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RESEARCH ARTICLE

Emerging Stock Market Prediction Using GRU Algorithm: Incorporating Endogenous and Exogenous Variables

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ABSTRACT Stock market prediction poses significant challenges due to the inherent noise and volatility of the data. These challenges are further amplified in emerging stock markets, where data volatility increases due to numerous endogenous and exogenous variables. Despite the progress made in models for stock market prediction, such as Autoregressive Integrated Moving Average (ARIMA), Support Vector Machines (SVMs), and deep learning models, there is still a need for further research in emerging stock markets. This study addresses the complexity and non-linearity of emerging stock market data by proposing a deep learning model that utilizes Gated Recurrent Unit (GRU) algorithm to predict the next-day closing price. The proposed model leverages the inclusion of exogenous variables to enhance the model's performance. Three datasets are constructed for three main emerging market indices, specifically in Qatar, Saudi Arabia, and China. Using mean absolute percentage error (MAPE), the inclusion of exogenous variables led to a noticeable improvement over the related work results from 0.74, 1.68, and 0.72 for indices of Qatar, Saudi Arabia, and China respectively to 0.16, 0.6, and 0.2. Furthermore, the results demonstrate the appropriateness of GRU algorithm for predicting emerging stock markets.

INDEX TERMS Emerging stock market prediction, GRU, time series data.

I. INTRODUCTION

The stock market holds immense importance in the global economy. It serves as a vital platform for companies to raise capital and provide significant growth opportunities for investors. As financial markets become increasingly interconnected, understanding and predicting stock market performance has become paramount for investors, economists, and policymakers alike [1].

While traditional stock markets have long been studied, emerging stock markets have gained significant attention in recent years. These emerging markets, characterized by rapid economic growth and expanding financial sectors, provide unique opportunities and challenges. Investors are drawn to these markets in search of higher returns, and exposure to new investment opportunities. However, emerging stock markets also face distinct challenges, including market volatility, limited liquidity, political instability, and regulatory uncertainties [2]. India (National Stock Exchange of India - NSE), China (Shanghai Stock Exchange - SSE), Mexico (Bolsa Mexicana de Valores - BMV), Qatar (Qatar Stock Exchange - QSE), Saudi Arabia (Saudi Stock Exchange - Tadawul) are examples for emerging stock markets and their main indices [3].

The emerging markets pose a significant challenge for researchers in understanding the factors that influence them. These factors can be categorized into endogenous and exogenous factors. Endogenous factors such as market data, technical indicators, fundamental factors, while exogenous factors such as the impact of developed markets, oil prices, interest rates, exchange rates, gold prices, news events, and other economic and political factors. These external factors are more pronounced in emerging markets [4].

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Moreover, Stock market data is inherently sequential, as it consists of time series data such as daily or hourly stock prices, trading volumes, and other relevant indicators. The temporal dependencies and patterns within the stock market data are crucial for making accurate predictions, as the current and past market behavior can influence future price movements. The stock market is also known for its high volatility, where prices can fluctuate significantly from one day to the next, driven by various economic, political, and market-specific events, resulting in a high degree of uncertainty and unpredictability. Furthermore, the statistical properties of stock market data, such as mean, variance, and correlation, can change over time, resulting in a nonstationary process, which can be caused by changes in market sentiment, regulatory changes, or other structural shifts in the underlying economic or financial conditions. This unique dynamic, necessitate the need for new and innovative models to address these challenges. Traditional statistical models and machine learning algorithms such as Autoregressive Integrated Moving Average (ARIMA), Support Vector Machines (SVMs) have limitations in capturing the intricate relationships between variables and handling time-series data. Therefore, new models, such as deep learning models, that can learn and represent complex relationships and long dependencies between variables are required [2], [5].

One notable algorithm in this field is Gated Recurrent Unit (GRU), a deep neural network model used for processing time series data and forecasting future values due to its ability to effectively capture temporal dependencies and handle sequential data [6].

This paper contributes to the field of stock market prediction by considering the unique dynamics of emerging markets. The first step involves constructing three comprehensive datasets that encompasses both exogenous and endogenous variables for the stock market indices in Qatar, Saudi Arabia, and China. Subsequently, a deep learning model based on GRU algorithm, in conjunction with a correlation-based feature selection method, is employed to predict the next-day closing price of the stock market indices. Furthermore, this paper aims to investigate the influence of exogenous variables, such as the impact of developed markets, crude oil price, gold price, and exchange rates, on the indices of the mentioned markets.

The next sections of this paper are structured as follows: In Section II, an overview of related work is provided, encompassing previous studies for emerging stock market prediction, and a comparison between emerging markets and developed markets. The methodology employed in this study is described in Section III. Section IV presents the findings and results obtained. Finally, Section V concludes the paper and discusses avenues for future research.

II. RELATED WORK

Despite the relative scarcity of studies in emerging stock markets as compared to developed markets, many studies have been conducted. The studies encompassing a range of machine learning algorithms, neural networks, and deep learning models. However, SVM, ANNs, GRU, and LSTM tend to be better in terms of delivering good results. The study in [7] employed a basic deep learning neural networks model (DLNN) to predict the movements of Chinese stock prices. They utilized stock price charts and five stock fundamental parameters as inputs from 2009 to 2020. The model achieved an average accuracy rate of 55.46%.

Nayak et al. [8] utilized decision-boosted tree approach to predict the next day's trend in the Indian stock market. They integrated sentiment analysis of news articles and social media tweets with historical stock price data acquired from Yahoo Finance for three companies. The researchers leveraged two datasets: a historical stock price dataset comprising open, close, low, high, adjusted close prices, and trading volume for 261 transaction dates, with 182 used for training and 79 for testing, as well as a sentiment dataset. This integrated analysis enabled them to achieve an accuracy of 70% in their stock market trend predictions. Ahmar et al. [9] conducted a study that aimed to identify the most suitable models for capturing the trend in closing stock prices for BRIC (Brazil, Russia, India, and China) countries. They evaluated two different approaches: SutteARIMA and Holt-Winters. For the Shanghai Stock Exchange Composite (SSEC) index, they utilized the SutteARIMA model, which combines the ARIMA method and the α-Sutte indicator to generate predictions. They obtained stock market data from Yahoo Finance, covering the period from November 1, 2019, to December 11, 2020. They divided the data into a training set (November 1, 2019, to December 2, 2020) and a test set (December 3, 2020, to December 11, 2020). To measure the model performance, the researchers calculated the Mean Absolute Percentage Error (MAPE) and Mean Square Error (MSE). The results showed that the SutteARIMA model was the most appropriate for predicting the stock prices of Russia (IMOEX.ME), India (BSESN), and China (SSEC) when compared to ARIMA and Holt-Winters. Specifically, for the SSEC index, the SutteARIMA model achieved a MAPE of 0.72.Yassin [10] obtained a MAPE of 0.74 on Qatar stock exchange by employing an LSTM model, utilizing only endogenous variables as input over a dataset of 10 years. Malibari et al. [11] developed a transformer neural network model that utilized only endogenous variables to predict the closing prices of the Saudi stock market (Tadawul) on the next trading day. The experimental results indicate that the proposed model architectures, which split the time series data into patches, could effectively capture the dynamics and complex patterns present in the irregularities of the financial time series. Their model achieved a MAPE of 1.681 over a 20-year dataset. While previous studies represent valuable contributions to the field, it is worth noting that most of them do not account for the potential impact of exogenous variables on stock market prediction. Additionally, the majority of these studies focused on individual companies' stocks rather than examining market indices. This paper aims to address these gaps by considering the influence of exogenous variables on stock market performance. Furthermore, the paper will investigate main market indices, rather than solely focusing on individual stocks.

III. METHODOLOGY

In this paper, A GRU model is proposed for predicting the next-day closing price of three main emerging market indices: Tadawul All Share Index (TASI) in Saudi Arabia, Qatar Stock Exchange Index (QSI) in Qatar, and Shanghai Stock Exchange Composite Index (SSEC) in China. The aim is to evaluate the impact of incorporating both endogenous and exogenous variables in the prediction process.

TABLE 1. The included variables.

Endogenous variables	Exogenous variables
Open, high, low, volume, and change.	Crude oil price, gold price, exchange rate, and the impact of foreign markets "Japanese Nikkei Index 225 (N225), American Dow Jones Index (DJ), and S&P 500 Index (S&P).

The included variables are shown in Table 1. Figure 1 shows the overall research process.

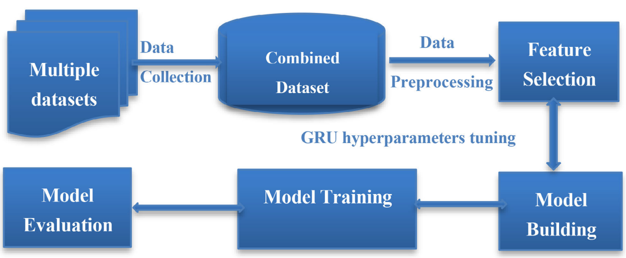

FIGURE 1. The overall research process.

A. GRU PROPOSED MODEL

Gated Recurrent Unit (GRU) algorithm is a type of recurrent neural network (RNN) architecture that was introduced as an improvement over traditional RNNs. GRU is designed to address the vanishing gradient problem, which can occur during the training of deep neural networks. GRU units have gating mechanisms that allow them to selectively update and reset their internal states, which helps in capturing long-term dependencies in sequential data. The main components of a GRU unit as shown in Figure 2 are:

Update Gate (z): This gate determines how much of the previous state should be retained and how much of the new information should be incorporated. It takes into account the current input and the previous hidden state.

Reset Gate (r): The reset gate decides how much of the previous state should be forgotten. It also takes into account the current input and the previous hidden state.

New Memory Cell (h′): This component combines the reset gate with the previous hidden state and the current input to create a new candidate state.

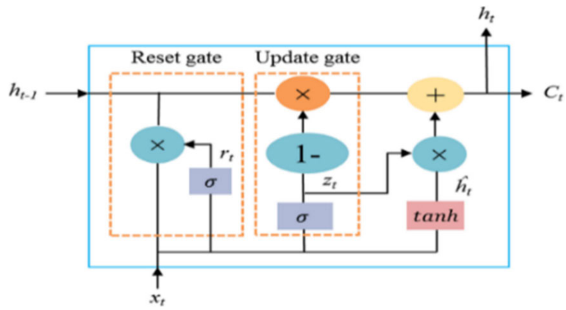

FIGURE 2. GRU architecture [12].

Hidden State (h): The hidden state represents the output of the GRU unit and is computed by interpolating the previous hidden state with the new memory cell, controlled by the update gate. The gating mechanisms in GRU units enable them to selectively retain or forget information from previous time steps, allowing them to capture both short-term and long-term dependencies in sequential data. This makes GRU particularly effective for tasks involving sequential data processing, such as natural language processing, speech recognition, and stock market forecasting [12] and [13].

The proposed model consists of the following layers as shown in Figure 3:

1) GRU INPUT LAYER

GRUs are a variant of RNNs that use a gating mechanism to control the flow of information, making them more efficient and effective in learning long-term dependencies compared to traditional RNNs. The GRU input layer takes the sequence of input features (both internal and external variables) and learns to extract relevant patterns and dependencies from the data. This allows the model to capture the temporal dynamics and relationships present in the stock market data.

2) DENSE HIDDEN LAYER

The dense (fully connected) hidden layer is a standard neural network layer that follows the GRU input layer. This layer is responsible for further processing the output from the GRU layer and learning to extract more complex features and relationships from the data. The use of a dense layer allows the model to capture non-linear relationships between the input features and the target variable (closing price). By stacking a dense layer after the GRU layer, the model can learn higher-level representations and complex patterns that may not be easily captured by the GRU layer alone.

3) DENSE OUTPUT LAYER

The final output layer is also a dense layer, but with a single output unit. This layer takes the output from the hidden dense layer and generates the predicted closing price for the stock market index. The output layer is designed to produce a single value, which represents the model's prediction for the next-day closing price of the stock market index.

The combination of the GRU input layer, the dense hidden layer, and the dense output layer forms a neural network architecture that can effectively capture the temporal dependencies in the stock market data and learn to predict the next-day closing prices. The hyperparameters, such as the number of units in each layer, the choice of activation functions, the optimizer, learning rate, batch size, and the number of training epochs are crucial factors that impact the model's performance. These hyperparameters must be tuned through experimentation and validation to achieve the best prediction results [14], [15], as described in the experiment section.

FIGURE 3. The GRU proposed model.

B. DATASETS

All the raw data can be obtained from the website: investing.com [16]. Six raw datasets are collected for each index, including all required variables. The CSV collected files cover the period from 1/1/2017 until the end of the year 2021. The data is integrated by combining the required datasets into one dataset for each index.

C. TUNING WORK HOURS AND HOLIDAYS

The markets are located in different time zones, which results in different work hours and weekend holidays. So, it's required to preprocess the data to establish a correspondence between the different stock markets. From Monday to Thursday, Tokyo market closes its trading sessions before opening of QSI and TASI. On the other hand, US markets open trading after QSI and TASI has closed. As a result, we can assume that the closing price of the Nikkei index will affect QSI and TASI indices on the same day. Also, the previous day's closing price of the US indices, oil price, and gold price will have an impact on QSI and TASI the next day. Accordingly, the objective is to predict QE and TASI closing prices, by utilizing the US indices closing price from the previous day and the Nikkei closing price from the current day. Additionally, QSI and TASI operate on Sundays when both the US and Tokyo markets are closed, thus we employ the last closing prices (from Friday) as data to affect QSI and TASI on Sundays. Similar preprocessing was applied to the data of the Chinese, Japanese, and American markets [17].

D. FEATURE ENGINEERING

Correlation and backward elimination, are employed to select the important features. During backward elimination, the correlation between each feature and the target variable is calculated. Features with low correlation coefficients can be candidates for removal from the model unless they show a good impact on the model performance. However, as long as there is a high correlation among certain features, it can make a multicollinearity problem as this can impact the stability and interpretability of the model [18], [19]. To address this issue, the following approach is implemented:

As shown in Figures 4, 5, 6 High, Low, and Open prices have a high correlation with each other. To mitigate the impact of this problem, a new useful feature named 'Mean_HL' is derived.

Mean_HL is the mean value of the 'high' and 'low' variables. Mean_HL was examined and it got better results. Also, Foreign markets (N225, DJ, S&P) have a high correlation among them. In this situation, only the one with the highest correlation to the target variable is selected. Table 2 shows Feature selection process results.

TABLE 2. Feature selection process results.

No.	Dataset	Features Selected
1	QCD	Mean_HL, Change, Oil, S&P
2	SCD	Mean_HL, Change, Oil, DJ
3	CCD	Mean_HL, Change, N225, Ex-rate

Figures 4, 5, and 6 demonstrate the correlation maps among the features in all the datasets.

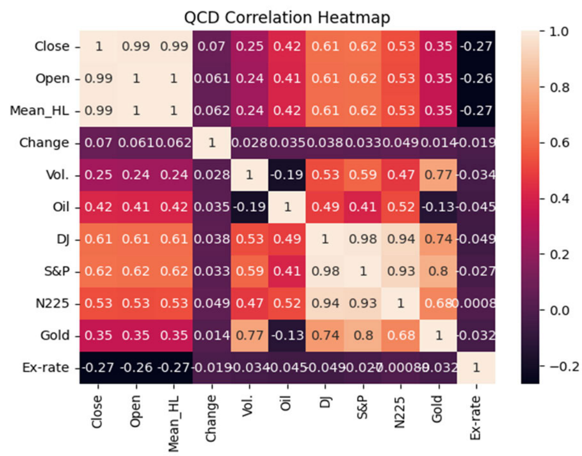

FIGURE 4. QCD correlation map.

IV. EXPERIMENT

Initially, Augmented Dickey-Fuller (ADF) test for time series data [20] is achieved to test data stationarity. The level of statistical significance p-value of all datasets indicates that they're nonstationary (p-value > 0.05). Combined dataset symbols, indices mean values, and ADF test results are shown in Table 3.

TABLE 3. ADF results and indices mean value.

No.	Index	Mean value	Dataset symbol	P_value	Result
1	QSI	9949.5	QCD	0.53	nonstationary
2	TASI	8322.6	SCD	0.92	nonstationary
3	SSEC	3156.0	CCD	0.576	nonstationary

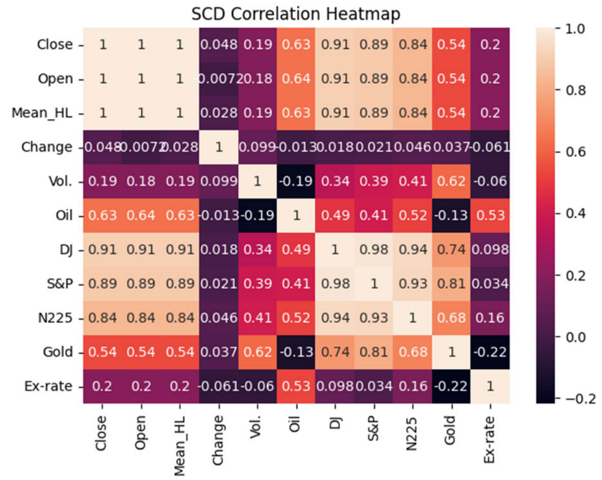

FIGURE 5. SCD correlation map.

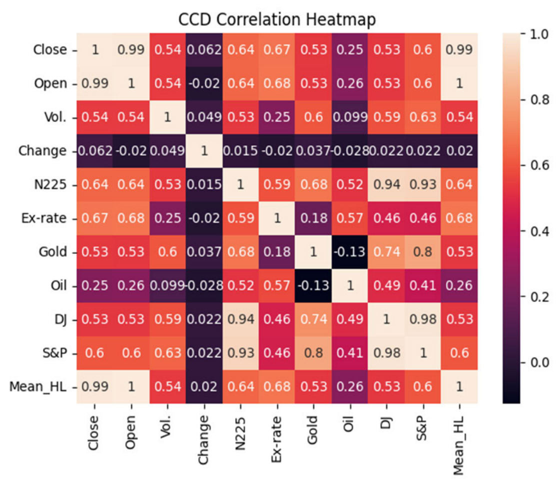

FIGURE 6. CCD correlation map.

Then data is split into training and testing sets. Time series data is split based on time, not at random [21]. Therefore, the years 2017-2020 (964 rows) are used for training and the year 2021 (246 rows) is used for testing as shown in Figure 7.

FIGURE 7. Train and test data split.

After that, the model is built, and hyperparameters are tuned to match what is indicated in Table 4. Appendix shows other hyperparameters tuning process. These hyperparameters are crucial in determining the performance and behavior of the neural network models. The number of epochs, or training iterations, suggests that the models were trained until an early stopping criterion was met. The batch size determines the number of samples processed at once. The learning rate controls the step size during the optimization process. The optimization setup employs the Adam algorithm, a popular and effective optimization method for training neural networks. Finally, the window size or time step means the models use a sequence of 20 time steps as input to make predictions.

TABLE 4. GRU hyperparameters tuning process results.

Hyperparameter	QCD	SCD	CCD
Epochs Number (Early stopping)	207	117	156
Batch Size	16	16	16
Neurons Number (Input and hidden layer)	Window size * No. of predictors (features).		
Hidden Layers	One dense layer		
Activation Function	Default (Tanh, Sigmoid)		
Learning Rate	1e-5		
Optimization Setup	Adam		
Window Size (Time Step)	20		

In terms of the computation time required for training the GRU models, it's an important consideration. For larger datasets or more complex models, the training time may increase significantly. In such cases, strategies such as the use of more powerful hardware, model optimization techniques, or the exploration of alternative architectures may be necessary to ensure efficient and timely model training. The GRU overall training time depends on factors such as the size of the training dataset, epochs number, time steps, and the hardware used for the computations. For the datasets and hyperparameters used in this paper, the training time required was reasonably efficient on system equipped with an Intel Core i5-6600K CPU. Specifically, the training time was approximately:

- 3.7 minutes for QCD dataset.
- 2 minutes for SCD dataset.
- 2.8 minutes for CCD dataset.

The training was performed using mini batches of size 16, time steps of 20, and the model was trained using early stopping in terms of the number of epochs as shown in Table 4.

RESULTS AND DISCUSSION

In this paper, where time series data is utilized to build a regression model, two performance metrics are employed: mean absolute error (MAE) and mean absolute percentage error (MAPE). They are defined by the equations 1 and 2:

$$\mathbf{MAE} = \frac{\sum_{i=1}^{n} |yi - \bar{y}i|}{n} \quad (1)$$

$$\mathbf{MAPE} = \frac{1}{n}\sum_{i=1}^{n} \frac{|\bar{y}i - yi|}{yi} \quad (2)$$

MAE gives a measure of how far the predictions are from the actual output because it aligns exactly with the original unit of the target variable. The error can be interpreted smoothly because the measure will be the same as the target variable. MAPE also helps to compare different situations.

As shown in Table 5, there are two groups of features for each index. The first group is the best results with only endogenous features, second is the best results with incorporated features "features selected".

TABLE 5. The proposed model results over all datasets.

Dataset	Features Group	MAE	MAPE%
QCD	Endo.: 'Mean_HL', 'Change'	19.5	0.19
	Inco.: 'Mean_HL', 'Change', 'DJ', 'Oil'	16.4	0.16
SCD2	Endo. : 'Mean_HL', 'Change',	98.2	0.9
	Inco.: 'Mean_HL', 'Oil', 'Change', 'DJ'.	63.01	0.6
CCD	Endo.: 'Mean_HL', 'Change',	9.46	0.27
	Inco.:'Mean_HL', 'Change', 'N225', Ex-rate	7.19	0.2

The learning curves of the model during the training process is also a crucial aspect to consider. As the model was trained over the course of epochs, the training and validation loss values were closely monitored to assess the model's convergence and generalization performance. The training loss, which represents the model's performance on the training data, showed a steady decrease over the training iterations, indicating that the model was effectively learning the patterns in the data. Conversely, the validation loss, which represents the model's performance on the testing set, initially decreased in tandem with the training loss, but then reached a point where it began to level off or even slightly increase.

The smooth and consistent learning curves observed during the training process suggests that the GRU model was able to effectively learn the underlying patterns in the datasets without encountering any major instabilities or convergence issues.

Figure 8 illustrates the harmonic relation between the Validation Loss and Training Loss for QCD, while Figure 9 highlights the good closeness between the actual prices and predicted prices of QCD.

Figures 10 and 11 show the relationship between the Validation Loss and Training Loss for SCD and CCD respectively. while Figures 12 and 13 demonstrate the good closeness between the actual prices and predicted prices of SCD and CCD respectively.

These indicators serve as evidence of the model's good performance and its capability to capture and predict the price patterns of the datasets.

The results in Table 5 show an obvious influence on the exogenous variables. The primary exogenous factor influencing the variables is the impact of developed markets. Developed stock markets can influence emerging markets through global economic conditions, investor sentiment, and

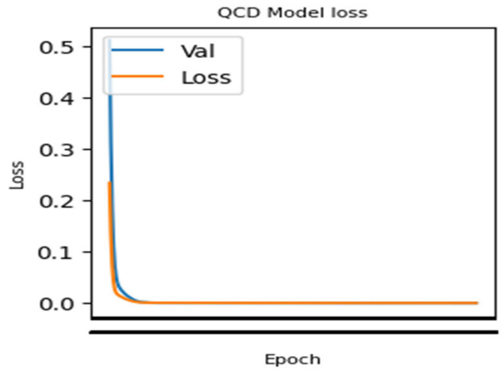

FIGURE 8. QCD validation loss versus training loss.

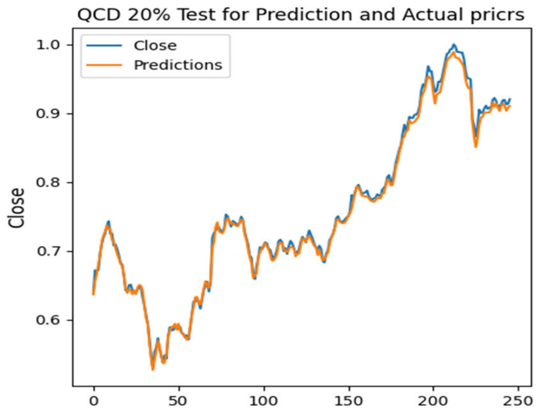

FIGURE 9. QCD actual prices versus prediction prices plot.

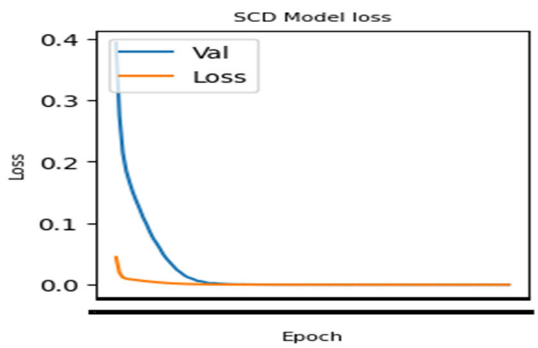

FIGURE 10. SCD validation Loss versus training loss.

capital flows. Interconnected financial systems and multinational corporations further contribute to the transmission of shocks and developments between the two market types, impacting emerging market dynamics [22]. The second exogenous variable, the crude oil price, exhibited its influence on Qatar and Saudi indices. Both Qatar and Saudi Arabia are oil-exporting countries where oil plays a crucial role in their GDP and significantly impacts their overall economic landscape [23]. The last exogenous variable is the exchange rate, which showed its impact on the Chinese index (SSEC). Fluctuations in the exchange rate affect the competitiveness

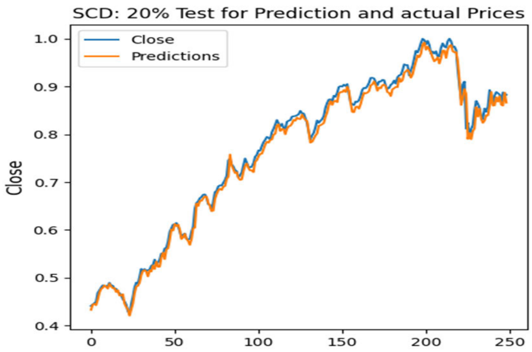

FIGURE 11. SCD actual prices versus prediction prices plot.

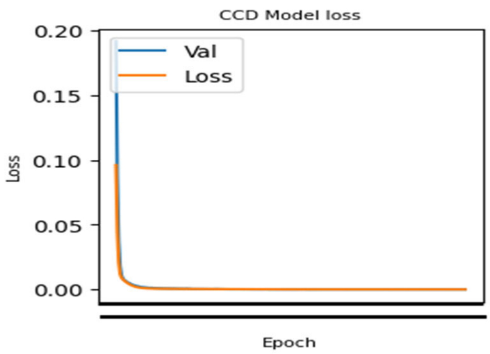

FIGURE 12. CCD validation loss versus training loss.

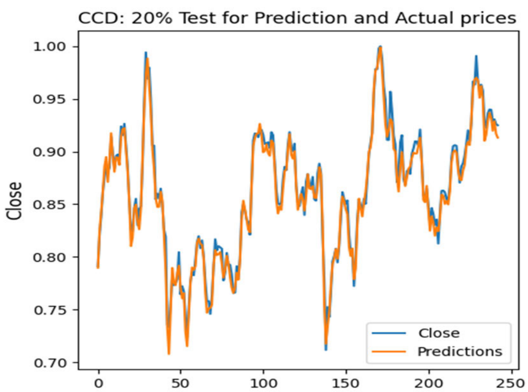

FIGURE 13. CCD actual prices versus prediction prices plot.

of Chinese exports, attract or deter foreign investment, and have broader implications for financial markets [24].

The best results are obtained for Qatar index QSI, followed by the Chinese index SSEC, which aligns with the results of ADF test for data stationery as shown in Table 2. It's observed that as the data becomes more stationary, the model performance deteriorates.

As shown in Table 6, compared to previous studies exploring the same market environments, the results of the current paper demonstrate a favorable performance. Although the number of existing studies in this area may be relatively limited, and the differences in working conditions and dataset periods, the outperforming of the results reported in this work provides a good indicator of the result's quality.

TABLE 6. Comparing with state of art models using MAPE.

QSI (Qatar) [10]	TASI (Saudi Arabia) [11]	SSEC (China)[9]
0.74	1.681	0.72
The proposed model		
0.16	0.6	0.2

TABLE 7. Hyperparameters tuning process.

Data-set	Optimizer tuning process			Window size tuning process		
QSD	Optimizer	MAE	MAPE	Window-size	MAE	MAPE
	Adam	16	0.16	5	69.75	0.62
	Adagrad	76.2	0.69	10	19.76	0.19
	Nadam	22.48	0.21	20	16	0.16
	RMSprop	154.9	1.4	30	19.74	0.18
	SGD	148.8	1.38	40	34.58	0.31
				50	16.07	0.15
SCD	Adam	60	0.6	5	167.3	1.52
	Adagrad	370.26	3.37	10	95.6	0.87
	Nadam	41.58	0.4	20	60	0.6
	RMSprop	57.71	0.54	30	116.65	1.09
	SGD	703.38	6.39	40	62.5	0.59
				50	44.49	0.42
CCD	Adam	7	0.2	5	18.65	0.53
	Adagrad	36.87	1.04	10	12.8	0.36
	Nadam	19.32	0.63	20	7	0.2
	RMSprop	83.8	2.3	30	25.05	0.71
	SGD	36.1	1.08	40	20.65	0.65
				50	12.5	0.35

V. CONCLUSION AND FUTURE WORK

The paper proposed a GRU model to predict stock prices in emerging markets, considering exogenous variables beyond just historical.The exogenous variables include the developed markets impact, crude oil prices, gold prices, and exchange rates, on three main emerging market indices in Qatar, Saudi Arabia, and China.The findings revealed that oil prices and developed markets influenced Qatar and Saudi Arabian indices. In contrast, the Chinese market index was found to be impacted by exchange rates and the performance of developed markets. This suggests that external factors play a crucial role in the performance and dynamics of emerging stock markets. In future work, some development of the feature selection method could be beneficial. In addition to using technical and other exogenous variables such as interest rate and news events. Also, future research could expand the scope to include additional emerging stock markets and explore the impact of external variables on sectoral indices, rather than focusing only on the main market indices.

DATA AVAILABILITY

All the datasets are available at: https://drive.google.com/file/d/1F-PZHowZKzaDT9oPUMYbrOTQa3lRAHZa/view?usp=sharing

CONFLICT OF INTEREST STATEMENT

The authors declare that the research article was conducted in the absence of every commercial or financial relationships that could be construed as a potential conflict of interest.

APPENDIX

See Table 7.

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