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Evaluating the Predictive Power of Deep Learning Models in Financial Markets

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Abstract

Stock price forecasting remains a prominent area of research in financial markets due to the complicated, nonlinear, and volatile nature of stock price paths. While high-performance deep learning models like Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU) demonstrate superiority in financial forecasting, their comparative efficacy in emerging markets, such as the KSE-100 Index, remains inadequately explored. This study examines the prediction performance of these models based on past stock prices of the KSE-100 Index and based on standard performance measures (root mean square error, mean absolute error, and mean absolute percentage error) to provide a holistic assessment of the models. Our research indicates that GRU consistently performs better than CNN and LSTM, with lower errors and higher predictive accuracy. This work enhances current forecasting methods by utilizing advanced data preparation, feature engineering, and hyperparameter optimization to augment model performance. The results have practical implications for policymakers and investors in emerging markets by emphasizing the applicability of deep learning to financial decision-making.

Keywords: Deep learning models, Stock price, prediction, CNN, LSTM, GRU, Forecasting.

1. Introduction

There are numerous complicated financial indicators, and stock market fluctuations are very unstable. Nevertheless, technology has grown the potentiality of making stable profits from the stock market. Besides, the technologies assist professionals in determining the most significant indicators for enhanced predictability. Proper prediction of market value is of utmost significance to maximize the profitability of stock option buying while keeping associated risks minimum. The prediction of stock prices presents significant complexity and challenges for corporations, investors, and equity traders in forecasting future profits. Stock markets have intrinsic traits that are noisy, non-parametric, non-linear, and deterministically

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chaotic. These characteristics offer substantial challenges to effectively and efficiently forecasting future prices.

The stock exchange is recognized as a very crucial component of contemporary global economic systems. Correct forecasting allows investors to make strategic investment decisions, ultimately yielding high returns. For this reason, financial time series forecasting has been on the increase. Previously, investors have utilized various asset price models to forecast returns over lengthy horizons to formulate long-term projections. Stock market volatility forecasting plays a crucial factor in determining the decision-making process of investors regarding investments. Stock exchange volatility is indicative of rapid and significant price alterations within the stock market occurring in relatively short duration. Volatility is affected by a broad assortment of factors ranging from the declaration of economic figures, geopolitical shocks, corporate results announcements, rate of interest, and general sentiment of the market. The outcomes of inventory trade volatility cascade within the financial sector, affecting the behaviour of investors, marketplace liquidity, and economic stability. Elevated volatility in the stock exchange may be both a risk and a project for investors. On the fine facet, it offers the capability for short profits seeing that inventory fees have the ability to surge sharply following advantageous news or a favourable market fashion. Conversely, it will increase the chance of big losses inside the case of surprising declines in inventory expenses. This unpredictability has a bent of inflicting extremely excessive ranges of hysteria and anxiety among buyers, which can result in frantic buying and selling activities as humans are trying to find to take benefit of short-time period trends or restrict potential losses. The concept of stock exchange volatility is at the coronary heart of economic markets, in which it is far used to represent the significance of fluctuation in inventory charges over a given time c programming language. Volatility can be tormented by a variety of factors, which include macroeconomic tendencies, political occasions, booklet of company profits, or even sentiment within the marketplace. Volatility captures the chance and possibility that outline the inventory marketplace, leading to dynamic surroundings that may be tough to traders' expectations. In periods of high volatility, stock prices might also differ erratically, main to huge gains or losses within a very quick time. Conversely, low volatility suggests a extra strong market, in which fee actions are more modest and predictable.

Stock market analysis forms a vital location of monetary forecasting, with deep mastering (DL) fashions an increasing number of outstanding in the discipline. The modern-day literature reviews the usage of DL models in a range of financial packages, which include alternate fee, inventory market, and oil rate forecasting. The deep gaining knowledge of algorithms employed on this research have diverse abilities in analysing and forecasting the stock market, and each contributes uniquely to it. CNNs are suitable for figuring out complex records styles in facts due to the fact they can routinely research full-size features from high-dimensional statistics. Conversely, RNN fashions like LSTM and GRU are suitable for modelling sequential characteristics of time collection statistics due to the fact they could automatically learn relationships within the information stream and discover temporal relationships. These traits make the 2 fashions beneficial to use in time series forecasting, although each is better in a distinctive manner.

CNNs are higher in identifying and studying complicated styles in the information, However, when it comes to modeling time relationships between the data, LSTM and GRU do better. The goal of this strategy is to use the algorithms' complementary features to produce more thorough and precise forecasts. The overall goal of this study is to objectively compare the performance of several deep learning algorithms using historical stock price data. While CNN, LSTM, and GRU are examples of deep learning (DL) models that have been widely used to estimate stock values (e.g., S&P 500, NIFTY 50), their performance in highly volatile emerging markets like Pakistan's KSE-100 Index remains unexplored. Existing research Roondiwala et al. (2017) and Kexin and Zhijin (2022) considered stable markets, and hence, there is a lacuna in the exploration of DL resilience to sudden price fluctuations due to geopolitical and economic upheavals characteristic of KSE-100.

This paper adds to the corpus of research on deep learning models for stock market prediction, particularly for the KSE-100 Index, a representative emerging market with difficulties. The current analysis provides a crucial comparison of the CNN, LSTM, and GRU models in terms of performance in predicting stock rate movement in a turbulent and illiquid marketplace situation, in contrast to previous studies that have focused mostly on developed stock markets.Additionally, the study makes use of a marketplace-precise data set to highlight how traits of high volatility, abrupt rate movement, and extrinsic financial variables are the drivers of forecasting fulfilment. The study uses enhanced evaluation methods, including the utilization of multiple overall performance measures such as Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE), thereby presenting a rigorous evaluation of model accuracy. The findings provide crucial insights to investors, monetary analysts, and policymakers to facilitate the selection of the most effective device mastering techniques to inventory marketplace prediction in rising economies.

2. Literature Review

In research, Roondiwala et al. (2017)use NIFTY 50 ancient records from 01-01-2011 to 31-12-2016. They use five years records to predict the NIFTY 50 open charges, outcomes indicates that long brief-time period reminiscence approach has great accuracy.

Xiuyun et al. (2018)the usage of GRU version to be forecasting power intake in China. Utilizing four monetary indicators: population size, imports, exports, and GDP. The period protected by the data turned into 1965–2015. Results show that the best predictive accuracy of GRU version.

Kim and Won (2018) carried out deep getting to know architectures for forecasting the stock market primarily based at the daily remaining charges from India's National Stock Exchange (NSE). The dataset levels from January 1, 1996, to December 30, 2016. The consequences indicate that the overall performance of the other models being investigated is outperformed by means of convolutional neural networks (CNN).

An LSTM model is used by Rita, 2019 to predict stock market volatility. From January 1, 2006, to January 1, 2018, the Dow Jones Industrial Average Index (S&P 500) provided the dataset. According to the results, the Long Short-Term Memory approach has the highest accuracy level.

Jia et al., 2020 Deep learning models (LSTM and CNN) for stock price prediction. They are applying past data of the NIFTY 50 index that has been traded on India's National Stock Exchange (NSE). They utilized data from 29 December 2008 to 31 July 2020. All models are highly accurate for the prediction of the opening values of NIFTY 50.

Hussain et al., 2021using GRU model predicts Intelligent Traffic Flow. The data was directly captured in real-time from the PEMS dataset, and the dataset was sampled to be tested. There were no missing points for the entire month of January 2019 in the provided time interval. The outcomes indicate a higher efficacy of the proposed method in error reduction, with a mean improvement of the optimized network over the baseline model.

Gao et al. (2021) employed LSTM and GRU models to predict stock market volatility. The experiment data employed are data of the Shanghai Composite Index (000001) from April 11, 2007, to August 3, 2021. The experimental results show that LSTM and GRU models are effective in predicting stock prices.

Pokhrel et al. (2022) forecasted mine gas concentration using the GRU model. The dataset, comprising 10,419 data points of mine gas concentrations, was gathered from January to March 2014, with measurements taken at 5-minute intervals. Results show the gated recurrent unit model is provide more effective and accurate results.

Zafar et al. (2022) forecast stock values using Long Short-Term Memory (LSTM) models and Convolutional Neural Networks (CNN). The accuracy of the CNN model for short-term forecasting is demonstrated by using a sizable dataset of historical data for Tata Consultancy Services.

Zaheer et al. (2023) forecasting Shanghai Composite Index volatility based on LSTM and deep learning techniques. Shanghai Composite Index data from July 3, 1997, to January 24, 2022, was used. Shanghai Composite Index daily data was used. The RNN (LSTM) model is superior to then CNN model.

Ku et al. (2023) used the long short-term memory approach to forecast the volatility of the Malaysian stock market. Yahoo Finance provided historical data. The information comprises the Malaysian stock market's open, close, high, low, volume, and adjusted closing prices. The information was collected between January 1, 2019, and June 30, 2022. The outcomes demonstrate the superiority of the suggested model over the prediction method.

Recent progressions in deep learnings were, in a noteworthy way, an advancement for accuracy prediction of prices in stock markets. Noorbakhsh and Shaygani (2024)did an analyzation of how CNN, LSTM, together with GRU models, were effective for market financial forecasts, and found out that handling sequences of dependencies was where recurrent models excelled over CNN. On similar lines, Deng (2024)set various model machines of learning into comparison for predicting stocks and showcased GRU's better superiority in managing volatility of series time. While stock market explorations by these studies were in varied regional configurations, specifically they did not the KSE-100 Index examine, being a market emerging with characteristics uniquely. Our research takes forth these findings and displays that GRU not only does its excellent traditional models of deep learning outperforms, but also more effectually proves itself in the natures volatile of the Pakistani market stock.

3. Proposed Methodology

For this study, we're looking at historical stock price data from the KSE-100 Index, spanning from January 3, 2000, to December 29, 2023. We've got daily closing prices, trading volumes, and market trends all gathered from [data source, e.g., Pakistan Stock Exchange]. Now, when you compare this to earlier studies like Noorbakhsh and Shaygani (2024), which focused on more stable financial markets, or Deng (2024), who looked across multiple international indices, wee see that the KSE-100 dataset has challenges. Being an emerging market, it tends to be more volatile, has lower liquidity, and is influenced by external economic factors. This is the reason we need stronger prediction models like GRU to really tackle those complex price fluctuations. The dataset has been divided into training and testing sets. Three distinct metrics—root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE)—are being used to assess the performance of our suggested Deep Learning model.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - \hat{X}_i)^2}. \tag{1}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|X_i - \hat{X}_i\right|. \tag{2}$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\left|\hat{X}_i - X_i\right|}{X_i}\right). \tag{3}$$

3.1. The convolutional neural network (CNN) model

LeCun and Bengio (1995) introduced the convolutional neural network model. CNNs are used in a few domains, including time series analysis, speech recognition, and picture processing. An input layer, an output layer, and several hidden layers make up a convolutional neural network. Hidden layers of a CNN model typically consist of a series of convolutional and pooling layers arranged according to a certain pattern. These layers are then flattened and joined to form a fully linked network as shown in Figure 1.

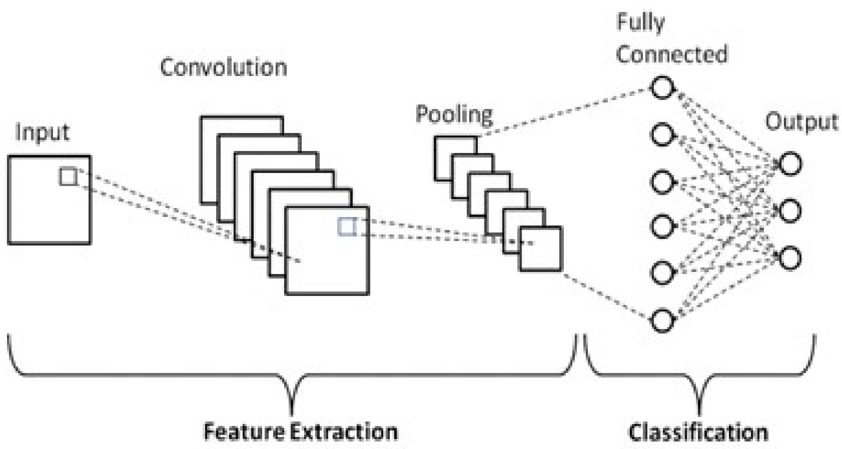

Figure 1: Structure of CNN model.

3.2. Long Short-Term Memory (LSTM) model

The LSTM model was introduced by Hochreiter and Schmidhuber (1997). LSTM is a form of Recurrent Neural Network (RNN) that can remember information over long periods of time. It consists of memory blocks that contain memory cells. LSTM has three gates: the forget gate, denoted by f_t; the input gate, denoted by i_t; and the output gate, denoted by o_t. The vector of input variables is represented by x_t; C_{t-1} denotes the cell state at time $t-1$, while C_t represents the updated cell state. The hidden state at time $t-1$ is denoted by h_{t-1}, and h_t represents the hidden state at time t. The forget gate is responsible for removing unnecessary information from the memory cell.

$$f_t = \sigma(W_f h_{t-1} + N_f x_t + b_f), \tag{4}$$
$$i_t = \sigma(W_i h_{t-1} + N_i x_t + b_i), \tag{5}$$
$$\tilde{c}_t = \tanh(W_c h_{t-1} + N_c x_t + b_c), \tag{6}$$
$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{c}_t, \tag{7}$$
$$o_t = \sigma(W_o h_{t-1} + N_o x_t + b_o) \tag{8}$$
$$h_t = o_t \odot \tanh(C_t), \tag{9}$$
$$\hat{y}_t = h_t, \tag{10}$$

where, W_f, W_i, W_o, W_c, N_f, N_i, N_o, and N_c are the weight matrices, and b_f, b_i, b_o, and b_c represent the biases of the forget gate, input gate, and output gate, respectively. The sigmoid activation function is denoted by σ, and tanh is a nonlinear function used to generate a vector of candidate values to update the cell state C_t.

3.3. The gated recurrent units (GRU) model

GRU is a simpler version of LSTM. Information may be retained for a long time using the GRU (Gated Recurrent Unit) model, which was first presented by Cho et al. (2014). The GRU is comparable to an LSTM. A GRU model consists of just two gates: the reset gate is identified by, and the update gate is identified by. A variation of the Recurrent Neural Network (RNN) is the GRU. Recurrent neural networks (RNNs) struggle to accurately capture and process long-range data, which is addressed by the addition of a gating component input. In Figure

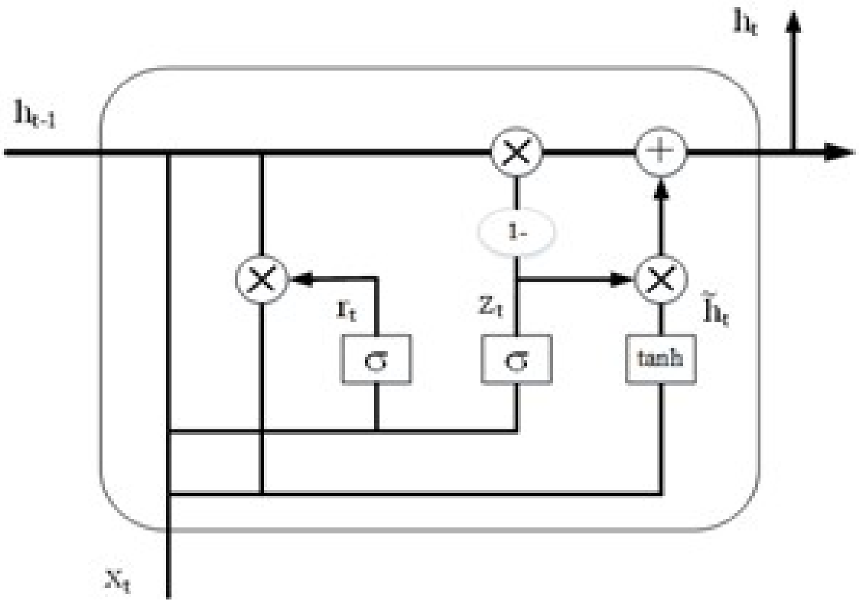

Figure 2: Structure of GRU model.

2, x_t denote the input at time t, h_{t-1} indicates the previous hidden state at time $(t-1)$ and h_t represents the hidden state at time t. The reset gate chooses how much historical data to discard, while the update gate chooses how much of the current input (x_t) and the previous observation (h_{t-1}) move to the next cell. The current memory content ensure that only relevant information is forwarded to the next iteration, which is determined by the weight W. Where tanh is the activation function which update the candidate values $\tilde{h}_t$.

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z), \tag{11}$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r), \tag{12}$$

$$\tilde{h}_t = \tanh(W_h x_t + U_h(r_t * h_{t-1}) + b_h), \tag{13}$$

$$h_t = \sigma((1 - z_t) * h_{t-1} + z_t * \tilde{h}_t). \tag{14}$$

4. Results and discussion

In this study, the stock price of the KSE-100 index was predicted using the LSTM, CNN, and GRU models. For the study, information was collected from the investing.com website. The data collection spans a period of 5929 days, from

March 1, 2000, to December 29, 2023. The closing price is one of the stock price data criteria used in the study. In total, three different error statistics were used in the investigation. The RMSE, MAE, and MAPE are these error coefficients. Each model was created, trained, and assessed using a particular set of data. Table 1 displays the model's training results.

Table 1: Training results of CNN, LSTM, and GRU models.

Models	RMSE	MAE	MAPE
CNN	13191.9050	13191.9046	49880918.52%
LSTM	12854.4940	12854.4936	48605714.62%
GRU	12722.0790	12722.0793	48105069.99%

These training results showed that the GRU model outperformed the other models by a wide margin. This model makes the most accurate predictions about the data, with the lowest values for RMSE (root mean square error), MAE (mean absolute error), and MAPE (mean absolute percentage error). These findings imply that complicated data sets are better modeled by the GRU model. Additionally, it has been demonstrated that, in comparison to alternative approaches, the GRU algorithm improves closing stock price prediction results and reduces error values. Nonetheless, the error coefficients derived from the model's test results are displayed in Table 2. The GRU strategy was shown to have the best projected cost-matching

Table 2: Test Results of CNN, LSTM and GRU Models

Models	RMSE	MAE	MAPE
CNN	13191.9050	42790.5521	6908395.98%
LSTM	12854.4940	42580.6314	6874504.97%
GRU	12722.0790	42368.0684	6840187.37%

charge and to be closer to the genuine value when compared to the other two prediction strategies (CNN and LSTM). As the forecast increases, the MAE number should decline further. A lower reduction in the RMSE range is required for more distinct predictions. Reduced margins of error (MAE, MAPE, and RMSE) (the difference between the predicted and true values) are evidence of higher prediction accuracy. For each model, however, the true versus strain and check information is shown in Figures 3– 5, while the purple line indicates the train expect and the green line indicates the test predict for each version, the dashed blue line shows the actual final inventory fee for each forecasting model simultaneously. On the other hand, Figures 6–8 displays the actual and predicted stock price for each of the models.

The results in Tables 1–3 show that GRU outperforms LSTM and CNN in predicting stock prices for the KSE-100 index, as indicated with the aid of its decrease in RMSE, MAPE, and MAE values. This more desirable overall performance is due to GRU's simplified gating mechanism, which retains important sequential facts while avoiding vanishing gradient troubles commonplace in LSTM. Furthermore, GRU is computationally extra green, requiring fewer parameters, making it enormously suitable for actual-time economic forecasting. Given the high volatility and non-desk-bound nature of stock price moves, GRU's potential to capture short- and long-term dependencies proves beneficial, enhancing forecasting accuracy over different deep-gaining knowledge of fashions.

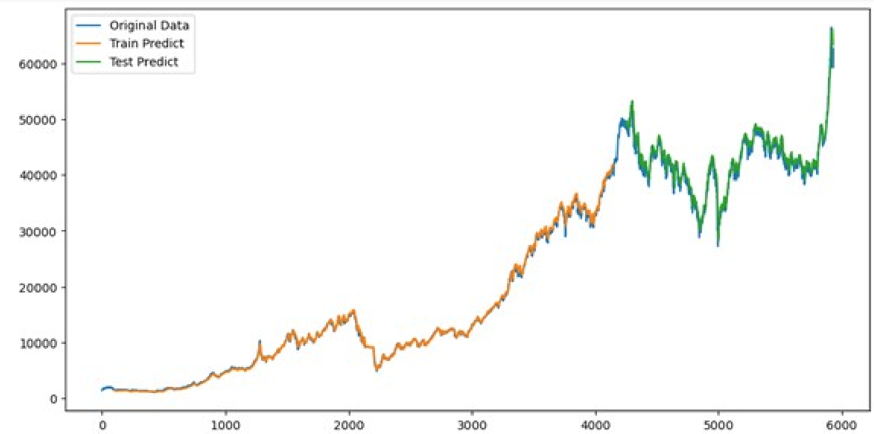

Figure 3: Actual v/s train and test data of the CNN model.

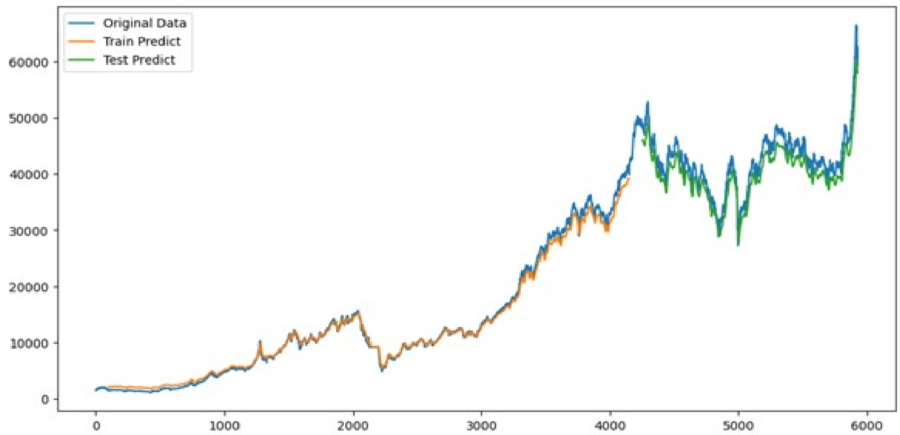

Figure 4: Actual v/s train and test data of the LSTM model.

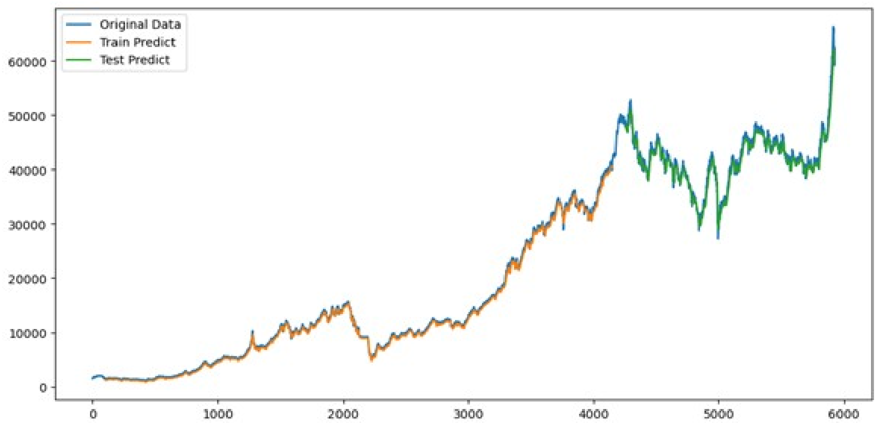

Figure 5: Actual v/s train and test data of the GRU model.

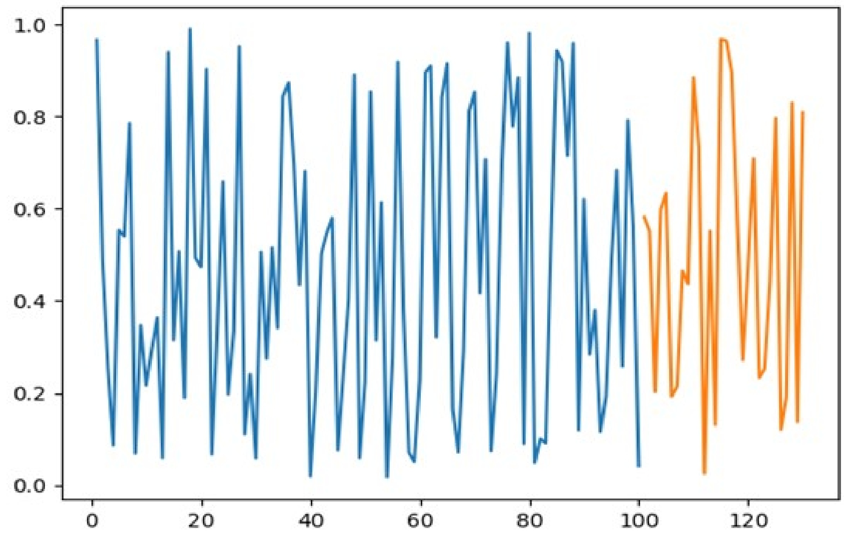

Figure 6: Actual and predicted stock price with CNN model.

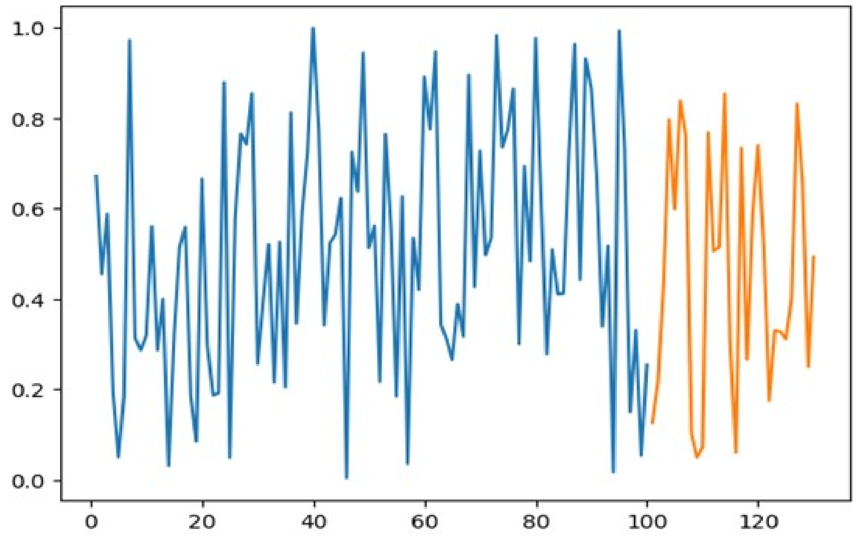

Figure 7: Actual and predicted stock price with LSTM model.

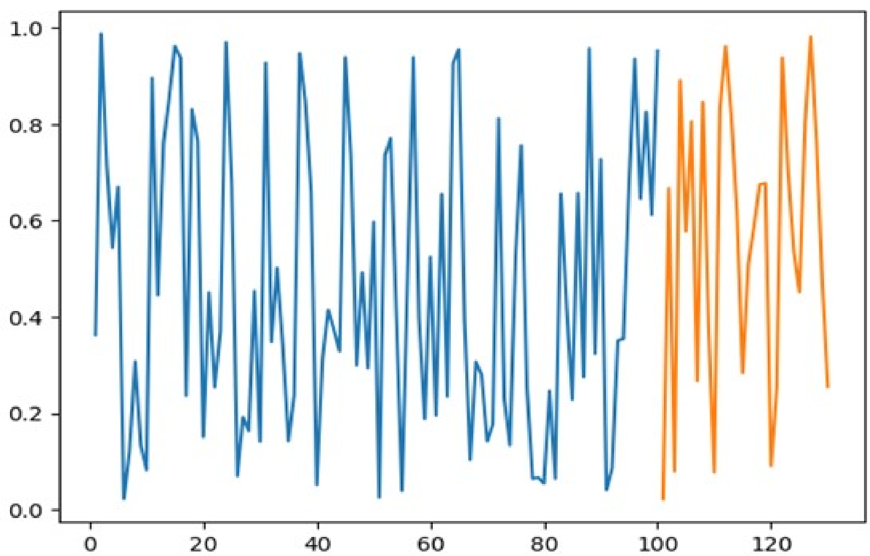

Figure 8: Actual and predicted stock price with GRU model.

Table 3: Input and output values for CNN, LSTM, and GRU models.

CNN Input	CNN Output	LSTM Input	LSTM Output	GRU Input	GRU Output
0.0911	0.8986	0.4911	0.8443	0.1644	0.2886
0.1730	0.4297	0.4005	0.8691	0.2445	0.9432
0.2257	0.2565	0.5126	0.8994	0.4469	0.5089
0.1345	0.6178	0.5385	0.3309	0.8797	0.7417
0.6875	0.7055	0.6016	0.4323	0.2566	0.8646
0.5234	0.6759	0.4723	0.6851	0.9695	0.1155
0.9944	0.8883	0.1274	0.9758	0.0374	0.3763
0.3537	0.5538	0.0966	0.0389	0.2117	0.5629
0.6011	0.0083	0.5245	0.6553	0.7419	0.1732
0.3460	0.4508	0.1055	0.9535	0.3246	0.6075
0.4111	0.0446	0.4458	0.4084	0.1325	0.6235
0.1648	0.8793	0.3494	0.2887	0.8211	0.9899
0.5954	0.2834	0.0593	0.8325	0.2709	0.0014
0.8781	0.3197	0.7796	0.1888	0.9363	0.2201
0.3274	0.2063	0.6843	0.8515	0.8477	0.1648
0.0669	0.3084	0.4185	0.3335	0.3911	0.4469
0.0386	0.5518	0.7508	0.8193	0.1317	0.7694
0.5956	0.6024	0.4492	0.9043	0.7279	0.1575
0.0433	0.8266	0.7415	0.4756	0.6961	0.6334
0.5323	0.6341	0.4556	0.8964	0.6258	0.5496
0.3906	0.8413	0.4249	0.9987	0.6514	0.6318
0.4469	0.1187	0.6154	0.8466	0.8265	0.5035
0.7403	0.9774	0.2284	0.9127	0.6995	0.9849
0.3533	0.7542	0.9407	0.8056	0.3549	0.1921
0.6894	0.6704	0.2696	0.5522	0.9933	0.0667
0.9137	0.3882	0.6298	0.9414	0.6585	0.2532
0.9389	0.2340	0.6831	0.7999	0.3873	0.9629
0.5468	0.0718	0.7813	0.8878	0.1724	0.7742
0.5321	0.2863	0.1364	0.9463	0.9945	0.4028
0.8986	0.4297	0.8443	0.8691	0.2886	0.9432
0.0911	0.8986	0.4911	0.8443	0.1644	0.2886
0.1733	0.4297	0.4005	0.8691	0.2445	0.9432
0.2257	0.2565	0.5126	0.8994	0.4469	0.5089
0.1345	0.6178	0.5385	0.3309	0.8797	0.7417
0.6875	0.7055	0.6016	0.4323	0.2566	0.8646
0.5234	0.6759	0.4723	0.6851	0.9695	0.1155
0.9944	0.8883	0.1274	0.9758	0.0374	0.3763
0.3537	0.5538	0.0966	0.0389	0.2117	0.5629
0.6011	0.0083	0.5245	0.6553	0.7419	0.1732
0.3465	0.4508	0.1055	0.9535	0.3246	0.6075
0.4111	0.0446	0.4458	0.4084	0.1325	0.6235

Three algorithms were employed in the test to estimate the stock closing rate, and the results were compared to determine that the GRU model provides the lowest RMSE, MAE, and MAPE. The LSTM model offers significantly greater outcomes than a naive forecast and performs better than the CNN version. Compared to CNN, the LSTM model predicts greater proximity. When compared to the other models, the GRU version performs better overall.

5. Conclusion

In order to forecast stock market movements, with a specific focus on the KSE-100 Index, we used sophisticated deep learning models in this study, such as GRU, LSTM, and CNN. In terms of predictive accuracy, our results show that GRU performs better than other models, underscoring its ability to accurately capture sequential dependencies in financial data. By offering a strong framework for analyzing market trends and helping investors make data-driven decisions, this research advances the field. To further improve prediction accuracy, future research can investigate the incorporation of other macroeconomic data and hybrid models. We used deep learning models, data, and tools from Investing.com, Python's Pandas library, and the Matplotlib module to forecast stock market values. To predict the future value of the daily return and the stock closing price, we trained the models using historical data. Our GRU model exhibited the lowest mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean squared error (RMSE) of all the models we examined. As a result, our GRU model is the most effective at forecasting stock prices, allowing investors to make wise and timely choices.

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