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Enhancing Stock Market Predictability: A Comparative Analysis of RNN And LSTM Models for Retail Investors

Nevendra Kumar Upadhyay1, Vineet Singh2, Shikha Singh3, Pooja Khanna4

[1,2,3,4]Amity School of Engineering and Technology, Amity University (AUUP), Lucknow, (Uttar Pradesh), India.
nav7up@gmail.com[1], vsingh@lko.amity.edu[2], ssingh8@lko.amity.edu[3], pkhanna@lko.amity.edu[4]

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Abstract

The stock markets are important components of the global financial system and have a considerable impact on an economy's growth and stability. This research article uses algorithms, notably deep learning, to increase the prediction of stock values. The efficacy and precision of long short-term memory (LSTM) and recurrent neural networks (RNN) algorithms to estimate stock prices are compared in this study. The paper investigates the potential of deep learning algorithms in creating a more predictable and trustworthy environment for the stock market. The study utilizes historical market data obtained from the Alpha Vault API and evaluates the performance of the RNN and LSTM models in forecasting stock prices. The results indicate that LSTM exhibits superior precision and is better suited for stock price prediction, while RNN faces certain challenges. Overall, this research contributes to the understanding of the application of deep learning algorithms in stock market analysis, to make informed investment decisions, thereby reducing risks and maximizing returns.

Keywords

Stock market, Prediction, RNN, LSTM

1. Introduction

The aim of our research is to bring a bit more predictability in the stock prices with the help of algorithms. So, in this research paper is going to compare deep learning and machine learning algorithms and will show some modifications to bring more validity in the obtained results. The stock markets are very significant mechanisms of the international financial system and plays a substantial role in the progress and constancy of an economy. Ordinary investor (i.e., retail investor) can also become part of this growth by buying a small percentage of equity of a company. Every investor wants to reduce risks and earn good returns. But it has been found that retail investor mostly hesitates to participate in market and thinks that it is just a gamble because of the uncertainty present in the market. They tend to think like that because of the lack of proper information and analyzing capabilities. But, with the development of data science, big data, and the availability of information about the past and future trading sessions, the misconception or doubt among the retail investor has been bit decreased. The stock market is very important institution for a country's economy as well as a place for small investors to become part of nations growth.
In share market the companies basically offer equity of the company in the form of shares, the shares trade on stock exchange. When a company offer its equity to public for the first time it is called Initial Public Offering (IPO) and after that it is called Follow-on Public Offering. Companies basically lend their share to brokers, the public buy shares from these brokers and these brokers take some charges for doing this job [1]. Broker are basically banks, or any small company having license to trade shares.

The most important part of the stock market is the awareness among the investors, the investors should have a proper idea about the present price, trending stocks, and the fundamentals of the company. This information can be used to analyze the probable price of stocks in future. All these things can be done by machine learning, deep learning algorithms. So, we can accept that growth of data science has been beneficial for the investors in stock market as well as in other relevant fields.

The objective of this paper is to discuss algorithms and open-source libraries which will help in making this uncertain market a bit more predictable. The proposed method of the paper has two sections first, to compare machine learning and deep learning algorithms to find out which would be more effective and accurate for our purpose of forecasting the price of a stock. Moreover, the author of this paper has shown some modifications that can be done to achieve more validity in application of these algorithms. These algorithms will make investors take better decision before investment do that the investor can make good return by reducing risk.

The need to address the unpredictability and volatility in the stock market, particularly for individual investors, is what motivated this research. This study attempts to offer investors more trustworthy and accurate stock price predictions by utilizing the developments in data science and machine learning algorithms. This study contributes by contrasting machine learning and deep learning algorithms, suggesting changes for increased accuracy, and eventually enabling investors to make accurate choices and reduce market risks.

The Literature Review section represents the review of relevant literature on the use of neural networks models, deep learning, and recurrent neural network (RNNs) for stock price prediction. The paper highlighted shows the use of machine learning in this field. The methodology section explains the steps followed in the research. It begins with data collection from the Alpha Vault API and the splitting of data into training and testing sets. Data preparation and cleaning are discussed, followed by model training and cross-validation. The section also mentions the visualization of data to assess the performance of the algorithms. Next section is Performance evaluation, this section presents the results of the research. It focuses on the use of RNN and LSTM models for stock price prediction, specifically for TATAMOTORS stock. The performance of the models is evaluated based on price error ratio, loss, and mean edit distance. The results show that LSTM outperforms RNN in terms of accuracy. The section Challenges faced in RNN, discusses the challenges faced during RNN training, specifically the issues of vanishing and exploding gradients. It explains the impact of these problems on the training process and suggests techniques such as gradient clipping, weight initialization, batch normalization, and truncated backpropagation through time to address them. The final section Discussion and Conclusion, summarizes the key findings of the research and provides a discussion on the power of deep learning models in capturing market aspects. It highlights the superior precision of LSTM compared to RNN and acknowledges the challenges faced by RNN. The paper concludes by emphasizing the potential of machine learning algorithms, particularly LSTM, in stock price prediction.

2. Literature Review

Several of the papers focus specifically on the use of linear regression and neural network models for forecasting stock prices and tourist arrivals. Rezaul Karim's paper [1], for example, examines the use of both linear regression and decision tree regression in stock market analysis, while Selcuk Cankurt and Abdulhamit Subasi [3] compare linear regression and neural network models for forecasting tourist arrivals in Turkey.

Another paper in which we examine more advanced techniques such as deep learning and recurrent neural networks (RNNs) for stock market analysis and prediction. Eugene [8] C's Introduction to Deep Learning provides a general overview of deep learning techniques, while Pouyanfar [9] et al.'s survey paper offers a more in-depth exploration of the topic, covering deep learning algorithms, techniques, and applications. Meanwhile, Zachary Chase [10] Lipton's critical review paper focuses specifically on RNNs for sequence learning.

Several papers which also explore the use of more complex models that combine multiple machine learning techniques. T. Kim and H. Y. Kim [11], for example, use a feature fusion LSTM-CNN model for stock price prediction, while S. Selvin [12] et al. explore the use of LSTM, RNN, and CNN-sliding window models for the same task. Hiba Sadia [13] et al. also explore the use of machine learning algorithms for stock market prediction, comparing the performance of several different algorithms, while Felix Gers' [14] paper provides an early exploration of long short-term memory (LSTM) in RNNs.

This work investigates the application of deep reinforcement learning for stock price prediction, employing both historical price information and market pointers. Wang, Y., Chen, W., & Li, Z. (2021) [16]. Mohiuddin, M., Khan, F. A., and 2022 [17] The numerous machine learning methods used in stock market prediction are thoroughly examined in this review article, outlining their advantages and disadvantages. S. Aggarwal, V. Kumar, and others (2022) [18], This research gives a comprehensive analysis of hybrid models for stock market prediction that integrate several machine learning approaches, such as genetic algorithms, fuzzy logic, and neural networks. Y. Jiang, X. Yan, and S. Zhang (2021) [19], Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and generative adversarial networks (GANs) are only a few of the deep learning approaches covered in this survey study.

Overall, these papers provide a comprehensive overview of the state of the art in machine learning for stock market analysis and prediction, as well as highlighting the potential of these techniques in other domains. While the specific techniques and models vary from paper to paper, the overall message is clear: machine learning has the potential to revolutionize the way we approach data analysis and prediction in a wide range of fields.

3. Methodology

The first step before working on any algorithm is the collection of data. It is a mandatory step. Here our requirement is historical data of market on which we will do our analysis. Our information will come via the Alpha Vault API. The data are then split into training and testing data as the following phase. We will train our system to forecast prices before visualizing the outcomes.

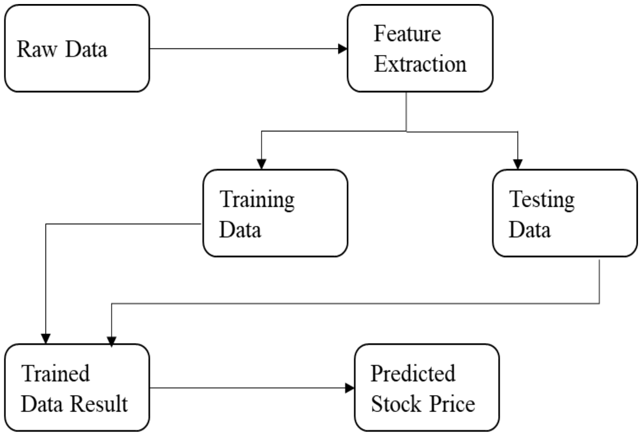

Figure 1. Flow Diagram of Methodology

In Table 1 all the parameters which has been used to train the model has been mentioned along with their meanings.

Table 1. List of Data/Symbols used in this analysis

Used	Meaning
Date	Date of Stock Price
Open	Open Price of a share
Close	Closing price of a share
Volume	Numbers of share traded
High	Highest share value for the day
Low	Lowest share value for the day
Turnover	Total Turnover of the share

Prior to starting the data pre-process, it is essential to collect market info. We will get info for our analysis through the Built - in functions nsepy as alpha vantage. NSEpy gathers data from the domestic stock market, whereas alpha vantage offers data from the international market. I will acquire real time data for our study. The next step is data preparation. Data cleaning is the main step we perform entire preparation phase [13]. We must pre-process the data before utilizing it to training our algorithm since it may be inconsistent. This process is known as data preparation. The preparation of the model includes cross-approval, a very well-founded, predicted execution of the model using the preparation data. The purpose of the tuning simulation is to specifically alter the calculation training and improve the computation by adding more details. The samples are perfect since a model should not be chosen based on inside information. Improve the information to include the costs associated with the actual offer. The next stage is to visualize information using a method that shows how the data may change based on how well our algorithm works.

4. Performance Evaluation

The use of a planned RNN and LSTM model in Python that analyses past data to forecast the TATAMOTORS equity prices in the future. The representation TATASHARE's projection appears in the image below. The entire data set and a portion of the training datasets were shown on the chart. The chart shows the starting price of the TATAMOTORS equity for the 1800 days with a very substantial reduction. The method successfully created a plot with the anticipated value original value (Green) and predicted price (Yellow). The forecasted price of TATAMOTORS stock is shown on the graph below from our method. The displayed output of our method, which used 50 epoch units to obtain correctness, is presented in figure 1 and figure 2.

The observation provides the result of the 50-nodes architecture experiment. It shows that in Price error ratio the LSTM shows better results than RNN. Similar outcomes may be observed in Loss, where RNN and LSTM are, respectively, 186.61 and 160.51. With a score of 0.3853 for Mean Edit Distance, LSTM has produced superior results. It shows that LSTM is best suited algorithms for the stock price prediction models.

Table 2 provides the result of the 50-nodes architecture experiment. It shows that in Price error ratio the LSTM shows better results than RNN. Similar results can be seen in Loss where RNN and LSTM is 186.61 and 160.51 respectively. In case of Mean Edit Distance, LSTM has achieved better result with a score of 0.3853. It shows that LSTM is the best suited algorithm for the stock price prediction models.

Table 2. Results for 500-epoch layer architecture

MODEL	Price Error Ratio (%)	LOSS	MEAN EDIT DISTANCE
RNN	87.02%	186.61	0.4484
LSTM	77.55%	160.51	03853

In figure 2, we have plotted the price error ratio value of RNN and LSTM graphically, the figure clearly shows that LSTM has better value than RNN.

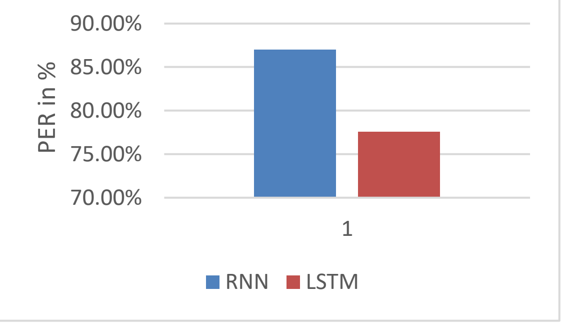

Figure 2. Price Error Ratio results in percent

In figure 3 and figure 4, we have plotted the results of both the model RNN and LSTM respectively, In Graph we can clearly see that in RNN the discrepancy between the predicted value and the original value Which shows that LSTM results are more accurate and closer to original value.

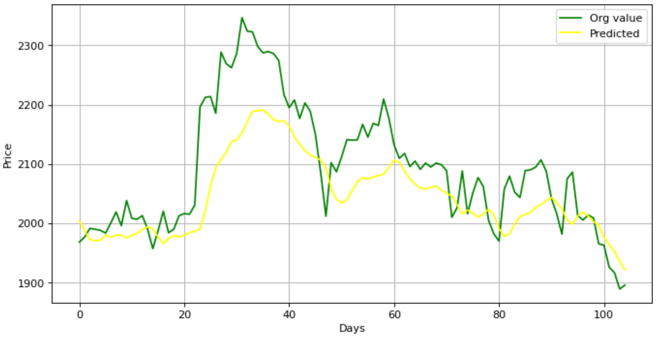

Figure 3. Plot of original value and predicted value in RNN Model

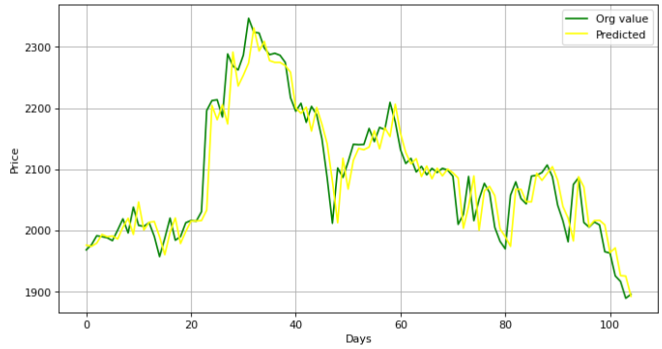

Figure 4. Plot of original value and predicted value in LSTM Mode

5. Challenges faced in RNN

A unique class of neural network known as neural networks that recur (RNNs) is particularly good at processing sequential input. Nonetheless, they do have issues, much as any neural networks. The two biggest problems that might occur during RNN training are vanishing gradients and exploding gradients.

5.1. Vanishing Gradient

Because when gradients of the loss function in comparison to the network weights are so minimal, the term "vanishing gradient" is used. This may occur because the gradients of the network are calculated by adding several multipliers to each time period in the sequence. The product of these matrices will eventually will reach to zero, when the number of time steps rises, if the eigenvalues are smaller than 1. This basically implies that with each time step the gradient will decrease and become small, which would lead to challenges and will make it difficult to train the network successfully.

5.2. Exploding Gradient

Whenever the gradients of the loss product with reference to the system's weights become extremely large, exploding gradients occur. In this case as well, this may happen because network's gradients are determined by multiplying a series of matrices together for every time interval in the sequence. The product of these matrices will eventually become very large, when the number of time steps rises, if the eigenvalues are greater than 1. As the gradient grows significantly and become large, it causes weights to update excessively, this might cause numerical destabilization and prevent the network from learning.

Effective RNN training can be hampered by both vanishing and bursting gradients, particularly when the sequences are quite lengthy. These problems may be solved using a variety of methods, including regularization, weight initialization, and gradient cutting. Setting a maximum value for the gradients is known as "gradient clipping," which can stop explosive gradients from creating numerical instability. The network's weights can be initialized in a way that lessens the possibility of disappearing or bursting gradients by using weight initialization techniques like the Xavier initialization or the He initialization. Finally, regularization methods like dropout can assist avoid overfitting and minimize the influence of any individual weights on the entire network [14].

In conclusion, it might be challenging to efficiently train RNNs since disappearing and exploding gradients are frequent issues that can occur. Nevertheless, these problems may be minimized and RNNs can be effectively trained on sequential data by using several strategies such gradient clipping, weight initialization, and regularization. Vanishing and exploding gradient problems can be addressed in several ways in LSTMs. Here are some techniques that can be used to solve these issues

A. Gradient clipping: This technique involves setting a maximum value for the gradients during training. When the gradients exceed this threshold, they are rescaled to ensure that they do not become too large. This can prevent exploding gradients from causing numerical instability in the network.

B. Weight initialization: The choice of initial weights can play a significant role in the occurrence of vanishing or exploding gradients. Weight initialization methods, such as Xavier or He initialization, can help to ensure that the weights are initialized in a way that reduces the likelihood of these issues.

C. Batch normalization: Batch normalization is a technique that can be used to improve the stability of the gradients in deep neural networks, including RNNs.

D. Truncated backpropagation through time: This technique involves breaking long sequences into shorter ones during training. This can help to reduce the impact of vanishing and exploding gradients by limiting the number of time steps.

6. Discussion and Conclusion

In this paper, author shows how Deep learning models have the power to be built on big and varied databases, which helps them to catch a variety of market aspects, such as emotion in social media and the news. This empowers the Deep Learning algorithms models in generation of more precise share prices forecasts based on live market information. The aim of this paper is to compare RNN and LSTM algorithms for equity price forecasting. Long Short-Term Memory provides superior precision for both small and large datasets, according to the results. Recurrent Neural Network, on the other hand, communicates a low prediction price as a result of the difficulties it encounters. Future research can explore the integration of additional deep learning techniques, such as convolutional neural networks (CNNs) and transformer models, for stock price prediction. The inclusion of external factors, such as news sentiment analysis and economic indicators, can be investigated to improve the accuracy of predictions and capture market sentiment. Ensemble methods, such as stacking and boosting, can be employed to combine predictions from multiple models and enhance forecasting accuracy. Further studies can focus on real-time prediction, interpretability of models, risk assessment, and portfolio optimization to provide valuable insights for investors and guide industry practices.

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