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RESEARCH ARTICLE

Forecasting Stock Market Movements with LSTM: A Case Study of Amazon and NASDAQ Performance Across Different Economic Cycles

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ABSTRACT: The paper investigates the predictive performance of artificial intelligence (AI)-based models. Amazon and NASDAQ are used as proxies for individual stocks and the market index, respectively. We employ long short-term memory (LSTM) models across pre-crisis, crisis, and post-crisis periods. The study aims to demonstrate how LSTM models perform under various economic conditions, and how their prediction accuracy varies between individual stocks and aggregate stock market indices. LSTM models were varied in aspects like train-test splits, denser layer, and layer type output shape while keeping other parameters constant to find the best optimized LSTM model for each level of economic turbulence. It was observed that the train-test splits have a major impact on the LSTM models' ability to predict during different economic cycles. A higher training dataset resulted in more accuracy in prediction during stable periods like pre-crisis and post-crisis and vice versa. The findings of this study can aid investors, decision-makers, and regulators optimize their own LSTM models specifically tailored to the level of market turbulence, thus allowing them to make comparatively more accurate predictions of the stock market behavior.
KEYWORDS: Robotics and Intelligent Machines, Machine Learning, LSTM, Stock Prediction, Economics Cycles.

Introduction

Artificial intelligence (AI) algorithms are increasingly used for predicting financial market data because of their capacity to efficiently examine complex data patterns. These models provide a strategic advantage for effectively managing volatile market conditions. Their capacity to generate more precise forecasts enables decision-makers to make well-informed decisions in rapidly changing financial markets.

Accurately predicting the future performance of the US stock market is crucial for various reasons. Investors rely on these predictions to optimize their portfolios, while policymakers use them to assess the effectiveness of monetary and fiscal policies. Business managers also use stock market forecasts to plan for future growth and adapt to changing market conditions. Given the US stock market's substantial influence on the international economy, accurate forecasting is vital not only for the US economy but also for the global economy. Analyzing stock market predictions during different time periods (pre-crisis, crisis, and post-crisis) is essential for understanding the influence of economic conditions on forecasting performance.

The purpose of this paper is to determine an effective forecasting model for predicting the performance of both individual stocks and stock market indexes. This study uses Amazon as an individual stock and NASDAQ as a stock market index. This study explores machine learning-based models, with a particular focus on the Long Short-Term Memory (LSTM) model, to achieve accurate and reliable prediction. LSTM models are a strong choice for stock market forecasting especially because they can effectively capture long-term dependencies and model sequential data. LSTM models can additionally identify complex patterns and trends in historical market data, making them suitable for predicting future stock behavior. Furthermore, this paper investigates how economic cycles—pre-crisis, crisis, and post-crisis—affect the reliability of LSTM predictions. Previous research has typically focused either on predicting individual stocks or the aggregate stock market index. This paper aims to test the applicability of a single prediction model to both individual stock and aggregate stock market indices.

The literature indicates that artificial intelligence-based models generally perform better in forecasting than traditional methods.[1,2] Thus, it contributes to the literature by assessing forecasting performance not only for stable economic periods but also for turbulent periods. Moreover, by studying data spanning pre-crisis, crisis, and post-crisis phases, it aims to expand our understanding of how economic cycles influence the reliability and robustness of LSTM-based predictions.

For Amazon, it is clear that the best predictive model varies across different periods. Model 5 performs best in both pre-crisis and post-crisis periods, whereas Model 3 performs best during the crisis period. For NASDAQ, Model 1 performed the best in both the pre-crisis and crisis periods, while Model 5 stands out for its accuracy in the post-crisis period.

You cannot use the same model for different periods, and the same forecasting model does not apply to both individual stocks and aggregate market indices. By examining data across the economic cycles, this study also shows evidence of how these economic cycles impact the accuracy and reliability of LSTM-based prediction. This paper proceeds as follows:

DOI: 10.36838/v7i3.22

Section 2 provides background information on the existing literature; Section 3 highlights the methods; Section 4 showcases the results and discussion; and Section 5 concludes the paper.

Literature Review

This study distinguishes itself from the existing literature by integrating an artificial intelligence-based forecasting model across different economic cycles (pre-crisis, crisis, and post-crisis), specifically focusing on both individual stocks and market indices. By using the LSTM model to forecast the performance of both the market index and individual stocks, this study fills the gap left by prior research, which frequently focused on either individual stock predictions or broader market index predictions. In 2009, Mahla Nikou *et al*. highlighted the superior predictive performance of LSTM approaches compared to traditional models.[3] In addition, Körs and Karan employ the MIDAS model to estimate volatility in several markets and highlight its excellent ability to predict future volatility.[4] In 2022, Ding *et al*.[1] and Akhtar *et al*.[5] conducted a thorough evaluation of artificial intelligence models and their dependability in predicting stock market performance in China and Pakistan. They assessed these models across various economic scenarios, providing a comprehensive review.

Recent financial forecasting research has utilized a variety of approaches to improve the accuracy of predictions in various stock markets around the world. In 2019, Mahla Nikou *et al*. specifically examined the LSTM model.[3] In 2020, Körs and Karan proposed that the MIDAS model offers a benefit in predicting performance.[4] In 2021, Xu and Zhang proposed the Shrinkage Composite Model as the optimal choice for predicting the Chinese stock index because of its high reliability.[6] In 2022, Akhtar *et al*. determined that the ARCH class model exhibits greater prediction performance.[5] In 2024, Tan *et al*. presented the Functional Time Series Approach as a method for accurately predicting intraday volatility in the Chinese stock market.[7] In 2011, Harrison and Moore emphasized the efficacy of the asymmetric volatility model in predicting the level of fluctuation in the stock market in Central and Eastern European nations.[8] By combining the Maximum Overlapping Discrete Wavelet Transform (MODWT) with the Adaptive Network-based Fuzzy Inference System (ANFIS), Alenezy *et al.* make daily stock price index predictions for Saudi Arabia's stock market more accurate.[9] In 2019, Mallikarjuna and Rao found that conventional linear or non-linear models are more effective than artificial intelligence models in forecasting daily stock market returns in several worldwide marketplaces.[10] In 2024, Song *et al*. demonstrated that the CNN-GRU model enhances the accuracy of predicting stock market volatility in both China and the US.[11] It is clear that many different methodologies and variables were employed in stock market forecasting to better understand market dynamics.

Various performance metrics are used to evaluate forecasting models in stock markets, to determine their accuracy and effectiveness. For example, some studies highlight RMSE (root mean square error) as the optimal loss function for evaluating forecasting accuracy,[1,3,4] while some other studies apply MSE (mean square error), MAPE (mean absolute percentage error), and MAE (mean absolute error) as the ideal loss functions for getting better forecasting performance.[5,6] In addition to these loss functions, other metrics such as predicted R-squared and hit rate were also used to get accurate forecasting performance.[9,12]

Stock market forecasting involves analyzing different types of data to make predictions about future market trends and behaviors. This includes examining closing price data,[1,11] volatility data,[8,13] exchange rates,[5] interest rates,[14] long-term historical data,[13] and intraday data.[7] Every study utilizes different forms of data to tackle various forecasting difficulties, which can range from predicting closing prices to analyzing intraday data.

Several studies emphasize the geographical diversity in recent stock market forecasting, demonstrating how the market dynamics of various countries or regions have a substantial impact on the accuracy of forecasts. For example, in 1998 Brooks focused on the US,[13] while Bjørnland and Hungnes focused on Norway.[14] In 2020, Körs and Karan examined multiple regions, including the US, Japan, Hong Kong, and the UK.[4] In 2011, Harrison and Moore focused on Central and Eastern European countries;[8] Xu and Zhang focused on China,[6] and Akhtar *et al*.[5] and Alenezy *et al*.[9] focused on Pakistan and Saudi Arabia, respectively.

The influence of various market conditions on predicting performance has been empirically demonstrated by several studies.[15-17] For example, Lim *et al*. investigate the financial crisis's impact on the efficiency of eight Asian stock markets.[15] They emphasize that the crisis significantly reduced market efficiency. Most markets improved in efficiency post-crisis. The increased inefficiency during the crisis is attributed to investor overreactions to both local and foreign adverse news.

Methodology

This study investigates the predictive performance of LSTM models for stock market behavior, using Amazon and NASDAQ as proxies for individual stocks and market indices, respectively, across pre-crisis, crisis, and post-crisis economic conditions. The Long Short-Term Memory (LSTM) model is known as a recurrent neural network (RNN) proposed by Hochreiter and Schmidhuber in 1997.[19] Issues encountered in training traditional RNN neural networks have been completely addressed in LSTM. The methodology includes data preparation, model architecture design, training, and performance evaluation, as outlined below.

Data Collection and Preparation:

Data Source: The data is gathered from Yahoo Finance and includes individual stock data for Amazon (ticker symbol: AMZN) and US stock market index data (ticker symbol: NASDAQ). The data covers the daily percentage equity return for three selected periods: pre-crisis (1st January 2003 to 14th September 2008), crisis (15th September 2008 to 31st March 2010), and post-crisis (1st April 2010 to 30th December 2016). We can differentiate between the crisis and non-crisis periods by following the existing literature.[18]

Data Preprocessing: Data was preprocessed through normalization to ensure values lie within a range suitable for LSTM models, accelerating training and improving model converge-

DOI: 10.36838/v7i3.22

nce. Time series data were structured into sequences, using lagged values of stock/index prices to predict future prices.

Train-Test Splits: Each model was trained separately for each period (pre-crisis, crisis, post-crisis, and the total period) to evaluate performance under varying economic conditions. A standard train-test split of 70%-30% was used for Models 1–4, while Model 5 used an 80%-20% split to test whether a larger training set impacts accuracy in a more stable post-crisis period.

Model Architecture Design:

LSTM Layers: LSTM was chosen for its ability to retain information over extended sequences, which is ideal for stock data with temporal dependencies.

Layer Output Shape: The number of LSTM units was modified to optimize model complexity. For instance, some models had an output shape of 50 units, while others used 30 units.

Dense Layer Configuration: Each model used different LSTM layer configurations (output shapes: 50 or 30) and dense layer configurations to explore the effects of complexity on predictive accuracy.

Training Parameters and Optimization:

All models used a fixed learning rate of 0.001, with different combinations of epochs and batch sizes. Models were trained using the Adam Optimizer.

Learning Rate: Set at 0.001 across models to balance learning speed and stability.

Batch Size: A batch size of 1 was selected to handle time-series data effectively, enabling the model to update weights after each prediction.

Epochs: Each model was trained for 15 epochs, enough to achieve convergence without overfitting.

Optimizer: The Adam optimizer was used for its adaptive learning rate and computational efficiency, enhancing the models' ability to converge quickly and handle non-stationary data.

Evaluation Metrics:

To compare LSTM model performance across economic conditions, several metrics were used:

Mean Squared Error (MSE): Measures the average squared difference between actual and predicted values, with emphasis on larger errors.

Root Mean Squared Error (RMSE): The square root of MSE, providing error measurements in the original units of stock prices.

Mean Absolute Percentage Error (MAPE): Reflects the average error as a percentage, offering an easily interpretable error rate.

Mean Percentage Error (MPE): Assesses model bias by showing whether predictions generally overestimate or underestimate actual values.

Model Comparison and Analysis:

Models were compared based on their performance across pre-crisis, crisis, and post-crisis periods to understand how different configurations respond to market stability and volatility. By evaluating the train-test split's impact on prediction accuracy, the study identifies patterns in LSTM model effectiveness relative to economic conditions.

Results and Discussion

Forecasting Outcome:

Table 1: Descriptive statistics of daily percentage equity returns for selected periods: Pre-crisis period (1st January 2003–14th September 2008), crisis period (15th September 2008–31st March 2010), post-crisis period (1st April 2010–30th December 2016)

Equity Name	*Sample Period*	*Mean*	*SDev*	*Max*	*Min*	*Skewness*	*Kurtosis*
Amazon							
	Pre-crisis period	0.0991	2.7487	23.8621	-24.6182	0.2524	14.7155
	Crisis period	**0.1415**	**3.7298**	**23.7402**	**-13.6759**	**0.7190**	**6.0757**
	Post-crisis period	0.1005	2.0387	14.6225	-13.5325	0.1251	7.3853
	Total Sample	0.1106	3.5054	29.6181	-28.4568	0.4514	9.4431
NASDAQ							
	Pre-crisis period	0.0004	0.0113	0.0470	-0.0394	-0.0319	0.7950
	Crisis period	**0.0002**	**0.0235**	**0.1116**	**-0.0959**	**-0.1365**	**3.3963**
	Post-crisis period	0.0005	0.0111	0.0516	-0.0715	-0.4024	3.2695
	Total Sample	0.0004	0.0127	0.1325	-0.1315	-0.3665	9.5133

The empirical findings from Table 1 highlight distinct patterns in daily percentage equity returns for the Amazon and NASDAQ indexes across various economic cycles. Amazon's mean return during the crisis period unexpectedly rose to 0.1415, but with higher volatility (SDev = 3.7298) compared to both the pre-crisis (mean = 0.0991, SDev = 2.7487) and post-crisis periods (mean = 0.1005, SDev = 2.0387). This period also exhibited increased skewness (Skewness = 0.7190) and kurtosis (Kurtosis = 6.0757), indicating a shift toward a more volatile and extreme return. Conversely, as expected, NASDAQ had a minimum mean return (mean = 0.0002) with higher volatility (SDev = 0.0235) than both pre-crisis (mean = 0.0004, SDev = 0.0113) and post-crisis periods (mean = 0.0005, SDev = 0.0111). Its kurtosis (Kurtosis = 3.3963) reflects higher market risk compared to other periods, while negative skewness (Skewness = -0.1365) indicates an extremely negative return during the crisis period.

Tables 2 and 3 below reflect data gathered with different LSTM models which vary based on parameters such as Layer Type Output Shape, Dense, and Train-Test Split. Parameters such as Loss Function (MSE), Layer Type (LSTM), Training Parameter, Epochs (15), Batch Size (1), and Optimizer (Adam) have been kept the same for all models. The effectiveness and accuracy of the models have been measured with values of Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Percentage Error (MPE). To find out which model performs the best, a closer look is taken at MSE and RMSE values. If the values of MSE and RMSE are comparatively the lowest, that model is considered to have the most predictive accuracy. Vice versa, the model with the highest MSE and RMSE values is considered to have the worst predictive accuracy.

Table 2a: Model Results for AMZN for the Pre-Crisis Period

Pre-Crisis Period	Model 1	Model 2	Model 3	**Model 4**	**Model 5**
Loss Function	MSE	MSE	MSE	MSE	MSE
Layer Type	LSTM	LSTM	LSTM	LSTM	LSTM
Layer Type Output Shape	(None, 50)	(None, 30)	(None, 50)	(None, 30)	(None, 50)
Dense	(None, 1)	(None, 1)	(None, 3)	(None, 3)	(None, 1)
Training Parameter	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)
Epochs	10	10	10	10	10
Batch Size	1	1	1	1	1

Optimizer	Adam	Adam	Adam	Adam	Adam
Train-Test Split	70%-30%	70%-30%	70%-30%	70%-30%	80%-20%
Param #	31121	11481	31143	11503	31121
MSE	0.001434	0.002019	0.001059	0.000932	0.000518
RMSE	0.037873	0.044938	0.032537	0.030530	0.022764
MAPE	0.055811	0.067180	4.554400	4.278167	0.030741
MPE (%)	5.261980	6.359669	2.343942	1.093000	0.212785

Table 2b: Model Results for AMZN for the Crisis Period

Crisis Period	Model 1	Model 2	Model 3	**Model 4**	**Model 5**
Loss Function	MSE	MSE	MSE	MSE	MSE
Layer Type	LSTM	LSTM	LSTM	LSTM	LSTM
Layer Type Output Shape	(None, 50)	(None, 30)	(None, 50)	(None, 30)	(None, 50)
Dense	(None, 1)	(None, 1)	(None, 3)	(None, 3)	(None, 1)
Training Parameter	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)
Epochs	15	15	15	15	15
Batch Size	1	1	1	1	1
Optimizer	Adam	Adam	Adam	Adam	Adam
Train-Test Split	70%-30%	70%-30%	70%-30%	70%-30%	80%-20%
Param #	31121	11481	31953	12013	31121
MSE	0.000797	0.005789	0.000398	0.000897	0.000587
RMSE	0.028228	0.076084	0.019952	0.029945	0.024225
MAPE	0.028772	0.090747	2.140101	2.966875	0.025106
MPE (%)	2.764856	9.074683	-0.121532	2.655964	-1.934079

Table 2c: Model Results for AMZN for the Crisis Period

Post-Crisis Period	Model 1	Model 2	Model 3	**Model 4**	**Model 5**
Loss Function	MSE	MSE	MSE	MSE	MSE
Layer Type	LSTM	LSTM	LSTM	LSTM	LSTM
Layer Type Output Shape	(None, 50)	(None, 30)	(None, 50)	(None, 30)	(None, 50)
Dense	(None, 1)	(None, 1)	(None, 3)	(None, 3)	(None, 1)
Training Parameter	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)
Epochs	20	20	20	20	20
Batch Size	1	1	1	1	1
Optimizer	Adam	Adam	Adam	Adam	Adam
Train-Test Split	70%-30%	70%-30%	70%-30%	70%-30%	80%-20%
Param #	31901	11961	31953	12013	31901
MSE	0.001197	0.001999	0.000660	0.001743	0.000243
RMSE	0.034593	0.044705	0.025694	0.041749	0.015590
MAPE	2.130706	2.724255	1.394622	2.435194	0.791039
MPE (%)	2.068559	2.666680	0.985248	2.304916	0.369667

Table 2d: Model Results for AMZN for the Crisis Period

Total Period	Model 1	Model 2	Model 3	**Model 4**	**Model 5**
Loss Function	MSE	MSE	MSE	MSE	MSE
Layer Type	LSTM	LSTM	LSTM	LSTM	LSTM
Layer Type Output Shape	(None, 50)	(None, 30)	(None, 50)	(None, 30)	(None, 50)
Dense	(None, 1)	(None, 1)	(None, 3)	(None, 3)	(None, 1)
Training Parameter	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)
Epochs	15	15	15	15	15
Batch Size	1	1	1	1	1
Optimizer	Adam	Adam	Adam	Adam	Adam
Train-Test Split	70%-30%	70%-30%	70%-30%	70%-30%	80%-20%
Param #	31121	11481	31953	12013	31121
MSE	0.000262	0.000721	0.000401	0.002637	0.003149
RMSE	0.016191	0.026845	0.020018	0.051353	0.056115
MAPE	0.005872	0.010997	0.760497	2.226610	0.025547
MPE (%)	0.017800	0.956503	0.304450	2.157148	2.545318

Table 2 shows the performance of different LSTM models applied to Amazon's stock data across sub-periods: pre-crisis, crisis, post-crisis, and total period. In the pre-crisis period, Model 5 exhibits the lowest MSE and RMSE, indicating superior predictive accuracy. During the crisis period, Model 3 showed the lowest MSE and RMSE, suggesting its effectiveness in turbulent market conditions. In the post-crisis period, Model 5 again displays the lowest MSE and RMSE. Overall, across the total period, Model 1 demonstrates the lowest MSE and RMSE, highlighting its robust performance in predicting Amazon stock prices consistently throughout the analyzed period. It is clear that the best predictive model varies across different periods. Model 5 performs best in both the pre-crisis and post-crisis periods, whereas Model 3 performs best during the crisis period.

This showcases that Model 5, which contains a higher layer type output shape and a higher training dataset (80%-20% train-test split), is most suitable during stable economic cycles. Model 5 could be comparatively a better option due to its reliability in long-term forecasting and strategic planning where economic conditions are more stable. On the other hand, Model 3, which has a higher dense layer and lower training data (70%-30% train-test split), has superior performance during the crisis period. This highlights the model's ability to react relatively efficiently to the market's volatility and abrupt changes. This model would be more effective in the short-term and it can provide insights for risk-management and decision-making for investors and traders during turbulent times.

Table 3a: Model Results for NASDAQ for the Pre-Crisis Period

Pre-Crisis Period	Model 1	Model 2	Model 3	**Model 4**	**Model 5**
Loss Function	MSE	MSE	MSE	MSE	MSE
Layer Type	LSTM	LSTM	LSTM	LSTM	LSTM
Layer Type Output Shape	(None, 50)	(None, 30)	(None, 50)	(None, 30)	(None, 50)
Dense	(None, 1)	(None, 1)	(None, 3)	(None, 3)	(None, 1)
Training Parameter	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)
Epochs	10	10	10	10	10
Batch Size	1	1	1	1	1
Optimizer	Adam	Adam	Adam	Adam	Adam
Train-Test Split	70%-30%	70%-30%	70%-30%	70%-30%	80%-20%
Param #	31121	11481	31143	11503	31121
MSE	0.000119	0.000154	0.000158	0.000188	0.000147
RMSE	0.010890	0.012423	0.012588	0.013715	0.012113
MAPE	0.000947	0.001119	0.107126	0.110445	0.001025
MPE	0.013608	0.046753	-0.001420	-0.040254	-0.014641

Table 3b: Model Results for NASDAQ for the Pre-Crisis Period

Crisis Period	Model 1	Model 2	Model 3	**Model 4**	**Model 5**
Loss Function	MSE	MSE	MSE	MSE	MSE
Layer Type	LSTM	LSTM	LSTM	LSTM	LSTM
Layer Type Output Shape	(None, 50)	(None, 30)	(None, 50)	(None, 30)	(None, 50)
Dense	(None, 1)	(None, 1)	(None, 3)	(None, 3)	(None, 1)
Training Parameter	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)
Epochs	15	15	15	15	15
Batch Size	1	1	1	1	1
Optimizer	Adam	Adam	Adam	Adam	Adam
Train-Test Split	70%-30%	70%-30%	70%-30%	70%-30%	80%-20%
Param #	31121	11481	31953	12013	31121
MSE	0.000099	0.000100	0.000180	0.000171	0.000167
RMSE	0.009957	0.010005	0.013427	0.013079	0.012922
MAPE	0.000888	0.000781	0.101938	0.098868	0.001188
MPE	0.026828	-0.016547	-0.084891	-0.058234	-0.005951

Table 3c: Model Results for NASDAQ for the Pre-Crisis Period

Post-Crisis Period	Model 1	Model 2	Model 3	**Model 4**	**Model 5**
Loss Function	MSE	MSE	MSE	MSE	MSE
Layer Type	LSTM	LSTM	LSTM	LSTM	LSTM
Layer Type Output Shape	(None, 50)	(None, 30)	(None, 50)	(None, 30)	(None, 50)
Dense	(None, 1)	(None, 1)	(None, 3)	(None, 3)	(None, 1)
Training Parameter	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)
Epochs	20	20	20	20	20
Batch Size	1	1	1	1	1
Optimizer	Adam	Adam	Adam	Adam	Adam
Train-Test Split	70%-30%	70%-30%	70%-30%	70%-30%	80%-20%
Param #	31901	11961	31953	12013	31901
MSE	0.000134	0.000104	0.000100	0.000118	0.000093
RMSE	0.011589	0.010219	0.009986	0.010876	0.009659
MAPE	0.103799	0.088458	0.077696	0.090554	0.070731
MPE	0.080034	0.057053	-0.001287	0.037100	-0.038323

Table 3d: Model Results for NASDAQ for the Total Period

Total Period	Model 1	Model 2	Model 3	**Model 4**	**Model 5**
Loss Function	MSE	MSE	MSE	MSE	MSE
Layer Type	LSTM	LSTM	LSTM	LSTM	LSTM
Layer Type Output Shape	(None, 50)	(None, 30)	(None, 50)	(None, 30)	(None, 50)
Dense	(None, 1)	(None, 1)	(None, 3)	(None, 3)	(None, 1)
Training Parameter	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)	(0.001, 1, 1)
Epochs	15	15	15	15	15
Batch Size	1	1	1	1	1

DOI: 10.36838/v7i3.22

Optimizer	Adam	Adam	Adam	Adam	Adam
Train-Test Split	70%-30%	70%-30%	70%-30%	70%-30%	80%-20%
Param #	31121	11481	31953	12013	31121
MSE	0.000219	0.000198	0.000344	0.000271	0.000852
RMSE	0.014788	0.014055	0.018534	0.016456	0.029182
MAPE	0.001216	0.001085	0.151933	0.131038	0.002742
MPE	-0.102762	-0.005482	-0.129678	-0.047800	0.272744

Table 3 shows the performance of different LSTM models applied to NASDAQ's stock data across different periods. In the pre-crisis period, Model 1 exhibits the lowest MSE and RMSE, indicating strong predictive accuracy. For the crisis period, Model 1 again exhibits the lowest MSE and RMSE, suggesting its effectiveness in volatile market conditions. In the post-crisis period, Model 5 displays the lowest MSE and RMSE. Overall, across the total period, Model 2 demonstrates the lowest MSE and RMSE, highlighting its robust performance in predicting NASDAQ index values throughout the studied period. The best predictive model for the NASDAQ index also varies across different periods: model 1 performs best in both pre-crisis and crisis periods, while model 5 performs best during the post-crisis period.

This showcases that Model 1, which contains a high layer type output shape and a lower training dataset (70%-20% train-test split), is most suitable during pre-crisis and crisis periods. This can suggest that Model 1 would be proficient in capturing market dynamics with heightened volatility and rapid shifts. This can be due to its lower train-test split which was also observed in Amazon stock prediction, making it effective during periods of uncertainty and instability. Alternatively, Model 5, which has the same layer type output shape and a higher training dataset (80%-20% train-test split), is most suitable for post-crisis periods with stable economic activity. This highlights the model's ability to capture slower, more stable trends and gradual recoveries. Investors can use this information and accordingly adjust parameters like the train-test splits to tailor their models for specific market conditions.

You cannot use the same model for different periods, and the same forecasting model does not apply to both individual stocks and the aggregate market index. This is critical to consider when making predictions. Combining the analysis of an individual stock and an aggregate market index allows for a more comprehensive understanding of stock dynamics where both micro-level trends and broader market movements at the macro-level are analyzed. This combined perspective is better as it allows insights into market correlations and diversification benefits that separated analyses may overlook.

Conclusion

The study investigated the use of the Long Short-Term Memory (LSTM) model for predicting the performance of individual stock and stock market indices across various economic phases—pre-crisis, crisis, and post-crisis periods. This paper aimed to bridge the gap in the existing literature by evaluating the effectiveness of AI-based forecasting models under various market conditions, focusing on Amazon as an individual stock and NASDAQ as a stock market index.

Our findings highlight several key insights. Firstly, LSTM models exhibit varying predictive accuracies across different economic phases. Model performance for Amazon and NASDAQ differed significantly between pre-crisis, crisis, and post-crisis periods, demonstrating the need for adaptive forecasting approaches responsive to different economic conditions.

Secondly, the study emphasizes the importance of considering both individual stockpredictions and market indices in forecasting frameworks. While certain LSTM models showed strong performance for Amazon during the crisis period, others achieved notable accuracy in predicting the NASDAQ index in stable economic environments. It has been observed that a higher train-test split (80%-20%) has higher predictive accuracy in long-term and stable market dynamics. This has been observed in the pre-crisis and post-crisis periods of Amazon along with the post-crisis period in NASDAQ. Vice versa, it has been observed that a lower train-test split (70%-30%) has higher predictive accuracy in short-term and unstable market dynamics. This has been observed in the crisis period of Amazon along with pre-crisis and crisis periods in NASDAQ.

Furthermore, our empirical evidence contributes to our understanding of the impact of economic cycles on the reliability of AI-driven predictions. This study evaluates data from several sub-periods to demonstrate the influence of economic conditions on forecast accuracy and model selection. The findings have practical implications for decision-makers, investors, and policymakers. These stakeholders can use the findings on train-test splits' effects on prediction accuracy to modify LSTM models based on their needs, stock type (individual stock or aggregate market index), and market dynamics of those stocks. Additionally, they can adjust other parameters like layer type output shapes and densities for more optimization. This allows investors, decision-makers, and policymakers to plan risk management during turbulent crisis periods and significant financial growth during stable pre-crisis and post-crisis periods.

In conclusion, this study extends the boundaries of financial forecasting by showing the effectiveness of LSTM models in capturing complex market dynamics across distinct economic cycles. The findings not only enrich academic literature but also provide practical implications for stakeholders seeking to optimize their strategies.

This study showcases the capabilities of LSTM models in forecasting stock market trends by capturing and modeling complex, time-dependent patterns. The findings indicate the need for adaptive models that can respond to shifting market conditions and economic cycles. A takeaway from this study could be that the employment of such models that offer a competitive edge in stock market prediction can be inaccurate and the perfect model with maximum accuracy that can adapt to volatile market conditions does not exist yet.

In the field of further studies, the number of individual companies has expanded across many sectors, specifically in relation to the development of AI-based models for diverse industries. Furthermore, we can compare LSTM's performance with other AI-based methodologies to determine which AI-based models performed better across different sub-periods

Future research can also explore LSTM performance in emerging markets, where volatility and low availability of data give rise to unique challenges, or investigate their application in more diversified stocks such as stocks and indices from other countries like China and India to assess broader marker adaptability and robustness.

Acknowledgments

I would like to thank my mentor, Dr. Abdullah Yalaman, for guiding me through the process of conducting this research.

References

1. Ding, Y., Sun, N., Xu, J., Li, P., Wu, J., & Tang, S. (2022). Research on the Shanghai Stock Exchange 50 Index Forecast Based on Deep Learning. Mathematical Problems in Engineering, 2022(1), 13679 20.
2. Lv, J., Wang, C., Gao, W., & Zhao, Q. (2021). [Retracted] An Eco nomic Forecasting Method Based on the LightGBM-Optimized LSTM and Time-Series Model. Computational Intelligence and Neuroscience, 2021(1), 8128879.
3. Nikou, M., Mansourfar, G., & Bagherzadeh, J. (2019). Stock price prediction using the DEEP learning algorithm and its comparison with machine learning algorithms. Intelligent Systems in Account ing, Finance, and Management, 26(4), 164–174.
4. Körs, M., & Karan, M. B. (2023). Stock exchange volatility fore cas ting under market stress with MIDAS regression. International Jo urnal of Finance & Economics, 28(1), 295–306.
5. Akhtar, S., Ramzan, M., Shah, S., Ahmad, I., Khan, M. I., Ahmad, S., ... & Qureshi, H. (2022). Forecasting the exchange rate of Pakis tan using time series analysis. Mathematical Problems in Engineer ing, 2022(1), 9108580.
6. Xu, X., & Zhang, Y. (2021). Individual time series and composite f orecasting of the Chinese stock index. Machine Learning with Ap plications, 5, 100035.
7. Tan, Y., Tan, Z., Tang, Y., & Zhang, Z. (2023). Functional volatility forecasting. Journal of Forecasting.
8. Harrison, B., & Moore, W. (2012). Forecasting stock market volatil ity in central and eastern European countries. Journal of Forecastin g, 31(6), 490-503.
9. Alenezy, A. H., Ismail, M. T., Wadi, S. A., Tahir, M., Hamadneh, N. N., Jaber, J. J., & Khan, W. A. (2021). Forecasting stock market vol atility using a hybrid of adaptive network of fuzzy inference system and wavelet functions. Journal of Mathematics, 2021(1), 9954341.
10. Mallikarjuna, M., & Rao, R. P. (2019). Evaluation of forecasting methods from selected stock market returns. Financial Innovation, 5(1), 40.
11. Song, Y., Lei, B., Tang, X., & Li, C. (2024). Volatility forecasting for stock market index based on complex networks and hybrid dee p learning model. Journal of Forecasting, 43(3), 544-566.
12. Umstead, D. A. (1977). Forecasting stock market prices. The Jour nal of Finance, 32(2), 427–441.
13. Brooks, C. (1998). Predicting stock index volatility: can market vo lume help?. Journal of Forecasting, 17(1), 59-80.
14. Bjørnland, H. C., & Hungnes, H. (2006). The importance of inte rest rates for forecasting the exchange rate. Journal of Forecasting, 25(3), 209-221.
15. Lim, K. P., Brooks, R. D., & Kim, J. H. (2008). Financial crisis and stock market efficiency: empirical evidence from Asian countries. *International review of financial analysis*, 17(3), 571–591.
16. Audrino, F. (2014). Forecasting correlations during the late-2000s financial crisis: the short-run component, the long-run component, and structural breaks. *Computational Statistics & Data Analysis*, *76*, 43–60.
17. Borio, C., Drehmann, M., & Xia, F. D. (2020). Forecasting recessions: The importance of the financial cycle. Journal of Macroecon omics, 66, 103258.
18. Chowdhury, B., Dungey, M., Kangogo, M., Sayeed, M. A., & Vol kov, V. (2019). The changing network of financial market linkages: the Asian experience. *International Review of Financial Analysis*, 64, 71–92.
19. Hochreiter, S. (1997). Long Short-term Memory. Neural Compu tation MIT-Press.

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DOI: 10.36838/v7i3.22