Deep Learning Analysis of Australian Stock Market Price Prediction for Intelligent Service Oriented Architecture

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Abstract. Stock exchanges are economic entities facilitating various trading assets like monetary values, activities, valuable metals, etc., among stockbroker participants. Prediction of Stock market rates and observing the behaviour of daily closing rates is a crucial task for many businesses and investment authorities. This acts as a precaution to know the suitable period for stakeholders to invest. Deep Learning, in this regard, is considered to perform forecasting tasks efficiently with better accuracy. For this purpose, our study performs forecasting of Australian Stock Market daily closing rates based on Deep Learning approaches of LSTM and GRU from January 4 2000, to January 17 2017. This work predicts the closing rates for the next 216 days. A comparative analysis of prediction accuracy between Deep Learning methods like Long Short-Term Memory (LSTM) along with Gated Recurrent Unit (GRU) is performed. Results reveal that the deep learning model LSTM performs better than the other approach based on the results obtained. Performance of the models is measured using metrics such as RMSE and R^2 scores, where LSTM achieved a comparatively less RMSE value of 0.072 and the largest R^2 score of 0.855.

Keywords: Stock market · Price prediction · LSTM · GRU · Service oriented architecture

1 Introduction

Stock market prediction is a difficult endeavour when it comes to predicting future stock prices. The stock market is too tough to determine because of its volatile nature. Every day, stock values fluctuate dramatically. Stock market forecasting is in high demand among stock consumers [1]. To forecast future stock costs with high accuracy, implementing all derived criteria at every time is a big challenge. Data regarding stock market prices are generated in large quantities and fluctuate per second [2]. The stock market is a complicated and difficult process through which people can make money or be

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deprived of their life savings [3]. Since the stock market is among the essential vital sectors wherein investors invest, predicting stock market prices has always been a popular subject for researchers regarding economic and technical fields [4, 5].

Stock exchanges are financial bodies that facilitate the trading of various assets like monetary values, activities, and valuable metals etc., among stock broker participants [6]. With a trading volume of thousands of billions of dollars, it piques people's interest in generating a profit. Goods are purchased and sold on the marketplace, and the subsequent value is used to assess if the transaction was profitable or not. The stock value is determined in general by its listing on a stock market and the number of its transactions [7–9]. The maximum a share is traded, the more valuable it becomes; on the other hand, if a share is traded in a low margin, it is less significant to some traders and thus, its value falls. Depending on the ability to estimate future values, this market anticipation might result in gains or losses [10]. As a result, the difficulty becomes determining the best time to buy/enter or sell/exit a company for profit based on stock market history [11].

Since predicting the stock market prices remains a challenging task for many company experts and researchers, estimating stock market values is both an intriguing and demanding field of study. Predicting the stock market with 100% accuracy is extremely difficult due to extrinsic factors. The most common characteristics of stock market data are temporal variation and nonlinearity. In the stock market, stock market forecasting is crucial [12]. If investors do not have enough information and knowledge, their investments risk losing the most money. To make high volume profits, investors need to estimate how much a company's stock will be worth in the future [13]. Various prediction systems have been created to make accurate stock market predictions [14]. Deep Learning methods are observed to implement prediction tasks achieving high accuracy and precision [15, 16]. The paper's primary purpose is to analyze the behaviour of stock rates by implementing deep learning approaches like LSTM and GRU. Each method predicts the daily closing prices of the stock market for the last 216 days.

The rest of this paper is as follows. In Sect. 2, we briefly explain the literature review. In Sect. 3, we present our proposed method and performance evaluation results. Section 4 presents the results of our LSTM and GRU models. Finally, Sect. 5 describes the conclusion part.

2 Literature Review

Many kinds of research have been conducted on Stock Market Price forecasting using Time Series Analysis Techniques, Machine Learning and Deep Learning Techniques [28]. This section contains a brief description of literature implementing deep learning approaches for Stock Market Price prediction analysis.

2.1 Frameworks with Deep Learning-Based Stock Market Prediction Approaches

To estimate future stock market value, a deep learning-based technique is used by Kalyoncu et al. [1] to analyze previous stock data. It employed Long-Short Term Memory

(LSTM) to estimate the stock price of five famous Turkish firms listed on the stock exchange. As a result, it helped establish a highly reliable stock prediction model for assisting investors in making better investing decisions. To present a novel deep learning-based prediction approach that incorporates typical stock financial index variables and media platforms text elements as model parameters, Ji et al. [4] use Doc2Vec to create lengthy text feature vectors from media platforms, which are subsequently reduced in size using a layered auto-encoder to equalize the dimensions of text feature variables and stock financial index variables. Moreover, the time-series data of stock price is decomposed using the wavelet transform to remove the random noise induced by stock market fluctuations. Finally, the stock price is predicted using a long short-term memory model. The experiment's findings reveal that the technique outperforms all three benchmark models in terms of all types of assessment parameters and can accurately predict share price.

Hu et al. [7] performed a survey of all manuscripts using all the neural network-based approaches, such as LSTM, CNN, RNN, and GRU, to classify stock prices. In addition, this study examines each article's dataset, parameter, methodology, and outcomes. It is discovered that newer models integrating LSTM with additional approaches, such as DNN, have received a lot of attention. Reinforcement learning and other DL algorithms produced excellent results. Hiransha et al. [17] utilize day-by-day closing prices from two separate stock exchanges: the National Stock Exchange of India (NSE) and the New York Stock Exchange (NYSE) (NYSE). The training is performed on the stock price of a single NSE business and forecasted for five distinct NSE and NYSE companies. CNN has been discovered to surpass the other models. Despite being trained on NSE data, the network remained capable of predicting for the NYSE. This was achievable because both stock markets had similar internal characteristics. When the findings were contrasted to the ARIMA model, it was shown that neural networks outperformed the current linear model.

Shen and Shafiq [14] gathered two years' worth of data from the Chinese stock market and provided a complete feature engineering and deep learning-based model that predicts stock market price trends. The suggested approach is comprehensive since it incorporates stock market dataset preprocessing, several feature engineering methods, and a proprietary deep learning-based approach to predict stock market price trends. To observe if there was a link between changes in a company's stock price and the general public expressed opinions or sentiments regarding it, Mehta et al. [6] devised and deployed a stock price forecast accuracy method that took public mood into account. To estimate future stock values, the suggested algorithm considers public mood, views, news, and past stock prices. SVM model, MNB classifier, linear regression, Naive Bayes, and LSTM were among the machine-learning and deep-learning approaches used for the research.

This research of Li and Pan [18] provides a revolutionary deep learning technique for forecasting stock behaviour in the future. Using a blended ensemble learning approach, the model integrates different recurrent neural networks connected to a neural network. For the test case, they used the S& P 500 Index in the analysis. The results reveal that the proposed deep learning blending ensemble model surpasses the other available price-prediction models. The paper [10] aids in effective forecasting and identifies the primary elements influencing stock price fluctuations. An adaptive neuro-fuzzy model is used to quantify the predictive potential of business performance measures and their relevance for 58 listed corporations from the Abu Dhabi Securities Exchange and the Dubai Financial Market for 2014–2018. According to the study [19], ROE is the most important predictor, whereas ROA is the least important. The most significant profitability metric is EPS, whereas the least effective is PM.

Table 1. Summary of the literature work.

Authors	Time period for datasets	Model utilized	Results obtained
Kalyoncu et al. [1]	2014 to 2019	LSTM	Accuracy = 90% for 5 different datasets of BIST 30
Ji et al. [4]	January 2010 to November 2019	Doc-word with LSTM LSTM	RMSE value of Doc-Word LSTM = 0.110 and R2 score = 0.957 RMSE value of LSTM = 0.579 and R2 score = 0.774
Hu et al. [7]	2015 to 2020	LSTM CNN DNN RNN RL	Accuracy of LSTM = 43% Accuracy of CNN = 48% Accuracy of DNN = 53% Accuracy of Reinforcement Learning = 50%
Hiransha et al. [17]	1 January 1996 to 30 June 2017	RNN LSTM CNN MLP	MAPE of RNN = 5.82 MAPE of LSTM = 6.03 MAPE of CNN = 4.05 MAPE of MLP = 4.81
Mehta et al. [6]	1 October 2014 to 31 December 2018	Naïve bayes LR Decision tree SVC LSTM	Accuracy of Naive = 86.72% Accuracy of LR = 86.75% Accuracy of DT = 81.43% Accuracy of SVC = 89.46% Accuracy of LSTM = 92.45%
Li and Pan [18]	December 2017 to June 2018	LSTM DP-LSTM GRU	MPA of LSTM = 99.29% MPA of DP-LSTM = 99.48% MPA of GRU = 99.57%

3 Methodology

3.1 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) remembers long-term dependencies, which can help with sequence prediction. Because LSTM has feedback connections, it can interpret the entire data sequence [24]. Speech recognition, language processing, and other applications are some listed benefits [25]. The LSTM is an RNN-based neural network that remembers prior information and functions well on various gradient-related problems [20]. The input, forget, and output gates are the three gates that operate within an LSTM memory cell for data processing. Each fresh data entry is made through the cell's input gate. The forget gate eliminates the unneeded data from the cell by ignoring it [26]. The structure of the LSTM cell is explained in Fig. 1.

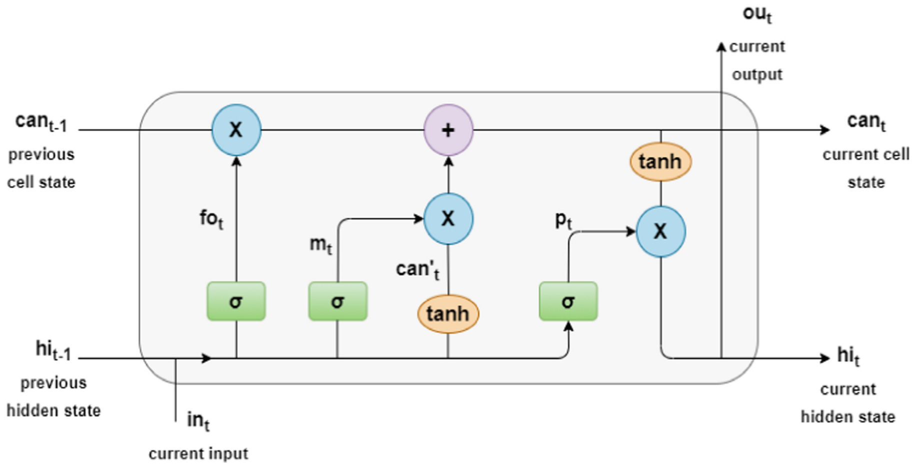

Fig. 1. Long short-term memory (LSTM) cell structure.

An input 'in' and the previous hidden state 'hi' are supplied to the sigmoid activation function to calculate the amount of data to forget for the forget gate 'fo' at a time 't'.

$$fo_t = \sigma\left[W_{fo} * (hi_{t-1}, in_t) + bias_{fo}\right] \tag{1}$$

Two equations determine the quantity of data to be kept in the memory cell. First, the sigmoid activation function is applied to the combination mentioned above. Second, using the identical inputs, the activation function has been substituted with tanh.

$$input_t = \sigma\left[W_{input} * (h_{t-1}, \ in_t) + bias_{input}\right] \tag{2}$$

$$can'_t = \tanh\left[W_{can'} * (hi_{t-1} , in_t) + bias_{can'} \right] \tag{3}$$

The previous cell state 'can(t-1)' is updated by using formula:

$$can_t = (can_{t-1} * fo_t) + (input_t * can'_t) \tag{4}$$

For the output gate, the equations are as follows:

$$ou_t = \sigma \mid\left[W_{ou} * (hi_{t-1}, in_t) + \ bias_{\ ou}\right] \tag{5}$$

$$hi_t = ou_t * can_t \tag{6}$$

3.2 Gated Recurrent Unit (GRU)

GRUs are a kind of RNN equivalent to LSTM but have two functional gates, the reset and update gates. These gates help to solve the vanishing gradient problem. GRU retains a hidden state in the place of cell state [21]. The reset gate is in charge of keeping the concealed state. As compared to LSTM, GRU is faster and requires minimum memory [27]. The structure of a GRU cell is shown in Fig. 2 as follows:

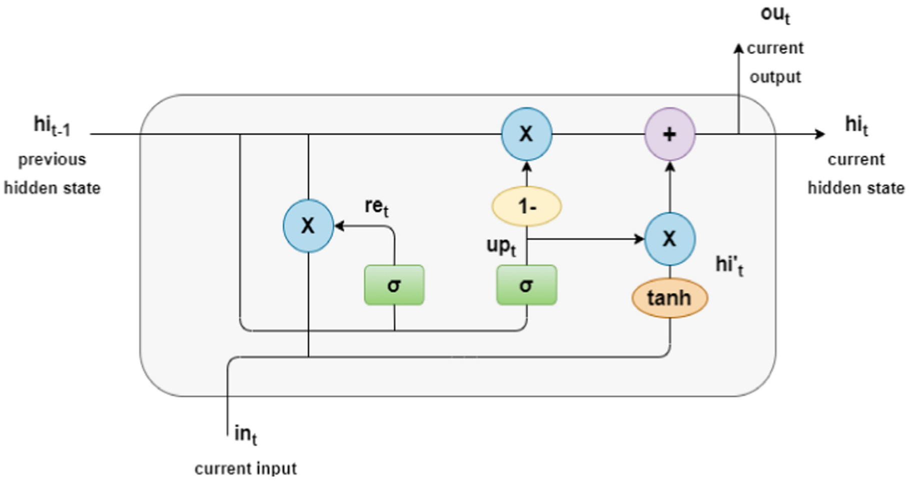

Fig. 2. Gated recurrent unit (GRU) cell structure.

The reset gate is responsible for maintaining a hidden state as follows:

$$\mathrm{re_t} = \sigma\left[\mathrm{W_{re}} * (\mathrm{hi_{t-1}}, \mathrm{in_t})\right] \tag{7}$$

The update gate handles the long-term memory of the cell as follows:

$$\mathrm{up_t} = \sigma\left[\mathrm{W_{up}} * (\mathrm{hi_{t-1}}, \mathrm{in_t})\right] \tag{8}$$

Hidden state ‘hi’ is determined by first calculating a candidate hidden state, as:

$$\mathrm{hi'_t} = \tanh\,[\,\mathrm{W_{hi}} * [\,(\,\mathrm{hi_{t-1}}\,,\,\mathrm{re_t}\,) + \mathrm{in_t}\,]] \tag{9}$$

The candidate hidden state is then used to achieve the current hidden state value:

$$\mathrm{hi_t} = (\,\mathrm{up_t} * \mathrm{hi_{t-1}}\,) + (1 - \mathrm{up_t}\,) * \mathrm{hi'_t} \tag{10}$$

4 Proposed Model

This section explains the implementation performed for Stock Market Price Prediction using DL techniques. A description of the Stock Market dataset, the hyper-parameter configuration of DL models, experimentation and forecast accuracy measure are given in the section.

4.1 Dataset Description

Firstly, we have used a stock market data posted on Australian Stock Market price. Their records are updated on daily basis. We considered the closing rates of stock market data from January 4 2000, to January 17 2017. The dataset conatins five columns: Date, Opening rate, Low price, High price and Closing rate of the date. Then, we split the dataset into a training set and a test set with a ratio of 95:05. The training set has 4104 entries, and the test set has a total of 216 data. The stock market closing prices are to be predicted for the next 31 days. Table 2 shows the division of the dataset into training and testing sets. However, Table 3 describes the hyper-parameters configuration of deep learning models.

Table 2. Division of training and testing samples in australian stock market dataset.

Australian stock market dataset	Training sample	Testing sample	Total
Total records	4104	216	4320
Percentage	95%	5%	100%

Table 3. Overview of hyper-parameter configuration.

Hyper-parameters	Australian stock market dataset
Model	Sequential
Epochs	30
Hidden layer	4
No of neuron	100 (each layer)
Optimizer	Adam
Activation function	Linear
Batch size	32

4.2 Experimentation

Two prediction models have been used, the deep learning model as LSTM and GRU. Figure 3 explains the step-by-step procedure for Deep Learning methods of LSTM and GRU from extracting the dataset, splitting it into training and testing datasets and using models for prediction purposes to obtain results [22]. Firstly we have taken the dataset and checked whether there is any missing value or not. After confirming the absence of missing value in our dataset, we applied the deep learning algorithms of LSTM and GRU.

According to Fig. 2, before using LSTM and GRU model, we preprocessed data. All data is converted to float then normalized between 0 and 1. After preprocessing, we have fit the LSTM and GRU model by using many parameters. We have selected parameters that give us a small RMSE value and the highest R^2 score to forecast stock market closing rates from March 11, 2016, to January 17, 2017 (216 days).

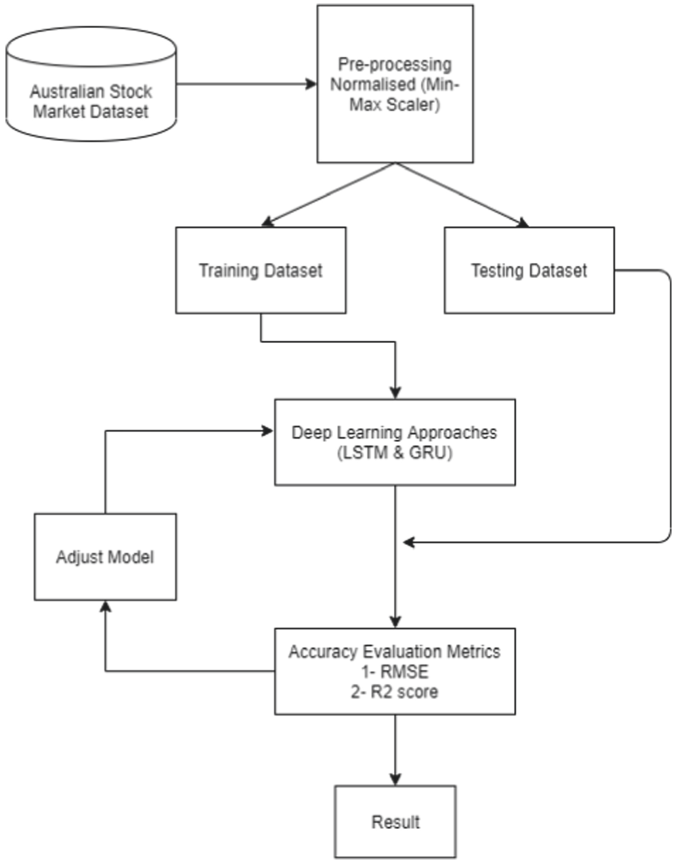

Fig. 3. Flowchart of deep learning models [23].

4.3 Forecast Accuracy Measures

We have used the root mean square error (RMSE) and R^2 score to forecast accuracy measures. The two accuracy measures can be expressed as follows:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (Q - P)^2}{N}} \tag{11}$$

In Eq. (11), where Q, P and N denotes actual value, predicted value and sample size.

$$R^2 \text{ score } = 1 - (\mathrm{RSS}/\mathrm{TSS}) \tag{12}$$

In Eq. (12), where RSS represents the sum of squares of residuals, TSS represents the total sum of squares.

5 Experimental Results

The main goal of this work has to predict stock market prices using deep learning techniques. We have also compared the results of both techniques and found the best model. For implementation, we have used Jupyter Notebook and python language. Many libraries were imported, such as pandas, Scikit-learn, Numpy, Keras, Tensorflow, Statsmodels etc. The dataset is loaded using pandas and then split into a 95% training and 5% testing set.

In the deep learning technique, we have used two algorithms such as LSTM and GRU. For LSTM and GRU model, first, we normalized all data between 0 and 1 using MinMaxScaler. We then divided the dataset into two parts training and testing set with a ratio of 95:05. Then fit LSTM and GRU model. For better results, we have done many times hyper-parameter tuning. According to Table 1, we have used different hyper-parameters such as epochs (30), hidden layer (4), number of neurons (100 each layer), batch_size (32), activation function (linear) and optimizer (Adam) for the best result. In Table 4, we performed a comparative analysis of two deep learning models- LSTM and GRU and observed their difference with the actual Closing rates of Stock market prices for the last 31 days of the test dataset. In Table 5, we calculated the RMSE and R^2 scores and concluded the LSTM model as the best model for forecasting stock market prices.

Table 4. Comparative analysis of actual and predicted closing stock market rates for the last 31 calendar days.

Dates	LSTM	GRU	Actual closing rates
12/1/2016	5436.258	5420.01	5500.2
12/2/2016	5438.539	5427.436	5444
12/5/2016	5434.315	5431.241	5400.4
12/6/2016	5419.95	5428.494	5428.7
12/7/2016	5408.714	5423.755	5478.1
12/8/2016	5410.544	5422.834	5543.6
12/9/2016	5430.789	5430.355	5560.6
12/12/2016	5459.278	5444.426	5562.8
12/13/2016	5486.307	5461.126	5545
12/14/2016	5503.566	5476.003	5584.6
12/15/2016	5519.718	5490.927	5538.6
12/16/2016	5523.638	5501.433	5532.9
12/19/2016	5519.909	5507.252	5562.1

(*continued*)

Table 4. (*continued*)

Dates	LSTM	GRU	Actual closing rates
12/20/2016	5518.818	5512.035	5591.1
12/21/2016	5524.979	5518.702	5613.5
12/22/2016	5537.93	5528.2	5643.9
12/23/2016	5557.398	5541.154	5627.9
12/28/2016	5573.169	5553.997	5685
12/29/2016	5594.502	5569.579	5699.1
12/30/2016	5616.89	5587.139	5665.8
1/3/2017	5629.156	5601.755	5733.2
1/4/2017	5646.611	5617.847	5736.4
1/5/2017	5663.838	5634.545	5753.3
1/6/2017	5680.89	5651.435	5755.6
1/9/2017	5695	5667.196	5807.4
1/10/2017	5714.672	5684.831	5760.7
1/11/2017	5724.523	5699.055	5771.5
1/12/2017	5729.8	5710.04	5766.9
1/13/2017	5731.046	5717.887	5721.1
1/16/2017	5721.773	5719.687	5748.4
1/17/2017	5714.559	5719.357	5699.4

Table 5. Comparison of RMSE, R^2 scores of applied deep approaches.

Model	LSTM	GRU
RMSE	**0.0724**	0.0855
R^2 Score	**0.8386**	0.7749

According to Table 5, LSTM and GRU model's RMSE values are 0.0724 and 0.0855, respectively, while the R^2 scores are 0.8386 and 0.7749. The smaller the RMSE value and larger the R^2 score of a model, the better the model performs prediction and achieves results [29].

6 Conclusion

This research collected the Australian Stock Market daily closing price dataset from January 4 2000, to January 17 2017. We forecasted the closing price of the last 216 days using two models LSTM and GRU. For deep learning models, we performed different hyper-parameter tuning to get the best results for prediction. Based on forecasting accuracy measures (RMSE and R^2 score), the LSTM model's performance is better than the GRU model. The RMSE and R^2 score of LSTM has obtained 0.0724 and 0.8386, respectively. This shows that LSTM performs best for long-time forecasting of Stock market prices.

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