Deep Learning-Based Approach for Stock Price Prediction

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ABSTRACT

This paper presents a deep learning-based approach for stock price prediction in financial markets. The problem of accurately predicting future stock price movements is of crucial importance to investors and traders, as it allows them to make informed investment decisions. Deep learning, a branch of artificial intelligence, offers new perspectives for meeting this complex challenge. Deep learning models, such as deep neural networks, are capable of extracting complex features and patterns from large amounts of historical data on stock prices, trading volumes, financial news and data. other relevant factors. Using this data, deep learning and machine learning models can learn to recognize trends, patterns, and non-linear relationships between variables that can influence stock prices. Once trained, these models can be used to predict future stock prices. This study aims to find the most suitable model to predict stock prices using statistical learning with deep learning and machine learning methods RNN, LSTM, GRU, SVM and Linear Regression using the data on Apple stock prices from Yahoo Finance from 2000 to 2024. The result showed that SVM modeling is not suitable for predicting Apple stock prices. In comparison, GRU showed the best performance in predicting Apple stock prices with a MAE of 1.64 and an RMSE of 2.14 which exceeded the results of LSTM, Linear regression and SVM. The limitation of this research was that the data type was only time series data. It is important to note, however, that stock price forecasting remains a complex challenge due to the volatile nature of financial markets and the influence of unpredictable factors. Although deep learning models can improve prediction accuracy, it is essential to understand that errors can still occur.

1. INTRODUCTION

Economic growth is one of the criteria and indicators of a country's development. Various factors can affect economic growth, including the stability of the financial system. A stable financial system can maintain or improve the national economy in terms of capital flows. The role of stability of the financial system belongs to the banking sector. Banks pursue several policies to maintain the stability of the banking financial system. Predicting stock prices remains one of the most complex and captivating challenges in finance. Financial markets, characterized by their dynamism and volatility, present fertile ground for exploring innovative methods to anticipate future movements in stock prices. Market participants, such as investors and traders, traditionally rely on fundamental and technical analysis to guide their decisions. However, the advent of deep learning has opened up new perspectives by enabling the creation of models capable of understanding and exploiting the complex structures inherent in sequential financial data. The main challenge facing stock price prediction lies in the unpredictable nature of the factors that influence the markets. Responses to economic, political and global events can be rapid and often difficult to anticipate using traditional methods. Thus, the use of advanced models based on deep learning offers a promising opportunity to improve the accuracy of predictions and provide more reliable guidance to market participants. A stock market is where companies issue their shares to expand their business, and investors can buy or sell their shares at certain prices. Investors around the world can buy and sell stocks, making a profit by selling at a higher price than they purchased [1]. The challenge is that fluctuating stock price movements can change within minutes or seconds [2], This is how the theory of stock price forecasting emerges. Stock forecasting involves accurately predicting stock prices in order to generate higher profits through trading [1]. However, it is difficult to obtain accurate forecasts from inventory trends due to non-linear and fluctuating data conditions. Traditionally, some who believe in the efficient market hypothesis argue that future

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stock prices can be predicted based on historical stock market data [3]. Experts have discovered a machine learning-based data modeling method that is more flexible; it does not require certain assumptions and does not have specific parameters [4]. Machine learning applies a concept that trains an artificial neural network that functions like a neural network in the human body. An artificial neural network, often called a Multi-Layer Perceptron (MLP), is a system built from several nodes called neurons [5]. Although traditional MLP models, such as back-propagation, can identify non-linear relationships between variables, they cannot reflect time series relationships between variables [6]. At the same time, the temporal relationship between variables and the logical relationship behind them is very important. Deep learning theory has developed rapidly in recent years with a rich set of tools widely used in climate, image processing, data mining, etc. In addition, the deep learning model has excellent time series data processing capabilities, which can achieve good economic and financial forecasts. This neural network component includes at least an input layer, a hidden layer, and an output layer. Artificial neural networks have several methods of use, such as recurrent neural networks (RNN), long short-term memory (LSTM), and gated recurrent units (GRU), which are a form of neural network architecture. artificial neurons (ANN) and are specifically designed to process continuous or sequential data (sequential data). In this case, all three models can be used in time series data.

2. LITERATURE REVIEW

Several previous studies have investigated the applications of machine learning in economics, including the use of LSTM to predict Indian stock market prices, which provides information that the LSTM model is preferred due to its greater stability [7]. Further research related to LSTM in stock price prediction [8]. RNN modeling for predicting stock prices was done by Jahan & Sajal [9] to predict Advanced Micro Device (AMD) stock prices. GRU modeling was carried out by Gupta et al. [10] to predict Indian stock market (CNX-Nifty). SVM modeling for stock market prediction using machine learning was done by Deepak Kumar et al [11]. Linear regression modeling was done by Seber, George [12] for stock market analysis. Support vector machines were applied to create a regression model of historical stock data and predict the stock trend [16]. The particle swarm optimization algorithm is used to optimize the parameters of the support vector machine, which can predict the stock value robustly [17]. This study improves the support vector machine method, but the particle swarm optimization algorithm requires a lot of time to calculate. LSTM was combined with a naive Bayesian method to extract market emotion factors to improve the prediction performance [18]. This method can be used to predict financial markets in completely different time scales with other variables. The emotional analysis model integrated with the LSTM time series learning model to obtain a robust time series model for predicting the opening price of stocks, and the results showed that this model could improve the accuracy of prediction [19]. Jia [20] discussed the effectiveness of LSTM in predicting stock prices, and the study showed that LSTM is an effective method for predicting stock profits. Real-time wavelet denoising was combined with the LSTM network to predict the East Asian stock index, which fixed some logic flaws in previous studies [21]. Compared with the original LSTM, this combined model is greatly improved with high prediction accuracy and small regression error. The bagging method was used to combine multiple neural networks method to predict the Chinese stock index (including the Shanghai Composite Index and Shenzhen Component Index) [22], each neural network was trained by backpropagation method and Adam's optimization algorithm, the results show that the method has different accuracy for predicting different stock indexes, but the closing prediction is not satisfactory. The evolutionary method was applied to predict the change in stock price trend [23]. The deep belief network with inherent plasticity was used to predict the stock price time series [24]. A convolutional neural network was applied to predict the stock price trend [25]. An advanced multi-layer neuron network model was created for future stock price prediction using a hybrid method combining technical analysis variables and basic analysis variables of stock indicators and the BP algorithm [26]. The results show that this method has higher accuracy in predicting daily stock prices than the technical analysis method. An efficient soft computing technology has been designed for Dhaka Stock Exchange (DSE) to predict the closing price of DSE [27]. The comparison experiment with artificial neural network and adaptive neural blur reasoning system shows that this method is more effective. Furthermore Jimbo *et* al [30]; proposed Kalman Filtering technique for predicting stock price.

3. METHODOLOGY

This section presents the methodology used to predict stock prices to enable stock managers to better manage their stocks. For this prediction, we used financial data containing stock price parameters. The process of these steps is elaborated in figure 1 below:

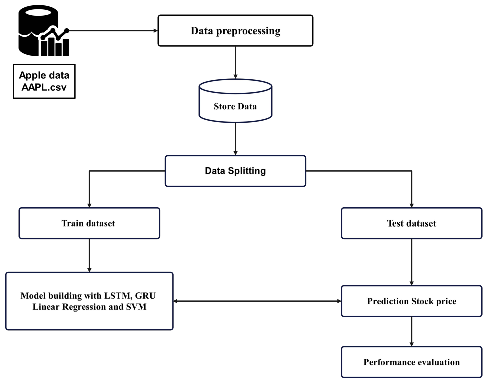

Figure 1: Stock price prediction steps

This section presents the basic concepts of our four models, namely: LSTM, GRU, SVM, and linear regression, and their uses in our work. We will start with a description of LSTM, followed by GRU, then SVM, and finally linear regression.

3.1. LSTM

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture designed to address the vanishing gradient problem in traditional RNNs. LSTMs are particularly effective in capturing long-range dependencies in sequential data, making them well-suited for tasks such as time series prediction, natural language processing, and speech recognition. Here's an overview of how LSTMs operate, along with their mathematical formulas:

- **Forget gate:** Determines which information from the previous cell state (C_{t-1}) should be discarded or kept. Sigmoid activation function is applied to the output of the forget gate.

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

- **Input gate:** Decides which new information should be stored in the cell state. Sigmoid activation is applied to the output of the input gate. Hyperbolic tangent (tanh) activation is applied to the candidate new cell state values.

$$i_t = \sigma(w_i * [h_{t-1}, x_t] + b_i) \tag{2}$$

$$I_t = tanh(w_i * [h_{t-1}, x_t] + b_i) \tag{3}$$

- **Update Cell State:** The old cell state is multiplied by the forget gate output, and the new candidate values are multiplied by the input gate output. These results are added to update the cell state.

$$C_t = f_t * C_{t-1} + i_t * I_t \tag{4}$$

- **Output Gate:** Determines the output based on the updated cell state. Sigmoid activation is applied to the output of the output gate. The updated cell state is passed through the tanh function.

$$o_t = \sigma(w_o * [h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = o_t * tanh(C_t) \tag{6}$$

3.2. GRU

GRU is a type of deep learning that can be used in datasets as an alternative solution to reduce the complexity of LSTM units. GRU has fewer trainable parameters because it does not have an output layer like LSTM. Within GRU, the information flow control component is called a gate, and GRU has two gates, namely a reset gate and an update gate [13]. The reset gate determines how to combine the new input with the past information, while the update gate determines how much past information should be stored when processing the sequence. The GRU architecture is displayed. The GRU architecture is shown in Figure 2 below:

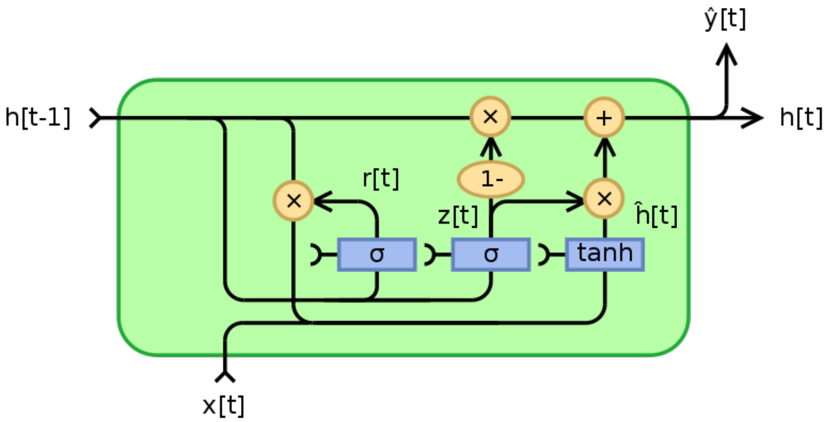

Figure 2: GRU architecture

Although LSTM and GRU are very similar, they have a few key differences. GRU has two gates (Reset and Update), while LSTM has three gates (Input, Output, and Forget). The reset gate in GRU manages how new inputs are combined with previous memory, and the update gate manages how much previous state should be retained. The update gate performs a similar function to the input and forget gates in LSTM. GRU has fewer parameters and complexity than LSTM.

$$z_t = \sigma(w_z * [h_{t-1}, x_t]) \tag{7}$$

$$r_t = \sigma(r_z * [h_{t-1}, x_t]) \tag{8}$$

$$\tilde{h}_t = \tanh(w \cdot [r_t \cdot h_{t-1}, x_t]) \tag{9}$$

$$h_t = (1 - z_t) \cdot h_{t-1} + z_t \cdot \tilde{h}_t \tag{10}$$

3.3. SVM

Support Vector Machine (SVM) is a supervised machine learning algorithm used for classification and regression tasks. It is a type of discriminative classifier that works by finding the hyperplane that best separates different classes in the input feature space. The main goal of SVM is to find a hyperplane in an N-dimensional space (where N is the number of features) that separates data points of different classes. The optimal hyperplane is the one that maximizes the margin, which is the distance between the hyperplane and the nearest data points from each class. In a two-dimensional space, a hyperplane is a line; in a three-dimensional space, it's a plane, and so on. The hyperplane in SVM is chosen to maximize the margin between classes. The SVM architecture is shown in Figure 3 below:

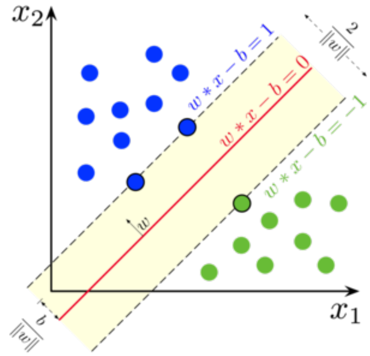

Figure 3: SVM architecture

3.4. Linear Regresssion

Linear regression is a statistical modeling technique used to establish the linear relationship between a dependent variable (or response) and one or more independent variables (or characteristics). The goal is to find the best line (or hyperplane, in the case of several independent variables) that represents the linear relationship between the variables. For a single independent variable X and a dependent variable Y, the simple linear regression model can be expressed as:

$$Y = \beta_o + \beta_1 * X + \epsilon \tag{11}$$

Where β_o is is the intercept, β_1 is the slope of the regression line and ϵ is the residual error. The Linear regression architecture is shown in Figure 4 below:

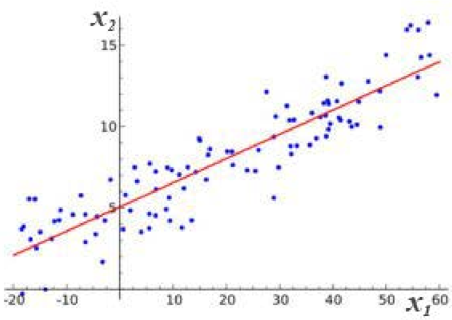

Figure 4: Linear regression architecture

3.5. Preprocessing Data

In this study, we will use Apple stock data from Yahoo Finance from January 6, 2000 to January 3, 2024 as research data. This sampling was deliberate because the data was limited to Apple stocks during a given period. Due to this limitation, this research only uses time series data containing open, high, low, close, volume, and adjusted close data. The adjusted close attributes in the data during stock split and dividend events were removed and the close was used as the target attribute. Then, the data was processed on Python and visualized with the Pandas library of Anaconda. Before proceeding with data analysis, it must be prepared according to needs. In this step, the data is prepared and transformed using the Z transformation, according to the equation 12 below:

$$Y = \frac{((X - min()))}{((max() - min()))} \tag{12}$$

Data transformation aims to eliminate data units and make model calculations easier because the data range becomes smaller, especially between -3 and 3 [14]. The deep learning and machine learning applications in this study, GRU and LSTM modeling, use two hidden layers, with the number of nodes in each layer 50 and a final dense layer that will make the predictions. Additionally, the activation function used is the relu function, the optimizer used is adam, the epoch used is 200, and the number of batches is 32. This study uses the root mean square error (RMSE), mean absolute error (MAE) to evaluate the different performance indicators and develop an accurate evaluation in equation 13 and 14 [15]:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_r - y_p)^2}{n}} \tag{13}$$

$$MAE = \frac{\sum_{i=1}^{n} |y_r - y_p|^2}{n} \tag{14}$$

3.6. LTSM, GRU, LINEAR REGRESSION AND SVM TRANING

After the pre-processing phase of our data, 1006 x 6 parameters or 6036 datasets were produced to be used as inputs to the LSTM, GRU, Linear Regression and SVM. 753 x 1 parameters or 753 datasets were produced for training and 251 x 1 to be used as testing for our models.

3.6.1. Stock Price Prediction

For this prediction step, LSTM, GRU, Linear Regression, and SVM architectures will be used to predict the stock price, with the training data used in the input layer. The architectures are presented in Figures 5 and 6 below:

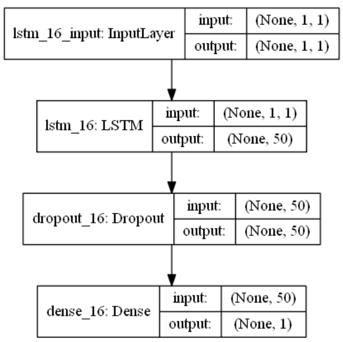

Figure 5: LSTM Architecture

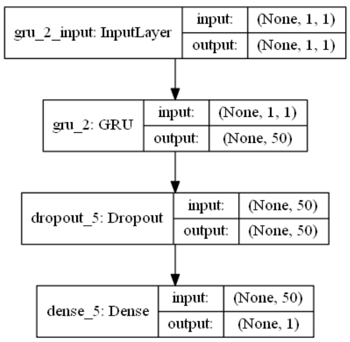

Figure 6: GRU Architecture

As shown in Figures 5 and 6 regarding the LSTM and GRU architectures used in this study to predict stock prices, there is 1 input layer, a hidden layer containing 50 neurons, and an output layer (dense layer) for predictions.

3.7. Prediction Results

Date	Open	High	Low	Close	Adj Close	Volume
2020-01-06	73.447502	74.989998	73.187500	74.949997	73.018684	118387200
2020-01-07	74.959999	75.224998	74.370003	74.597504	72.675278	108872000
2020-01-08	74.290001	76.110001	74.290001	75.797501	73.844345	132079200
2020-01-09	76.809998	77.607498	76.550003	77.407501	75.412857	170108400
2020-01-10	77.650002	78.167503	77.062500	77.582497	75.583359	140644800

Figure 7: Dataset of Apple

This study produced a stock price prediction based on Apple stock metrics. The prediction results can be seen in Figures 8 and 9 below:

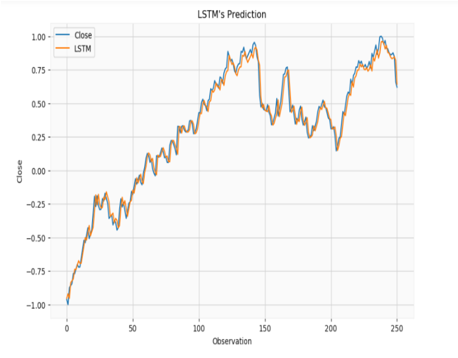

Figure 8: Figure of LSTM predict

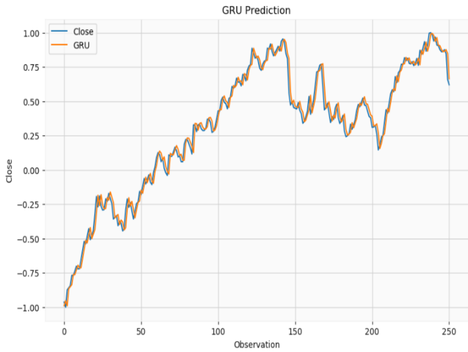

Figure 9: Figure of GRU predict

The results of these different models (LSTM and GRU) are given in Figures 10 and 11 below:

	Real Close	Predict Close (LSTM)
0	126.360001	125.656540
1	125.019997	126.910713
2	129.619995	125.607964
3	130.149994	130.090332
4	130.729996	130.608566

Figure 10: Result of LSTM predict

	Real Close	Predict Close (GRU)
0	126.360001	125.417801
1	125.019997	126.688202
2	129.619995	125.368614
3	130.149994	129.909607
4	130.729996	130.434738

Figure 11: Result of GRU predict

4. RESULTS AND DISCUSSION

After training our model and making predictions, we performed the optimization tests. At this level, an analysis of each parameter tested was carried out. Before carrying out tests on our different models, the training of these models was carried out using pre-processed data. The training of our models was carried out on LSTM, GRU, Linear Regression and SVM architectures. In addition, this training was carried out over 200 epochs for LSTM and GRU because Linear regression and SVM do not use epochs. For the SVM, we used a rbf kernel.

4.1. Optimization Model Influence Test

The performance test is carried out to determine which of our models best fits our predictions. The test accuracy results of our models can be seen in Table 4.1 below:

Models	correlation coefficient	MAE	RMSE
LSTM	0,984	1,67	2,17
GRU	0,984	1,64	2,14
Linear regression	0,986	2,78	3,62
SVM	-0,424	0,48	0,55

Table 1: Performance test of the LSTM, GRU, Linear Regression and SVM models.

4.2. Results Interpretation

To measure the performance of our models, we used the prediction results on metrics such as Correlation Coefficient (CC), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) below: The model (LSTM) has a Mean Absolute Error of 1.67, a root mean square error of 2.17, and a coefficient of determination of 0.984. The GRU model has a mean absolute error of 1.64, a root mean square error of 2.14, and a coefficient of determination of 0.984. The model (Linear regression) has an average absolute error of 2.78, a root mean square error of 3.62 and a coefficient of determination of 0.986. The SVM model has a MAE of 0.48 and a coefficient of determination of -0.42, this means that this model does not make very accurate predictions. Additionally, the negative coefficient of determination value suggests that the model's predictions are actually worse than simply using the average of the target values as a prediction (which would have a coefficient of determination of 0). Given that, these models have almost the same coefficient of determination except that of the SVM which is negative, and that we cannot limit ourselves only to this metric, this is why we focused on the two other metrics the MAE and the RMSE and after comparing these models we found that GRU give better results, which means that the GRU model is accurate in predicting stock prices and could be the most suitable model specification and data mining.

5. CONCLUSION

In conclusion, this study demonstrated the eË™ectiveness of deep learning-based approach for stock price prediction in financial markets. The LSTM and GRU models showed promising performance with relatively low mean absolute errors (MAE) and root mean square errors (RMSE), as well as high determination coefficients. On the other hand, the SVM model presented less satisfactory results. Based on these results, the GRU model seems to be the most suitable for predicting stock prices in this specific context. However, it should be noted that stock price prediction remains a complex challenge and further research is needed to improve model performance and take into account the volatility and uncertainty factors specific to financial markets. Although the deep learning-based approach for stock price prediction shows promising potential, one should be cautious about its limitations and actual performance. Deep learning models can provide additional information and interesting insights to investors, but they should not be considered foolproof tools for making financial decisions. A prudent approach based on a combination of different analytical methods and human expertise remains essential for making informed investment decisions.

Declaration of Competing Interest

There is no conflict of interest in this work.

Data Availability

Data are available on request.

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