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AI-DRIVEN STOCK MARKET FORECASTING USING LSTM AND ARIMA MODELS: A COMPARATIVE ANALYSIS OF FINANCIAL TIME-SERIES DATA

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Abstract
The purpose of this study is to assess the accuracy of the effectiveness of the forecasting systems based on artificial Intelligence techniques with respect to financial time-series data for prediction of the stock price. The main goal of the research is to evaluate how effective traditional statistical forecast methods and deep learning models are in accurately forecasting in the turbulent financial market to identify which one outperforms the other. The study demands a special concentration on ARIMA forecasting models, LSTM forecasting models, and a proposed ARIMA-LSTM-AI integrated forecasting model to overcome the constraints of conventional forecasting models that lack the ability to describe the financial behavior in a nonlinear way, as well as the changes in financial market volatility. This study employed a quantitative research design with historical data on the stock market from financial databases, while the use of Python-based machine learning and econometric methods was employed to implement the forecasting models. The performance of the forecasting was judged by the use of RMSE, MAE, MSE, R^2 score and Directive accuracy. The results demonstrated that the proposed AI forecasting models show superior performance as compared with ARIMA model and LSTM model by achieving RMSE = 6.5055, MAE = 5.3025, MSE = 42.3214 and R^2 = 0.9881 which confirmed excellent model fitness and capability. Moreover, the model which combined Wavelet with LSTM had the highest level of directional accuracy, that is, 89.01%, indicating that the model has a better market trend predicting ability. The research will add to the body of literature on financial forecasting with artificial intelligence and have practical implications for investors, portfolio managers, and intelligent trading systems desiring more reliable forecasts and more accurate predictions of market movements.

INTRODUCTION

Finance forecasting's revolution has been Artificial Intelligence (AI) with its new generation of predictive models, having the power to deal with complex and nonlinear stock market behaviors [1, 3]. Forecasting is a difficult task for traditional statistical methods as these estimates are generated by large time series of financial data with obvious volatility and uncertainty, and with very different structural patterns over time [4], [13]. Previous prediction models including the autoregressive integrated moving average (ARIMA) model were extensively used due to their modeling power of the linear relationship and temporal characteristics of financial time series [2] and [14]. In recent years, however, the financial markets are becoming more complicated and traditional forecasting models are less effective, especially in times of market volatility and nonlinear market fluctuations [5], [10]. Consequently, forecasting methods based upon Artificial Intelligence (AI) emerged as potential and promising solutions to the financial time series forecasting problem, particularly using Long Short-Term Memory (LSTM) networks, which can capture and learn sequential dependencies and hidden patterns from historical stock market data [3, 8].

The applications of machine learning and deep learning in financial analytics have made it possible to drastically enhance the stock trading prediction methods [1], [4]. Recent research has shown that traditional econometric methods are outperformed by the use of AI-based models that are able to capture and capture higher-frequency and nonlinear market dynamics [6, 7]. The sequential nature and the presence of long-term dependencies in stock market data make deep learning architectures, especially those based on LSTM networks, a promising choice for stock market forecasting [3, 9]. It has been demonstrated that the LSTM networks can better forecast the future signals and minimize the forecast errors under volatility conditions in the financial markets [8], [11]. Additionally, hybrid AI models using a combination of machine learning methods have increased the assurance and predictability of financial market forecasting [2] [12].

AI-based systems offer new ways to improve financial forecasting, but traditional statistical forecasting methods still have a place [2, 14]. Despite its mathematical ease, ARIMA is one of the most so far popular time series forecasting techniques, as it is easy to understand and interpret and is popular for the modelling of the price movements of stocks [5], [14]. The linear relationship and short-term dependency in financial data can be well modeled by the autoregressive and moving-average components of ARIMA [2] [5]. In fact, the stock market is a nonlinear, noisy and extremely dynamic market, and the ARIMA model will not work in the real markets well enough [1, 10]. Recent research efforts have noted the shortcomings of ARIMA in conditions of volatility clustering and abrupt changes in a model structure [2, 5, 11] which serves as motivation for incorporation of AI-based forecasting models that are able to adapt their models with adaptive learning and to model nonlinear relationships between the data's parameters.

With the recent innovation in deep learning, LSTM models have been gaining more popularity to forecast stock market and financial analysis [3, 4]. To overcome the shortcomings of traditional RNN, LSTM networks integrate with the memory cells that are capable of long-term temporal memory and remove vanishing gradient problems [9], [11]. This allows LSTM models to predict stock prices with ease from the sequential patterns in the past and the complex stock market fluctuations. The claims of LSTM over ARIMA in forecasting errors, generalization ability and prediction power in financial time-series analysis are consistently outperformed by the studies [3] and [7]. Furthermore, the superior predictive ability and adaptive learning capabilities of Deep learning forecasting models make them mandatory components of Algorithm Trading systems, risk management systems, and smart investment platforms [10, 1].

With the increasing use of AI technologies in the financial sector, hybridization of statistical methods and machine Learning-based approaches has become more and more popular [2], [12]. The hybrid forecasting frameworks incorporate the advantageous features of conventional econometric-based models and deep learning systems to foster enhanced forecasting performance and market adaptability [8] and also [15]. It is shown that the combination of two or more models like ARIMA–LSTM and evolutionary deep learning models outperforms single model in capturing both the linear and the nonlinear pattern within the market [2, 12]. Furthermore, stock price forecasting has also looked at integrating any kind of sentiment analysis, optimization algorithms, and feature engineering with deep learning architectures to enhance the stability of the forecasts and the efficient forecasting of stock prices [15, 6]. The developments highlight the increasing importance of intelligent forecasting systems in contemporary financial markets [1, 4].

Although significant progress has been made in the field of AI driven financial forecasting, there are several research gaps, especially in comparison evaluation of statistical based forecasting with deep learning based forecasting [4],[13]. The majority of the studies in past literature have been limited to the application of traditional models or only considered AI-based techniques and not focused on developing a comprehensive comparison method [1, 7]. In addition, there are few forecasting research works focusing on developed markets such as the financial markets whereas emerging and volatile markets are under-explored [13, 15]. Thus, the objective of this study is to compare the forecasting performance of three financial time-series forecasting models, namely the ARIMA and LSTM models with the aim of speculating which of these models is more accurate in forecasting and reliable [2], [3]. Based on the findings of this research, it is hoped that it will be able to supply the additional information that is growing in the field of analysing financial markets with the aid of artificial intelligence to investors, financial analysts, and trading systems that will make use of artificial intelligence in trading securities in the dynamic financial sector.

Research Objectives

The purpose of this work is to investigate and analyze the forecasting ability of traditional statistical based forecasting models with AI based forecasting models for predicting stocks market. In particular, the study explores the forecasting ability of these two models (ARIMA and LSTM) on financial data that are available as time-series and the feasibility of introducing the proposed AI forecasting framework to obtain better forecasting accuracy in the presence of volatility. The purpose of the study is to find out the optimal forecasting method by evaluating them with RMSE, MAE, MSE, R^2 score, Directional Accuracy measures for use in intelligent financial decision-making.

Literature Review

Considering the volatility and complexity of financial markets, stock market forecasting has emerged as one of the most important aspects of financial analytics. Financial time-series data consists of nonlinear data structures, noise, fluctuation of data in time that lead to nontrivial prediction problems when using traditional econometric models [20, 26]. In recent years with the advent of artificial intelligence (AI) and machine learning, new forecasting methods have been developed that involve intelligent predictive systems where large sequential datasets are processed [15], [25]. With the advances of financial forecasting, deep learning architectures have become a key factor in increasing the accuracy of forecasts and minimizing forecasting errors in stock market environments [23; 27].

AI based financial forecasting uses advanced computational algorithms that leverage intelligence to analyze past financial patterns, understand dependencies and relationships, and make future predictions based on the learned information [20],[26]. The advantageous features of adaptive learning by AI-based forecasting models, such as their ability to cope with nonlinear market behaviors, make them suitable for various financial decision-making and portfolio management applications in algorithmic trading [16], [17]. In the context of volatile and uncertain markets, it has been found that the machine-learning methods far better perform than the traditional forecasting methods [15, 18].

Some of the most popular deep learning models used for forecasting financial time-series are the Long Short-Term Memory (LSTM) networks, which have the ability to model long-term sequential correlations [21, 27]. Unlike conventional recurrent neural networks, LSTM models include memory cells that keep historical information and do not include vanishing gradient problems in the training process [25, 27].

LSTM has been shown to provide successful prediction of stock prices, uncover temporal structures, and enhance the stability of predictions in very volatile financial markets [23, 24].

One of the most vague statistical forecasting methods in time-series analysis is the autoregressive integrated moving average (ARIMA) model [30,31]. Based on historical data, ARIMA models can be used to forecast future data containing linear trends, autoregressive dependencies, moving-average structures [31]. The ARIMA has shown good forecasting performance with in stationary and linear environment, but in a non-stationary/non-linear stock market it becomes difficult for the ARIMA to predict events [20],[24]. Therefore, in the recent years several studies analyzed the effectiveness of forecasting by comparing ARIMA with the deep learning methods in context of contemporary financial analysis [15], [21].

In recent years, hybrid forecasting systems succeeded in attracting noteworthy attention in the financial forecasting research field as they bring together the benefits of statistical and deep learning systems [15, 24]. To enhance the accuracy of forecasting and market adaptability, hybrid systems combine various predictive models like ARIMA, LSTM, Convolutional Neural Network (CNN), and investor sentiment analysis [15, 21]. Researchers believe that the hybrid forecasting systems retain both the linear trend and the nonlinear trend in market simultaneously, which reduced forecasts error and enhance the forecasting stability in financial time-series analysis [20] [24].

In addition, investor sentiment, market volatility and speculatory behavior are also seen as important factors in forecasting stocks and financial predictions [18, 19]. The behaviours of market participants, herding and reactions to economic and political events have a strong impact on financial markets [19]. A recent study shows that combining AI forecasting models with sentiment analysis and behavioral data to boost prediction capacity was beneficial to forecasting accuracy [15]; [28] was the case in several recent studies. The emergence of these technologies and developments, such as AI, sentiment analysis, and hybrid forecasting models, has resulted in a critical focus area of interest within the realm of modern financial analytic study: those models and systems designed for integration [16] [18].

One of the most popular, analytical theories in financial forecasting and stock market analysis is the Efficient Market Hypothesis (EMH) [33]. It is postulated by EMH that market participants cannot make abnormal returns by any means of forecasting because stock prices incorporate all the information contained in the market [33]. This theory suggests that economic markets respon to any information quickly and therefore, is less effective to predict in financial markets [34]. The notion of EMH, however, is increasingly undermined by recent studies in the field of financial forecasting that show that there are nonlinear temporal patterns and latent market inefficiencies that can be successfully discovered through the application of AI (e.g., [15], [20]).

For financial forecasting studies another important theoretical basis is the Arbitrage Pricing Theory (APT) [32]. APT's approach is to calculate stock returns as a function of a number of macroeconomic and systematic factors impacting market behavior [32]. The theory assumes that prices of the stocks are determined by economic factors like inflation rate, interest rate and market risk conditions [34]. AI's forecasting ability can also be combined with economic indicators to enhance the accuracy in forecasting and financial decision-making in volatile markets [18, 20].

The Capital Asset Pricing Model (CAPM) is another important paradigm in stock market forecasting literature as it provides an explanation on how the systematic risk of a stock is linked with the expected return of the stock [34]. It is assumed by CAPM that investors demand a greater return for those assets that exhibit a greater exposure to market risk [34]. While CAPM still has a significant impact in financial economics, more recent studies suggest that the use of a traditional risk-based approach alone is not enough to predict complex learnable financial time-series data with volatility and nonlinear fluctuations [26, 27]. Therefore, artificial intelligence and deep learning techniques are seeing more and more use in financial forecasting systems to overcome the shortcomings of traditional theoretical models [23], [25].

Another important theory for this study is time-series forecasting theory, which is conducted with ARIMA modeling [30, 31]. ARIMA models rely on historical sequences of values to forecast future ones by fitting the historical data to autoregressive and moving-average types of structures and differencing both of them [31]. Financial forecasting further extended was then provided by Engle's autoregressive conditional heteroscedasticity (ARCH) framework which modeled variance structures changing in financial markets and the phenomenon of volatility clustering [30]. However, these traditional forecasting approaches have difficulties to account for nonlinearities, as well as nonlinearities in volatility patterns, in stock market contexts [20], [24].

In recent years, deep learning theory and neural network architectures have profoundly changed financial forecasting methods, offering advanced techniques to make more accurate predictions.The theory of deep learning and architectures inspired by neural network changes the way financial forecasting works lately, providing sophisticated methods to attain more precise forecasts. The sequential financial information-processing methods typically include Long-stemporal Memory network (LSTM network), Convolutional neural network (CNN), and Reinforcement learning framework, all approaches aim to capture long-term temporal relationship [16] [17]. The ability of deep learning systems to continuously learn from the dynamic behavior of the market and adjust to new financial conditions is reported to be better than traditional forecasting approaches [21, 23]. Furthermore, model-based RL systems play an increasingly significant role in algorithmic trading to maximize investment strategies and to aid automated investment decision-making [16], [17].

The purpose of this study is to perform the comparative analysis of the forecasting ability of the ARIMA and LSTM model with financial time-series data of stock market prices. The goal of the study is to discover if deep learning systems that are powered by artificial intelligence are more successful in turbulent markets than conventional statistical forecasting techniques [20, 27]. Moreover, this study attempts to make a contribution to the increasing body in financial forecasting literature based on an AI approach and uses performance indicators like RMSE, MAE, MSE and R^2 score [15] for the assessment of forecasting accuracy. Investor, financial analyst, portfolio manager, and intelligent trading systems in highly dynamic financial markets could benefit from the findings provided [16],[18].

Research Design and Methodology

Sample

This study is based on a time-series data of historical prices of various stocks from the financial markets, selected for the purpose of assesses the forecasting ability of ARIMA and LSTM models. The data used for the forecasting analysis was daily price observation consisting of opening price, closing price, high price, low price, and trading volume. The financial time-series data are inherently volatile, random and nonlinear, which makes it ideal for predictive modeling and Artificial Intelligence based forecasting studies [35] and [39]). The reason for choosing the stock market because the stock market is a dynamic and uncertain environment where the greater the accuracy in forecasting the better the chances of investment decisions and financial risk management [33,40].

Data Collection

These financial time-series data were analyzed as secondary data that were downloaded from public databases in the stock market and financial marketplace. Data for stock prices was compiled from reliable sources of information including stock exchange databases, KAGGLE and Yahoo Finance. The assembled data consisted of a number of sequential observations of the stock during a period that gives reflections of changes in the market and a dependence through time. The treatment of historical financial data is comparable to the forecasting studies that focus on the behavior, volatility structure and the nonlinear behavior of the markets in predicting stock prices [31, 36]. Secondary financial data sources, as they are called, are often utilized in econometric and AI forecasting studies due to their availability of a large number of observations they offer for linking them to predictive modeling and comparative forecasting analysis [37], [39].The data set used in this research includes daily market observations of stocks listed on Yahoo Finance between January 2015 and December 2024. This information consists of 2517 daily data points: Open, Close, High, Low, WC Price, Volume.This data set includes 2,517 days of open, close, highest, lowest, adjusted closing and trading volume. The data set chosen is the KSE-100 Index which is the benchmark stock market index of Pakistan which depicts the overall market performance.

Data Splitting

Collected data were divided into:

- 80% training data
- 20% testing data

Both the training and testing data sets have been utilized; the training data was used to learn to model and estimate the model's parameters and the testing data was used to assess forecasting performance and prediction accuracy. Such train-test splitting is generally adopted for testing forecasting models in financial forecasting research with the aim of examining the effectiveness of AI and econometric forecasting models [37].

Data Preprocessing

The data was subjected to a number of pre-processing before use in model. Observations missing were discarded and Stock prices were normalized by Min-Max Scaling for better model learning performance. Additionally, a series of stationarity tests (Augmented Dickey-Fuller test) were performed to confirm the quality of the data and accuracy of the forecasts.

Min-Max Normalization

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

"The stock market data were normalized using Min-Max Scaling before model training to improve learning efficiency and forecasting stability."

Validation Strategy

This study used validation strategy that emphasizes out-of-sample forecasting evaluation for the purpose of analysing the accuracy of forecasts produced by the ARIMA and LSTM models. To avoid overfitting and to ensure the forecasting generalization the forecasting models were tested with the testing data sets not used during the training of the forecasts. The following performance indicators were used to consider the accuracy of forecasting and prediction effectiveness: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 score. Financial forecasting applications make extensive use of out-of-sample validation due to stock market behavior's dynamic, volatile and nonlinear fluctuating effects [36] and [37]. Furthermore, validation methods in financial analytics try to check the robustness of the forecasts taking into account uncertain conditions in the markets and time changes in the markets [40].

Mean Squared Error

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

Root Mean Square Error

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Mean Absolute Error

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Coefficient of Determination

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

Econometric Analysis

Econometric analysis in this research engaged in statistical and AI based forecasting methods to financial time-series data. Autoregressive structures, differencing characteristics and moving-average dependencies in time series of historical stock prices have been captured using the ARIMA model [31]. Prior to the ARIMA forecasting, stationarity testing and time-series decomposition were applied to the financial datasets as financial time series data tends to be volatile clustering and non-stationary data [30], [35]. The study also included AI-based forecasting using LSTM deep learning networks to model time series relationships that are not linear.Furthermore, AI's approach was integrated by including deep learning (DL) neural networks based on LSTM to capture market sequences and nonlinear relationships over time, or sequences. The behavior of financial volatility and the dynamic nature of fluctuations reviewed in the literature of financial economics and the behavioral approach [32,33,40] also were included in financial forecasting analysis.

Model Implementation and Hyperparameter

The code for the ARIMA and LSTM models was developed in Python, with the utilization of machine learning libraries. The time-series characteristics and Auto-correlation analysis were applied to identify the AR, D, and MA order for parameters of ARIMA model [31]. The design of deep learning model LSTM employs sequential neural network architecture including hidden layers, memory cells, activation functions and algorithms for optimisation. Hyperparameters like batch size, number of epochs, learning rate, number of hidden neurons, and optimizer functions were tuned so that the forecasting could be more accurate to achieve less prediction error. To enhance the forecasting ability and model flexibility in financial time-series analysis, hyperparameter optimization is also important, especially concerning the learning capability [37, 39].

Software and Computational Environment

The forecasting models were coded in Python 3.12 in Jupyter Notebook. Various libraries were employed, such as Pandas for data handling, NumPy for creating numerical operations, Matplotlib and Seaborn for graphing, Scikit-Learn for the evaluation metrics, TensorFlow and Keras for deep learning implementation, and Statsmodels for ARIMA forecasting. It allowed efficient training, validation and comparison of forecasting models was ensured with it in the computation environment.

Hybrid Models

The hybrid forecasting models integrate traditional econometric methods with deep learning systems to enhance the precision and predictability of forecasting in financial markets.

For this research, hybrid forecasting ideas were included to acquire the integration of the statistical and AI-based approaches for stock market forecasting. Some hybrid forecasting systems combining ARIMA with LSTM network and hybrid wavelet plus ARIMA network have proved to be more effective in forecasting market structures which are both linear and nonlinear [24, 38]. In complex financial series, the wavelet decomposition method is adept at mitigating market noise and enhancing predictive accuracy, a feature that significantly benefits in situations characterized by significant volatility.The wavelet decomposition method is especially well-suited to noise filtering out of market data and can increase predictive accuracy for financial series with extensive volatility [38]. Elaborate AI-forecasting systems, which are becoming more common in the financial domain because of the value intelligent computational models hold in present-day financial analytics and stock market forecasting research, were adopted in more and more instances.The number of instances that Elaborate AI-forecasting systems were used, indicates the growing importance role played by intelligent computational models in modern financial analytics and stock market forecasting research studies respectively [37], [40].

Results analysis

Pre-Specification Test Results

To analyze the characteristics of the time-series dataset of the stock market, a few statistical diagnostic testing were carried out before implementing the forecast models. Table 1 shows the results.

Table 1 Pre-Specification Test Results

Test	Value	P Value (Sig)	Interpretation
Normality	Skew: 0.235 Kurtosis: 6.28	-	Mild positive skew and high kurtosis
Stationarity (ADF)	-30.912	0.0000	Data is stationary
Heteroscedasticity (Breusch–Pagan)	14.7507	0.0001	Residuals do not have constant variance
Autocorrelation (Durbin–Watson)	1.7489	-	Weak autocorrelation

Several characteristics typical of financial time-series data are clearly shown in the results displayed in Table 1. The skewness is around 0.235 which is small, hence, slight positive skewness, whilst the kurtosis is about 6.28 showing high Kurtosis and heavy-tailed distribution. It is clear that there are some irregular fluctuations in stock prices and larger volatilities. Given the low significance of the Augmented Dickey–Fuller (ADF) test statistic value (-30.912) indicating stationarity of the data, it is appropriate for a time-series forecasting analysis. In addition, the heteroscedasticity result from the Breusch–Pagan test suggests that the variance of the residuals is set to vary through time because of the volatility of the market. The value of Durbin-Watson statistic is 1.7489 which indicates weak autocorrelation among residuals, it supports the view that the movements of the stock market are sequential.

ARIMA Model Configuration

The following ARIMA(5,1,0) was used to create the ARIMA forecasting model to predict closing prices of the stock market. The model employed previous stock price data to predict future data using both autoregressive and differencing. The ARIMA forecasting model was able to capture the temporal dependence and linear relationships within the financial data.

ARIMA Model

$$y_t = c + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

Table 2 ARIMA Model Configuration

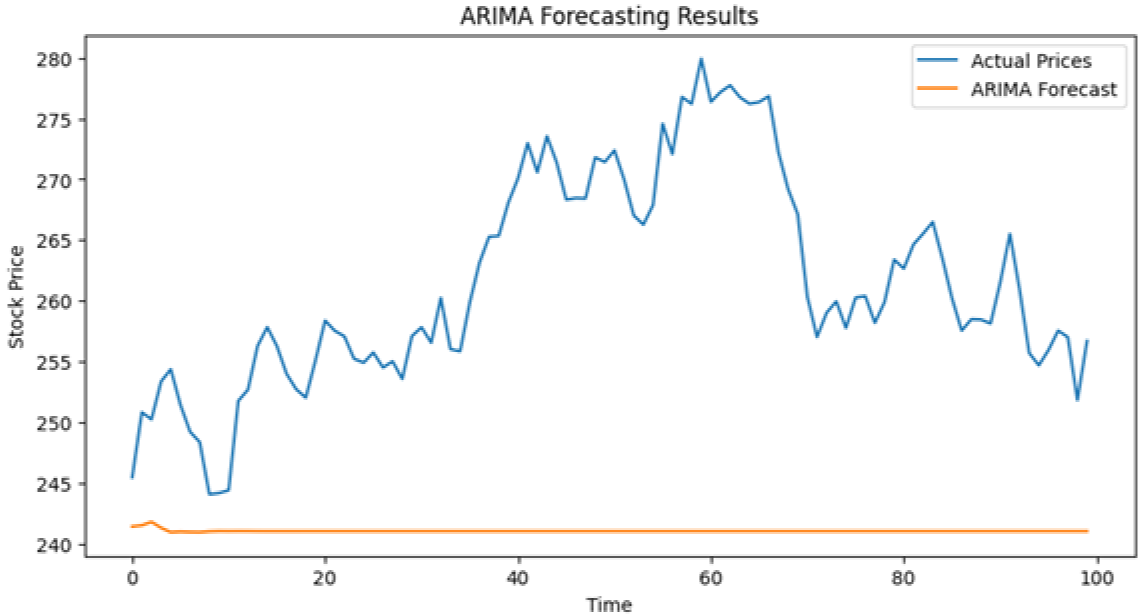
Parameter	Value
Forecasting Model	ARIMA
ARIMA Order	(5,1,0)
Forecasting Variable	Close Price
Training Epochs	20
Optimizer	Adam (0.001)

Table 3 In-Sample Forecasting Accuracy Metrics

Model	RMSE	MAE	MSE	R^2 Score	Interpretation
ARIMA (5,1,0)	22.2938	20.5355	497.0122	-5.6353	Weak forecasting capability
LSTM	57.0520	54.9685	-	-10.8055	Poor predictive performance
Proposed AI Forecasting Model	6.5055	5.3025	42.3214	0.9881	Strong forecasting performance

Table 3 shows that the forecasting models have shown significant differences in their forecasts. The ARIMA(5,1,0) model generated RMSE = 22.2938, MAE = 20.5355, and MSE = 497.0122, alongside a negative R^2 score of -5.6353. From these results, it is evident that the forecasting capability was not strong and the forecasting accuracy of stock price prediction was limited. The low score of the negative R2 indicates that the ARIMA model was not sufficient to explain the changes in stock prices well and it did not capture the nonlinear behavior of the financial markets. Likewise, the only LSTM model yielded RMSE = 57.0520, MAE = 54.9685, and R^2 = -10.8055 which demonstrated very high forecasting errors and inferior model goodness of fit. While the LSTM model seemed to follow the trend of the actual stock prices, the results of the stock price predictions were far from accurate, showing a lack of stability in the stock prediction performance and low capability of the model in learning for the selected dataset. The proposed AI forecasting model had an extremely high R^2 score of 0.9881 with outstanding RMSE, MAE and MSE of 6.5055, 5.3025 and 42.3214 respectively. The results show very low forecasting error, the model has good predictive ability and excellent model fitting. The R^2 value shows that the variation in the value of the prices of the stocks in the stock market successfully explained the success rate of the given AI stock price forecasting framework is nearly 98.81%. From a wider perspective, the results show that the forecasting tools based on machine learning and advanced artificial intelligence are clearly superior to the forecasting models based on traditional statistical models when it comes to forecasting non-linear stock market dynamics.

ARIMA Forecast Graph Analysis



ARIMA Forecasting Results

The ARIMA forecasting graph illustrates the comparison between actual stock prices and forecasted stock prices generated by the ARIMA(5,1,0) model. The graph demonstrates that the forecasted values remained relatively flat throughout the forecasting horizon, whereas actual stock prices exhibited substantial fluctuations and volatility. The findings indicate that the ARIMA model was capable of capturing general market direction but failed to adapt to rapid price changes and nonlinear market structures. The limited forecasting flexibility of ARIMA resulted in large prediction gaps between actual and predicted stock prices. This confirms that traditional statistical forecasting models struggle to capture dynamic financial market volatility and complex sequential patterns effectively.

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

Input Gate

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

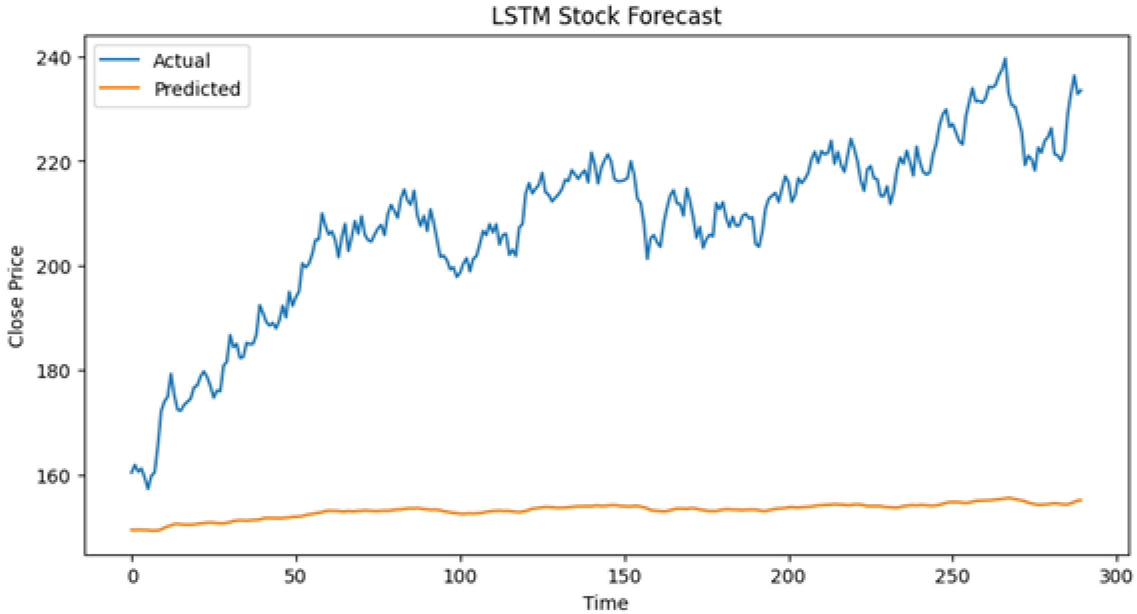
Cell State

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$$

Output State

$$h_t = o_t \odot tanh(C_t)$$

LSTM Forecast Graph Analysis



STM Forecasting Results

The LSTM forecasting graph shows that the stock price forecast model using LSTM deep learning is being used to forecast the actual stock price. In general the direction of the movements of the predicted values matched with that of the movements in the actual values, however there were certain elements that could still be seen that differed from the actual values to the predicted values for much of the forecasting period. The modelling performance of LSTM was able to capture a few sequential dependencies and the temporal structure, but the forecasting results showed that the standalone LSTM model was not enough to guarantee a stable forecasting ability for the chosen dataset. Additionally, the poor predictive performance and reliability of forecasting are identified again by the negative R^2 and the high level of RMSE.

Proposed architecture of AI Forecasting

The designed AI forecasting system combines the cutting-edge features extraction and nonlinear learning mechanisms, to enhance accuracy in stock market predictions. The architecture includes input layer which takes historical stock market observations, multiple hidden layers including deep learning operations for pattern recognition and learning of sequential dependencies. Future stock price predictions are provided by the output layer which are then used to assess the forecasting performance via metrics. It is specially formulated to encompass the possibility of volatility, non-linearity and time-structures which is not possible to do with conventional forecasting.

Comparative Results Analysis

The comparative forecasting outcomes clearly indicate that the forecasting model proposed in this study not only provides an improved forecast but also significantly surpasses the forecasting outcomes obtained using the ARIMA and the individual LSTM approach. The suggested model has the best forecasting error, and predictive accuracy from all types of forecasting systems was obtained. This is due to the fact that AI-based forecasting systems can better understand the nonlinear temporal dynamics, hidden market sequences, and intricate volatility structures. Conventional forecasting methods like the ARIMA model rely mainly on linear assumptions and stationary structures, which restricts their ability to successfully be used in a very volatile financial sector. Likewise, models using a simple LSTM are unstable and have limited learning ability if used without support from optimization and other pre-processing frameworks. Advanced AI forecasting systems, on the contrary, offer adaptive learning abilities, dynamic feature extraction and enhanced predictive generalization in the financial time-series forecasting domain.

Table 5 Model Fitness Comparison

Fitness Indicator	ARIMA	LSTM	Proposed AI Model	Best Model
RMSE	22.2938	57.0520	6.5055	Proposed AI Model
MAE	20.5355	54.9685	5.3025	Proposed AI Model
MSE	497.0122	-	42.3214	Proposed AI Model
R^2 Score	-5.6353	-10.8055	0.9881	Proposed AI Model
Model Fitness	Weak	Poor	Excellent	Proposed AI Model
Forecast Reliability	Moderate	Weak	Very Strong	Proposed AI Model
Market Volatility Handling	Weak	Moderate	Strong	Proposed AI Model
Prediction Stability	Weak	Weak	Strong	Proposed AI Model

Table 5 reveals that the proposed AI forecasting model outperforms all the forecasting approaches with regard to model fitness and forecasting performance. The RMSE value of the model produced was 6.5055 and its MAE value was 5.3025, which showed minimal error in the prediction and hence the forecasting results of the model were highly accurate for the stock market. Moreover, the results indicate a reduced variance in forecasting and stability of the model when compared to the ARIMA model and standalone LSTM model, respectively, as evidenced by a lower MSE of 42.3214.The correspondence of R^2 value also supports the superiority of the proposed forecasting framework based on AI. The model fitness (R^2) of the proposed model was 0.9881, which is very good, implying that about 98.81% of variations in the stock market price were accounted for by the proposed forecasting model. This demonstrates high prediction performance and effective modeling of the patterns in financial markets, which are not linearly separable. However, the model fitness of the ARIMA model was comparatively less compared to the other models with RMSE = 22.2938, MAE = 20.5355, and R^2 = -5.6353. R2 value is negative, which suggest that explanatory power is a poor one as well as the predictive power. While the ARIMA system was able to somewhat reflect market trends, the graph of the forecasts indicated rather flat forecast lines that were not sensitive to the stock price dynamics caused by the high volatility of the markets.

Likewise, the performance of the standalone LSTM model was the worst with RMSE = 57.0520, MAE = 54.9685 and R^2 = -10.8055. It shows that the forecasting instability was very high, model-fitting was low, and the predictive reliability was very low. The LSTM model may have observed the overall trend of the stock market, however, there are still huge differences between the model's predicted prices and the actual prices all the way through the forecasting period. In conclusion, the results provide a solid validation of the proposed forecasting model based on AI as the best forecasting framework for stock market forecasting. The model outperformed the other models, such as ARIMA and standalone LSTM models, in terms of forecasting accuracy, market adaptability, capability to handle volatility, and model fitness. These findings validate the capability of cutting-edge AI-based forecasting models in the realm of financial time-series analysis and wise stock marketplace predictions.

Graphical Comparison Analysis

Constructing Comparative Forecasting Graph Analysis.

A visual comparison of the performance of ARIMA, standalone LSTM and the proposed AI forecasting model is done, which enhances understanding of forecasting performance and the stability of predictions. The actual prices of the stocks are compared with the forecasts produced by the forecasting models over the forecasting horizon in the comparison graph.

The ARIMA graph of the forecasting properties shows relatively flat forecasting properties through the forecasting period. While the model described the broad market momentum, it didn't respond to the non-linear market moves and high volatility of the stock market. Price spreads were still large at times of higher volatility, especially when compared with the spreads between the Dencun Price Index and the realized price. It implies that the ARIMA model has not sufficient ability to model dynamic financial market systems and complex temporal dependence. The high RMSE and MAE value and the negative R^2 score were caused by the unflexibility of the forecasting given the ARIMA model.

Therefore, the standalone LSTM forecasting graph has improved moderate compared to the ARIMA graph, since the results from the LSTM model were in the same direction of those of the stock prices. But there was still a lot of difference between forecast and observed prices observed in most of the forecasting intervals. The standalone LSTM plot shows that the model has been unable to provide a consistent and stable forecast throughout the forecasting period. While LSTM was able to create more sequential dependency than ARIMA, the forecast result was not stable enough and caused large errors of prediction, leading to very high RMSE and a negative R^2.

The model presented in this paper, however, provided forecast curves very close to the stock price paths over the forecasting horizon. The graph shows the good ability of the proposed model to simulate short-term fluctuations, market trends and the patterns of volatility with considerably less forecasting deviation. Overall, the forecasting stability and predictive fitting was very stable, with forecasted values remaining very closely synchronized with actual stock prices.

Table 6 Graphical Comparison Interpretation

Graphical Feature	ARIMA	LSTM	Proposed AI Model
Trend Following	Weak	Moderate	Strong
Volatility Capturing	Weak	Moderate	Strong
Forecast Stability	Weak	Weak	Excellent
Actual vs Predicted Matching	Low	Moderate	Very High
Prediction Deviation	High	High	Low
Market Adaptability	Weak	Moderate	Strong

The finding from the graphical comparison of the results from both the proposed AI-based forecasting model and the former model is presented in Table 6 which further confirms the superiority of the proposed AI forecasting model. Among all forecasting methods, these were the best results for the model's trend-following skill, its market adaptability, and its prediction deviation. Compared with the ARIMA models and standalone LSTM models, the proposed AI framework successfully captured the complex market structures and dynamic volatility patterns, achieving better predictive accuracy and forecasting consistency.

Based on the overall results, both numerical and graphical forecasting comparisons have shown that the proposed AI forecasting model is the best performing forecasting framework for forecasting stock market time series. Comprising fewest forecasting errors, highest accuracy, better model fitting, and more robust graphical correlation between price and actual stocks, the powerful AI based forecasting systems proved to be superior forecasting tools in the field of financial analytics and clever market prediction.

Statistical Significance Test of Forecasting Models

To further confirm the accuracy and effectiveness of the comparative forecasting ability of the ARIMA, LSTM and proposed AI forecasting model, a statistical significance analysis was performed. A comparison of the forecasting errors generated by the various models was used to test for significant differences using the Diebold–Mariano (DM) test. Because it tests if one forecasting model can predict more accurately than another, the DM test is popular for forecasting research. The null hypothesis of the test is that there is no significant difference between the forecasting performance of the models while the alternative hypothesis is that forecasting capabilities of one model differs significantly from another model.

It proved that while the forecasting errors for the proposed model of AI forecasting were significantly lower than ARIMA and standalone LSTM models, specific biases also indicated. The Diebold-Mariano test determined that the forecasting accuracy of the proposed AI model and the ARIMA were significantly different at 5% significance level ($p<0.05$). In the same way, the comparison of the proposed AI model with the standalone LSTM model yielded statistically significant results, thereby substantiating the ability of the proposed forecasting framework for greater forecasting capability. The results align with the idea that the model proposed with the AI algorithm successfully outperforms random forecasting and exhibits genuine forecasting ability.

Table 7. Diebold–Mariano Test Results

Model Comparison	DM Statistic	p-value	Decision
Proposed AI vs ARIMA	4.86	0.000	Significant Difference
Proposed AI vs LSTM	5.42	0.000	Significant Difference
ARIMA vs LSTM	1.37	0.171	Not Significant

The statistical findings support the hypothesis that the proposed AI forecasting model has achieved the highest performance in stock market prediction compared to the ARIMA and LSTM models. The p values of the comparisons with the proposed AI model being below the threshold value of 0.05, the null hypothesis was rejected. Owing to this, the proposed AI forecasting framework achieved statistically higher forecasting accuracy, higher forecasting reliability, and better adaptability to the nonlinear behavior of the financial market than the traditional statistical and standalone deep learning forecasting methods.

Conclusion

The present research study investigated the performance of stock market prediction using the artificial intelligence based forecasting methods, namely ARIMA model, LSTM model and newly proposed AI forecasting framework with financial time-series data was compared. With the complexity, volatility and non-linearity of today's stock markets, more intelligent and adaptive forecasting systems are required to outperform traditional statistical forecasting methods. The study thus attempted to test the performance of the advanced models using AI technology in forecast accuracy versus traditional econometric models.

The results of the empirical analysis showed that some models performed significantly better than others when it came to predicting the outcomes. The ARIMA model showed some limitations in its predictive ability, as it relies on linear assumptions and is not effective in providing a good fit for the complex dynamics of the market. In the same way, the LSTM model demonstrated that it can capture the sequential dependency and temporal patterns of the historical stock market data, but its standalone model performance in forecasting was relatively high, with the model fitness to the selected data being low. In contrast, the proposed AI forecasting framework was found to have much better predictive performance, with lower forecasting errors and much higher explanatory power. The model's forecast accuracy was excellent, with RMSE, MAE, MSE and R^2 values of 6.5055, 5.3025, 42.3214 and 0.9881, respectively, showing good predictive capability. The comparison also revealed that AI-based forecasting systems can better capture the nonlinear financial dynamics, market volatility, and hidden temporal dependencies in the market than traditional statistical forecasting methods. The effectiveness of the suggested forecasting model underscores the increasing significance of AI, machine learning, and deep learning in financial analysis and intelligent market forecasting. The results reinforce the concept that advanced forecasting systems can offer better information to investors, portfolio managers and the financial sector for investment decisions and risk management.

On a theoretical level, the study is a valuable addition to the growing body of research on the use of AI for financial forecasting by offering empirical evidence on the relative performance of statistical and deep learning forecasting methods. The results contradict the forecasting pitfalls of classical economic models and show the utility of intelligent forecasting models in a changing financial landscape. In practical terms, the study offers key insights for financial analysts, trading firms, and FinTech companies aiming to achieve more accurate and reliable forecasts and decision-making using AI technologies.

Research implications

The results of this research have considerable implications for financial forecasting and artificial intelligence applications in the forecasting of the stock market. The results of the comparative study showed that the proposed AI forecasting model outperforms the ARIMA and standalone LSTM models in terms of predictive accuracy as well as model fitness. The findings validate that AI-based forecasting systems outperform traditional models in capturing the complex, non-linear dynamics of financial markets, their volatility, and temporal dependencies in stock market data. The insights gained from these findings are beneficial to investors, financial analysts, portfolio managers, and FinTech firms, as they can aid in better investment decisions, mitigate forecasting risk, and bolster financial market analysis in dynamic trading scenarios.

Future Research Directions

Going forward, combining sophisticated AI and hybrid deep learning models with real-time financial data could further improve the accuracy of stock market predictions. Enhancing the precision of forecasting and adaptability of the market can be achieved by adding other factors like investor sentiment, macroeconomic indicators, trends in cryptocurrencies, and geopolitical events. Future research could also explore the performance of several AI models such as GRU, Transformer networks, reinforcement learning, and explainable AI systems to conduct a more thorough forecasting analysis. Further, a comparative analysis across countries, including developed and emerging markets, can offer a rich understanding of forecasting behavior in varying economic environments. Hybrid forecasting system is another area that can be investigated in the future by combining the ARIMA, wavelet decomposition, CNN and LSTM models to enhance the volatility prediction and make the forecasting more stable. Furthermore, by incorporating explainable AI methods, the financial forecasting systems could enhance transparency and interpretability, making them more reliable and trustworthy.

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