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STOCK MARKET PREDICTION USING LONG SHORT-TERM MEMORY IN DEEP LEARNING

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ABSTRACT

These days, the stock market is rising. This study provides a new approach to market and stock price prediction using Python-based Long Short-Term Memory (LSTM) deep learning models. To detect the stock prize and capture temporal correlations, the research utilises LSTM architecture. The LSTM model is trained and assessed using a large, preprocessed dataset of several stock markets. Optical flow techniques or deep learning-based algorithms are used to extract robust features. These features are then used to train the LSTM model. Transfer learning makes use of large action recognition datasets to apply trained models. When measured in terms of accuracy, precision, recall, and F1-score, the LSTM model performs well, handling the temporal components of stock reward with great accuracy. Because of its real-time performance, it can be used for assistive devices and real-time interpretation assistance.

Keywords: F1-Score; LSTM; Deep Learning; Stock Market; RNN;

1. INTRODUCTION

An enhanced recurrent neural network (RNN) is the Long Short-Term Memory (LSTM) developed by Hochreiter and Schmid Huber. An advanced type of recurrent neural network (RNN) called Long Short-Term Memory (LSTM) networks was created to get around some of the drawbacks of more conventional RNNs, namely the vanishing gradient issue. This problem occurs when gradients become smaller as they are backpropagated over time steps, which makes it harder for RNNs to understand long-range relationships. LSTMs, which were first presented by Hochreiter and Schmid Huber in 1997, have an intricate design consisting of three basic gates: the input, forget, and output gates. LSTMs are particularly powerful for sequential data tasks, such as time series forecasting, natural language processing, machine translation, and speech recognition. In language modeling, for example, LSTMs can understand context and maintain coherence over long passages of text [5].

Traditional RNNs have difficulty detecting long-term dependencies since they only use one hidden state that is communicated throughout time steps. LSTMs address this issue by including a memory cell, which serves as a long-term information container. This makes LSTM networks perfect for use in time series forecasting, voice recognition, and language translation, among other applications, as they can effectively extract long-term correlations from sequential data [6].

This study uses a dataset of Apple stock prices from 2007 to 2024 and Google stock prices from 2004 to 2024 to build an LSTM-based model that tracks changes in stock prices every 30 days[7]. Our goal is to simply predict the stock prize after 30 days using this merely prediction model, and we will plot the results. By merging two well-known models—the Bi-Directional Long Short-Term Memory (BI-LSTM) model and the Recurrent Neural Network (RNN) model, or more specifically, the Long Short-Term Memory (LSTM) model—they suggest a novel framework for predicting stock prices. Simulations demonstrate that by adjusting the hyperparameters of two RNN models—BI-LSTM and LSTM—they are able to produce reliable predictions of future stock trends [8].

Additionally, our method is able to predict future market trends with good accuracy reliabilities [9]. To improve the accuracy of the prediction model, we have changed the epochs, dense layers, hidden layers, and hidden layer units [10]. We have also computed the root mean square error (RMSE) in LSTM and BI-LSTM.

The evaluations were conducted using a public data set that comprised the open, high, low, and close prices for the stock markets [3]. The goal of this study is to forecast future trends in several stock market sectors. Four categories were considered during the examination of a set of time slices that were taken from the Tehran Stock Exchange: diversified financials, petroleum, non-metallic minerals, and basic metals [11]. Over a ten-year period, historical data about these sectors was gathered. Seven forecasting time frames in all, ranging from one to thirty days ahead, are available [12].

We used a variety of machine learning techniques and models, including Adaptive Boosting (Adaboost), Gradient Boosting, eXtreme Gradient Boosting (XGBoost), Decision Trees, Bagging, Random Forests, Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM), to forecast the future values of the stock market sectors [13]. For every prediction model, ten technical indicators were combined to represent the inputs. Ultimately, four criteria were established that provided an explanation for all of the approaches' predictions [14].

Among all the algorithms examined for this study, LSTM had the highest model fitting power and was the most accurate[2]. Its main objective is to forecast the S&P 500 index's closing price for the next day by utilizing the Long Short-Term Memory (LSTM) neural network architecture. A meticulously constructed set of nine predictors, which include technical indicators, macroeconomic data, and fundamental market data, is used to provide an all-encompassing picture of stock market trends [15]. The single-layer and multilayer LSTM models are developed using these selected input variables. Standard measures, such as the correlation coefficient (R), mean absolute percentage error (MAPE), and root mean square error (RMSE), are used to evaluate the performance of these models [16].

Experimental Setup

The stock market is rising. Thus, a pick of the most popular and extensively used firms for stocks was Apple and Google. In the IT industry, these two businesses are the largest. In order to view LSTM performance on time series that were influenced by various circumstances, stocks from various sectors were selected for this study [17]. The company's Apple (212.29$) and Google (178.38$) both had closing prizes. The data series must be made stationary—that is, it must appear flat and lack of seasonality or long-term trends—before using time series techniques. Differencing is a popular technique to accomplish this, which entails deducting the prior observation from the present observation [18].

Because the first item in the series has no preceding value to differ from, it must be skipped, resulting in a series with one fewer element. To account for this, 2561 data points were added to the dataset.

$$Y_i = Z_i - Z_{i-1}$$

To recover the original series, the changes must be added back after LSTM predicting. The data also has to have an output component added to it. LSTM models assume the presence of input values (time series) that are used to predict output values [19]. Since the time series data only had input values, the stock price at time \ (t-1 \) was used as an input to predict the stock price at time \ (t \) as the output. A new input series was created by shifting the original series back by one time period, while the original time series contained the output variables [24]. For the LSTM model, the default activation function used was the hyperbolic tangent (tanh), which produces output values in the range of -1 to 1[20]. To align with this range, the input data was scaled down. Once the forecasts were made, they were scaled back up to match the original scale[6].

2. RESULT AND DISCUSSION

Stock prices of corporations fluctuate regularly due to various market factors, making them inherently unpredictable. Accurately predicting market trends is essential for investors as it helps them make informed decisions. The objective in this scenario is to forecast whether a stock’s value will rise or fall. This task is carried out using a Long Short-Term Memory (LSTM) model, a type of recurrent neural network (RNN) designed for time-series forecasting. LSTM models are effective because they can capture long-term patterns and dependencies from historical data [25]. In Figure 1, Google’s stock (traded under Alphabet Inc.) shows a higher value compared to Apple’s stock, which is illustrated in Figure 2. This suggests that Google’s stock performed better during the given period. However, stock performance is influenced by various factors, such as business performance, market conditions, and external events like geopolitical developments or changes in investor sentiment [21]. While Google may appear to have a higher value here, Apple’s stock could surpass it in a different time frame due to its strategies and growth potential. LSTM models are particularly well-suited for stock prediction because they can retain and analyze relevant data from previous time steps, making them more effective than traditional machine learning models [22]. Although the LSTM model provides insights into the direction of the stock trend—whether it will rise or fall—it does not predict exact prices. Investors must recognize that market forecasts, including those made with LSTM models, are not foolproof [23]. Combining predictions with other market insights and analytical tools is essential for making sound investment decisions.

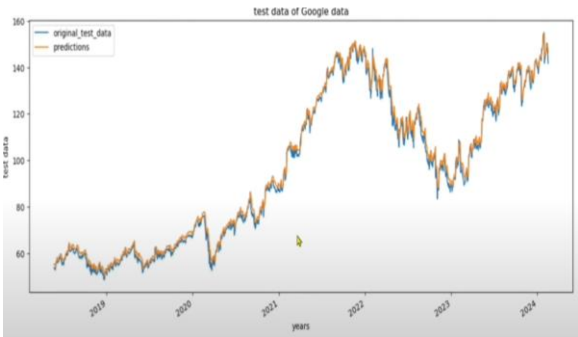

Figure 1 predication of google stock

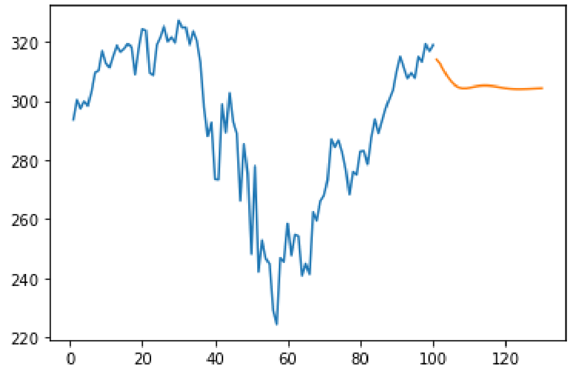

Figure 2: Stock prize Apple prediction

3. CONCLUSION & FUTURE SCOPE

There are many models available in deep learning for stock market prediction. In the future, websites could be developed where users simply input the target stock, whether from the IT sector, banking, or any other industry. These platforms could automatically fetch relevant stock data, train a model using that dataset, and provide predictions on whether the selected stock is likely to be profitable. This approach leverages deep learning models to analyze trends based on historical data. The predictions generated would indicate whether the stock value might increase or decrease, helping investors make informed decisions. However, it is important to note that these models rely heavily on the quality of the training dataset and market data. As a result, while these predictions can offer insights, they are not guaranteed to be accurate due to the inherent volatility of financial markets.

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