models significantly exceed the forecasting precision of LSTM models.

All the null hypotheses are rejected in each case of the indices. The alternate hypotheses, the ARIMA (rolling) models are significantly better than the LSTM models and ARIMA (recursive) models on forecasting accuracy; and LSTM models are significantly better than ARIMA (recursive) models on forecasting accuracy, are accepted for all three stock market indices under study. However, it also suggests that the rolling-window forecasting method (viz., ARIMA (rolling) and LSTM yield more precise predictions compared to the recursive forecasting method. Overall, ARIMA (rolling) remains the most effective model in this analysis, demonstrating the robustness of the rolling-window forecasting method and ARIMA technique. This approach may provide better adaptability to new data while reducing the risk of overfitting, particularly when compared to more complex models of Machine/Deep Learning like LSTM.

Table-3 Result of Diebold-Mariano (DM) tests

Index	Model Comparison	DM Statistics	p-value	Significance	Better Model
Nifty 50	ARIMA (rolling) vs. ARIMA (recursive)	-28.4796	0.0000	Yes	ARIMA (rolling)
Nifty 50	ARIMA (recursive) vs. LSTM	28.4162	0.0000	Yes	LSTM
Nifty 50	ARIMA (rolling) vs. LSTM	-8.2085	0.0000	Yes	ARIMA (rolling)
S&P 500	ARIMA (rolling) vs. ARIMA (recursive)	-34.6703	0.0000	Yes	ARIMA (rolling)
S&P 500	ARIMA (recursive) vs. LSTM	34.0893	0.0000	Yes	LSTM
S&P 500	ARIMA (rolling) vs. LSTM	-31.4539	0.0000	Yes	ARIMA (rolling)
SHCOMP	ARIMA (rolling) vs. ARIMA (recursive)	-28.4720	0.0000	Yes	ARIMA (rolling)

SHCOMP	ARIMA (recursive) vs. LSTM	27.9587	0.0000	Yes	LSTM
SHCOMP	ARIMA (rolling) vs. LSTM	-11.9113	0.0000	Yes	ARIMA (rolling)

Although, the LSTM, with its superior algorithms and memory structures, demonstrates strong adaptability to dynamic patterns and non-linear dependencies in the financial time series, the forecasting accuracy of LSTM is only superior to ARIMA (recursive) but lags significantly behind ARIMA (rolling) in terms of MAE, MSE, RMSE, MAPE, and R^2 and DM tests across all three indices. The LSTM technique is computationally intensive and requires careful fine-tuning, while more fine-tuning may lead to overfitting, which might be the case above.

While ARIMA, as a linear statistical and econometric technique, is relatively efficient in capturing short-horizon trends (Adebiyi et al., 2014), it struggles to adapt to nonlinear patterns which is gauged by the lower forecasting accuracy of ARIMA (recursive) against LSTM. The ARIMA technique with recursive prediction method may only be viable in relatively stable but informationally efficient markets (Timmermann & Granger, 2004). The Deep Learning or Machine Learning methods, even neural network methods are "black boxes" where algorithms are not easily decipherable and interpretable that's why they are mostly used for forecasting rather than for policy analysis (Petropoulos, et al., 2022). Due to its black box nature, the powerful and advanced technique like LSTM hampers the transparency, consequently, trust among users.

The statistical and econometric technique like ARIMA is more simple, transparent and easier to interpret. However, the incorporation of the methodological innovation of Rolling forecasting not only aligns ARIMA (rolling) with LSTM in terms of level playing field but, crucially, delivers significantly superior forecasting accuracy. Like LSTM, ARIMA (rolling) utilizes a certain portion of data for training from the long range of data and forecasts the values for next day but unlike LSTM's input of 60 look-back data, ARIMA models requires actual values only till p and q order of Autoregressive & moving average from the dataset. Furthermore, ARIMA (rolling) retains ARIMA's inherent advantages of simplicity, transparency, interpretability and established trust, unlike the black box problem of LSTM. The superior forecasting accuracy from ARIMA (rolling-window forecasting) technique is more useful due to advantages of ARIMA and disadvantages of LSTM. A notable novelty of this study lies in its adaptation of ARIMA within a rolling forecasting framework—an approach conceptually similar to J. Chassot and F. Audrino (in press) but extended here within a broader cross-market context that deepens understanding of the linear versus nonlinear forecasting performance debate.

The results of this study are consistent with Albeladi (2023), Kirelli (2024), Lahboub and Binali (2024), and Li (2024) specifying that ARIMA is better for time-series forecasting than LSTM based on the model evaluation parameters. The study highlights that while LSTM is effective in capturing non-linear & dynamic patterns and long-term dependencies, ARIMA demonstrates greater forecasting accuracy, reliability, stability and explainability.

5 Conclusion

This study evaluated the forecasting capabilities of Long Short-Term Memory (LSTM), ARIMA (recursive), and ARIMA (rolling) for stock index prediction, particularly for long-range time-series data. The results demonstrate that the ARIMA (rolling) offers superior forecasting accuracy across all five evaluation measures, consistently outperforming both LSTM and the ARIMA (recursive). Further, LSTM consistently predicted far better than ARIMA (recursive). Such surprising dominance of an adaptive statistical model over its deep learning equivalent and its static statistical equivalent can be explained due to the adaptive nature inherent with the rolling window method that is especially well-suited to the dynamic, non-stationarity involved in financial markets.

The different performance of the models offers robust empirical evidence for the Adaptive Market Hypothesis (AMH) as compared to the classical Efficient Market Hypothesis (EMH) in the stock index forecasting case. These finding sheds new light on how market efficiency varies over time and develops a better way of theorizing about market behavior by providing empirical validation for the AMH in a practical forecasting context.

The results of the study indicate that an equally well-tuned adaptive statistical model, say ARIMA (rolling), may lead to more accurate predictions than advanced deep learning models such as LSTM. This identifies the intrinsic trade-off among forecasting accuracy under realistic assumptions, data requirements, and model complexity. Decision-makers ought to carefully consider this trade-off given that less complex models with greater interpretability may still perform better in certain, actual, real-world financial market environments. This gives strong action guidance for financial professionals, toward a balanced choice strategy between models that will factor both forecasting power and actual-world practicability. To the best of our knowledge, this research is among the first to illustrate the continued performance superiority of ARIMA (rolling) compared to LSTM in stock index forecasting, especially when making an explicit comparison based on grounds of implications for EMH and AMH. This finding further challenges the prevailing assumptions regarding the universal superiority of Deep / Machine Learning techniques in complex financial time series, thereby extending the extant literature on comparative forecasting methodologies and market efficiency hypotheses.

6 Limitations of the study

Despite its robust findings, this study is subject to a few limitations that warrant consideration and provide avenues for future research. The analysis of the study focused on specific stock indices and a particular definition of 'long-range' time-series data. Even though the study contrasted EMH and AMH through recursive and rolling methods, it did not delve into the optimization of the rolling-window length, which has been shown to influence the degree of conformity with AMH. These limitations serve as crucial opportunities for future inquiry, demonstrating that the study delineates the inherent boundaries of the current contribution.

References

1. Adebiyi, A. A., Adewumi, A. O., & Ayo, C. K. (2014). Comparison of ARIMA and artificial neural networks models for stock price prediction. *Journal of Applied Mathematics*, 2014, Article ID 614342. https://doi.org/10.1155/2014/614342
2. Albeladi, B., Zafar, B., & Mueen, A. (2023). Time series forecasting using LSTM and ARIMA. *International Journal of Advanced Computer Science and Applications, 14*(1). https://doi.org/10.14569/IJACSA.2023.0140133
3. Bagul, J., Warkhade, P., Gangwal, T., & Mangaonkar, N. (2022). ARIMA vs LSTM Algorithm – A comparative study based on stock market prediction. In *2022 5th International Conference on Advances in Science and Technology (ICAST)* (pp. 49–53). IEEE. https://doi.org/10.1109/icast55766.2022.10039560
4. Baughman, M., Haas, C., Wolski, R., Foster, I., & Chard, K. (2018). Predicting Amazon Spot Prices with LSTM Networks. In *Proceedings of the 9th Workshop on Scientific Cloud Computing*, Tempe, AZ, USA (pp. 1-7).
5. Box, G.E.P. & Jenkins, G.M. (1970) *Time Series Analysis: Forecasting and Control*, San Francisco: Holden-Day, 1970.
6. Brownlee, J. (2018). *Deep learning for time series forecasting: Predict the future with MLPs, CNNs and LSTMs in Python*. Machine Learning Mastery.
7. Choudhury, S., Das, S., & Roy, S. (2020). Stock price prediction using ARIMA and LSTM models: A comparative study on Nifty 50 index. *International Journal of Computer Applications, 176*(30), 1–5. https://doi.org/10.5120/ijca2020920630
8. Choy, Y.-T., Hoo, M. H., & Khor, K.-C. (2021). Price prediction using time-series algorithms for stocks listed on Bursa Malaysia. *International Conference on Artificial Intelligence* (pp. 1–5). IEEE. https://doi.org/10.1109/AIDAS53897.2021.9574445
9. Di Persio, L., & Honchar, O. (2019). Recurrent neural networks for financial time series forecasting. *International Journal of Neural Systems, 30*(01), 1950008.
10. Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, *25*(2), 383–417.
11. Fischer, T., & Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. *European Journal of Operational Research, 265*(2), 654–669.
12. Gers, F. A., Schmidhuber, J., & Cummins, F. (2000). Learning to forget: Continual prediction with LSTM. *Neural Computation, 12*(10), 2451–2471.
13. Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation, 9*(8), 1735–1780.

14. Huck, N. (2009). Long memory in stock market volatility: A review. *Springer Science & Business Media*.
15. Jonathan Chassot, & Francesco Audrino. (in Press), HARd to beat: The overlooked impact of rolling windows in the era of machine learning, *International Journal of Forecasting,* ISSN 0169-2070, https://doi.org/10.1016/j.ijforecast.2025.06.003
16. Kara, Y., Acar Boyacioglu, M., & Dirican, A. (2021). Forecasting the direction of the stock market using deep learning algorithms: An application on the Istanbul Stock Exchange. *Academia.edu*.
17. Kuang, S. (2023). A comparison of linear regression, LSTM model and ARIMA model in predicting stock price: A case study: HSBC's stock price. *BCP Business & Management, 44*, 478–488. https://doi.org/10.54691/bcpbm.v44i.4858
18. Kırelli, Y. (2024). Comparative analysis of LSTM and ARIMA models in stock price prediction: A technology company example. *Black Sea Journal of Engineering and Science, 7*(5), 866–873. https://doi.org/10.34248/bsengineering.1445997
19. Lahboub, K., & Benali, M. (2024). Assessing the predictive power of transformers, ARIMA, and LSTM in forecasting stock prices of Moroccan credit companies. *Journal of Risk and Financial Management, 17*(7), 293. https://doi.org/10.3390/jrfm17070293
20. Li, H. (2024). Comparison of ARIMA and LSTM in different industries. *Advances in Economics, Management and Political Sciences, 57*, 294–302.
21. Liu, B., & Lai, M. (2024). Advanced machine learning for financial markets: A PCA-GRU-LSTM approach. *Journal of the Knowledge Economy, 16*(1), 3140–3174. https://doi.org/10.1007/s13132-024-02108-3
22. Lo, A. W., & Zhang, R. (2024). *The adaptive markets hypothesis: An evolutionary approach to understanding financial system dynamics*. Oxford University Press.
23. Lo, A. W. (2004). The adaptive markets hypothesis: Market efficiency from an evolutionary perspective. *Journal of Portfolio Management, 30*(5), 15–29. https://doi.org/10.3905/jpm.2004.442611
24. Lo, A. W. (2007). Efficient Markets Hypothesis. In L. Blume & S. Durlauf (Eds.), The New Palgrave: A Dictionary of Economics (2nd ed.). Palgrave Macmillan. Retrieved from MIT website
25. Namini, S. S., Tavakoli, N., & Namin, A. S. (2018). A comparison of ARIMA and LSTM in forecasting time series. In *2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA)* (pp. 1394–1401). IEEE. https://doi.org/10.1109/ICMLA.2018.00227
26. Nau, R. A. (2020). *Statistical forecasting: Notes on regression and time series analysis.* Duke University, Fuqua School of Business. Retrieved from https://people.duke.edu/~rnau/
27. Nelson, D. M. Q., Pereira, A. C. M., & de Oliveira, R. A. (2017). Stock market's price movement prediction with LSTM neural networks. In *2017 International Joint Conference on Neural Networks (IJCNN)* (pp. 1419–1426). IEEE. https://doi.org/10.1109/IJCNN.2017.7966019
28. Nti, I. K., Adekoya, A. F., & Weyori, B. A. (2020). A systematic review of fundamental and technical analysis of stock market predictions. *Artificial Intelligence Review, 53*(4), 3007–3057. https://doi.org/10.1007/s10462-019-09754-z
29. Ozdemir, O., Erdogmus, P., & Yavas, F. (2021). Performance Analysis of Long Short-Term Memory Predictive Neural Networks on Time Series Data. *Mathematics*, *11*(6), 1432. https://doi.org/10.3390/math11061432
30. Patel, J., Shah, S., Thakkar, P., & Kotecha, K. (2015). Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques. *Expert Systems with Applications*, *42*(1), 259–268.
31. Petropoulos, F., Apiletti, D., Assimakopoulos, V., Babai, M. Z., Bildersee, B., Borovykh, A., ... & Spiliotis, E. (2022). Forecasting: A view of the field and its future. *International Journal of Forecasting*, *38*(4), 1332-1372.
32. Pothuganti, S. (2021). Stock price prediction using LSTM. *Materials Today: Proceedings, 45*, 6904–6908.
33. Rana, M. S., Akther, M., & Rabbi, F. (2019). Stock price prediction using LSTM neural network. In *2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT)* (pp. 1–6). IEEE.
34. Sheth, D., & Shah, M. (2023). Predicting stock market using machine learning: Best and accurate way to know future stock prices. *International Journal of System Assurance Engineering and Management, 14*(1), 81–98.
35. Sing, N. B., & Singh, R. G. (2024). Testing the adaptive market hypothesis and time-varying efficiency in the Indian equity market. *Colombo Business Journal*, *15*(1).

36. Singh, A., Bansal, A., Nair, A., & Kaushal, A. (2022). Predictive analytics of stock market as a time series. In *4th International Conference on Advances in Computing, Communication Control and Networking* (pp. 770–777).
37. Taslim, D. G., & Murwantara, I. M. (2024). Comparative analysis of ARIMA and LSTM for predicting fluctuating time series data. *Bulletin of Electrical Engineering and Informatics, 13*(3), 1943–1951. https://doi.org/10.11591/eei.v13i3.6034
38. Timmermann, A., & Granger, C. W. (2004). Efficient market hypothesis and forecasting. *International Journal of forecasting*, *20*(1), 15-27.
39. Tong, Z., Li, H., & Zhang, Y. (2023). A comparison of ARIMA, LSTM, XGBOOST and hybrid in stock price prediction. In *2023 5th International Conference on Applied Machine Learning (ICAML)* (pp. 18–25). https://doi.org/10.1109/icaml60083.2023.00015
40. Vuković, D. B., Radenković, S. D., Simeunović, I., Zinovev, V., & Radovanović, M. (2024). Predictive patterns and market efficiency: A deep learning approach to financial time series forecasting. *Mathematics*, *12*(19), 3066.
41. Vuong, N. V., Ha, T. T., Le, H. T., & Le, T. T. T. (2022). Adaptive market hypothesis and stock return predictability: Evidence from an emerging market. *Journal of Economic Interaction and Coordination, 17*, 595–615. https://doi.org/10.1007/s11403-021-00331-2
42. Xia, X. (2024). Apple, Microsoft, and Amazon stock price prediction based on ARIMA and LSTM. *Applied and Computational Engineering, 53*(1), 181–189. https://doi.org/10.54254/2755-2721/53/20241352
43. Xiao, R., Feng, Y., Yan, L., & Ma, Y. (2022). Predict stock prices with ARIMA and LSTM (Version 1). *arXiv*. https://doi.org/10.48550/ARXIV.2209.02407
44. Yang, Z., & Wang, Z. (2024). The research of NVIDIA stock price prediction based on LSTM and ARIMA model. *Highlights in Business, Economics and Management, 24*, 896–902. https://doi.org/10.54097/dndygw34
45. Yavasani, R., & Wang, H. (2023). Comparative analysis of LSTM, GRU, and ARIMA models for stock market price prediction. *Journal of Student Research, 12*(4). https://doi.org/10.47611/jsrhs.v12i4.5888
46. Zhang, T., Shi, C., Sun, T., & Liu, C. (2018). A Study of Chinese Stock Price Prediction Based on LSTM and Time Series Linear Regression Model. In *2018 3rd IEEE International Conference on Cloud Computing and Big Data Analytics (ICCCBDA)* (pp. 370-374). IEEE.
47. Zhang, Y. (2023). Comparing the ARIMA and LSTM Models on the Stock Price of FinTech Companies. *Academic Journal of Business & Management*, *5*(8), 38-43. https://doi.org/10.25236/AJBM.2023.05080