IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.301

Volume 3, Issue 16, May 2023

Stock Price Prediction using Deep Learning Models

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Abstract: *The financial exchange is a portion of an organization's proprietorship. Each organization and everyone needs to improve their resources. Many methodologies and techniques have been utilized to decide the stock worth later on. The financial exchange is where stock worth ascents and falls at each moment. Lately, a few experts have proposed different ways to deal with attempt and distinguish the specific worth of the stock to expand the precision of stock expectations. The new pattern in financial exchange expectation advances is the utilization of ML which makes forecasts in light of the upsides of current financial exchange records via preparing on their past qualities. Where as in securities exchange expectation, the point later on worth of the monetary loads of an organization. The Variables which are viewed as open, close, low, high, volume. Securities exchange cost pattern expectation is consistently a hotly debated issue for scientists from both monetary and specialized spaces. In this examination, our goal is to fabricate a condition of-craftsmanship expectation model for cost pattern expectation, which centers around delivering best Precision utilizing different strategies.*

Keywords: Price Prediction, LSTM, Prediction, Deep Learning, Recurrent Neural Network (RNN), Current Neural Network (CNN)

I. INTRODUCTION

Basically, quantitative traders with a lot of money from stock markets buy stocks derivatives and equities at a cheap price and later on selling them at high price. The trend in a stock market prediction is not a new thing and yet this issue is kept being discussed by various organizations. There are two sorts to examine stocks which financial backers perform prior to putting resources into a stock, first is the central examination, in this examination financial backers take a gander at the natural worth of stocks, and execution of the business, economy, political environment and so forth to conclude that regardless of whether to contribute. Then again, the specialized examination it is a development of stocks by the method for concentrating on the insights created by market action, like past costs and volumes. In the new years, expanding conspicuousness of ML in different ventures have illuminated numerous dealers to apply ML strategies to the field, and some of them have delivered very encouraging results. This paper will foster a monetary information indicator program in which there will be a dataset putting away all verifiable stock costs and information will be treated as preparing sets for the program. The fundamental reason for the expectation is to lessen vulnerability related to speculation choice making. Stock Market follows the arbitrary walk, which suggests that the best forecast you can have about the upcoming worth is the present worth.

Unquestionably, the estimating stock lists is truly challenging a result of the market unpredictability that needs precise gauge model. The financial exchange lists are exceptionally fluctuating and it impacts the financial backer's conviction. Stock costs are viewed as an exceptionally unique and helpless to fast changes in light of hidden nature of the monetary space and to some degree due to the blend of a known boundaries (Earlier day's end value, P/E proportion and so forth) and the obscure variables (like Political decision Results, Bits of hearsay and so on.). There has been various end users to anticipate stock cost with ML. The focal point of each examination projects changes a great deal in three ways. (1) The focusing on value change can be close term (under a moment), present moment (tomorrow to a couple of days after the fact), and a long haul (months after the fact), (2) The arrangement of stocks can be in restricted to under 10 specific stock, to stocks specifically industry, to for the most part all stocks. (3) The indicators utilized can go from a worldwide news and economy pattern, to specific qualities of the organization, to simply time series information of the stock price. The likely securities exchange expectation target can be the future stock cost or the unpredictability of the costs or market pattern. In the forecast there are two sorts like sham and a continuous expectation which is utilized in securities exchange forecast framework. In Fake forecast they have characterize some arrangement of rules and anticipate the future cost of offers by computing the typical cost. In the ongoing expectation mandatory utilized web and saw current cost of portions of the organization. Computational advances have prompted presentation of AI procedures for the prescient frameworks in monetary business sectors. In this paper we are using Machine Learning technique and Python language for programming.

II. LITERATURE SURVEY

From the research paper “Stock Market Prediction: A Survey and Evaluation” written by Milon Biswas, Arafat Jahan Nova, Sudipto Chaki, Shamim Ahmed, Md. Kawasher Mahbub and Md Ashraful Islam in Bangladesh University of Business and Technology, they used 10 approaches or techniques utilized in the last few years such as Multilayer Perception (MLP), Convolutional Neural Network (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) and so on to forecast the stock value of a company depending on the historical prices available in the company, etc. to predict the next day stock price and a long-term stock price [2]. The machine learning algorithms used in the in stock market prediction and to concentrate on their pros and shortcomings. This article examined over 10 approaches or techniques utilized in the last few years which were introduced into the forecast of stock market values. This method can help both individual traders and business investors. They can forecast future market pricing behaviour and take suitable actions to benefit such as A. Recurrent Neural Network (RNN) W. Chen created an RNN boost model that predicts stock prices using technical data, sentiment and LDA. According to findings, the recommended model outperformed the single RNN model. Zeng. Z introduced a novel RNN (ARNN), which got denoted input from the wavelet. The prediction was made using the integrated moving mean Autoregressive (ARIMA) and the output ARNN model. B. Long Short-Term Memory (LSTM) One modification of the RNN is the LSTM model. The self-loop design is used as a crucial input to construct a steep path that can be freely followed for a long time. A technique using nonlinear parameters is used to model a time series. The LSTM model is effective at displaying the link between nonlinear time series and the stock prediction aim in delayed state space. C. Deep Neural Network (DNN) At least one hidden layer of neural network is present in a deep neural network (DNN). It may be able to offer complex non-linear functions as well as a huge abstraction capacity, implying that the model’s fitting power is considerably increased. To predict stock market crises, S.P. Chatzis developed a DNN model that employed boosted methods. Although his research is not limited to certain prediction approaches, he discovered that learning about stock market crises was helpful in predicting the price.

From the research paper “Stock Market Prediction Using Machine Learning” written by V Kranthi Sai Reddy from , Sreenidhi Institute of Science and Technology, Hyderabad, India. In this project the prediction of stock market is done by the SVM and Radial Basis Function(RBF). The SVM can be used to predict the data after training the learning samples and A radial basis function is the real-valued function whose value depends only on the distance from the origin. Support Vector Machine. All in all, the given marked preparing information (regulated learning), the calculation yields the ideal hyperplane which arranges new models. In the two-layered space this hyperplane is a line partitioning a plane into two sections where in each class lay in one or the other side. Recurrent neural network [5] is a kind of neural network where associations between neurons permit worldly, successive data to be put away and handled in the organization. One normal design is shaped by taking care of the result of the ongoing unit back to the contribution with a period delay so the organization can involve the data in handling the following information. Different procedures have been created throughout the years to prepare such sort of organization. One of the famous methodologies is backpropagation through time (BPTT) [6], whose focal thought is to unroll the repetitive organization into a feedforward network, where each layer addresses a timestep. Backpropagation with slope plunge could then be performed to streamline the organization, very much like the way that we upgrade a feedforward network. Sadly, it has been shown that methods like BPTT result in one or the other evaporating or detonating angles [7]. Disappearing slopes lead to ridiculously lengthy preparation time, and in some cases preparing is infeasible while detonating angles bring

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about fluctuating loads, which prompts unsound preparation. Both are unfortunate in neural network preparing. In this way, new preparation strategies and designs are needed to mitigate the problems.

Long short-term memory [8] was first presented by Hochreiter and Schmidhuber in 1997 to address the previously mentioned issues. Longshort term memory handles the issue of figuring out how to recall data throughout a period stretch, by presenting memory cells and door units in the neural network design. A run of the mill definition includes the utilization of memory cells, every one of which has a cell express that store recently experienced data. Each time an info is elapsed into the memory cell, and the not set in stone by a blend of the cell state (which is a portrayal of the past data), and the cell state is refreshed. At the point when one more information is passed into the memory cell, the refreshed cell state and the new input can be utilized to register the new output.

LSTM

LSTM has been widely used for stock price prediction due to its ability to capture temporal dependencies in time series data. When applied to stock price prediction, LSTM models can learn patterns and trends from historical price data to make future price predictions.

The basic process of using LSTM for stock price prediction involves the following steps:

1. Data Preparation: The historical stock price data is collected and preprocessed. This includes tasks such as normalizing the data, splitting it into training and testing sets, and creating input-output sequences or sliding windows.
2. Model Architecture: The LSTM model is designed and configured. It typically consists of one or more LSTM layers, possibly followed by additional layers such as Dense layers. The number of LSTM layers and the number of neurons per layer can be determined based on experimentation and the complexity of the problem.
3. Training: The prepared data is used to train the LSTM model. During training, the model learns to predict future stock prices based on the historical price patterns it has observed. The model parameters are updated iteratively to minimize the prediction error.
4. Prediction: Once the LSTM model is trained, it can be used to make predictions on unseen or future data. Given a sequence of historical prices, the model predicts the future price based on the learned patterns. It's important to note that stock price prediction is a challenging task due to the complex nature of financial markets. Many factors beyond historical price data, such as news, market sentiment, and economic indicators, can influence stock prices. Therefore, while LSTM models can provide insights and capture some patterns, they may not always accurately predict stock prices.

Additionally, it's crucial to perform thorough validation and evaluation of the model's performance using appropriate metrics and statistical techniques to assess its accuracy and generalization ability.

DNN

DNN stands for Deep Neural Network, which is a type of artificial neural network that contains multiple hidden layers between the input and output layers. DNNs are known for their ability to learn complex patterns and representations from data, making them suitable for various machine learning tasks, including stock market prediction.

Historical stock market data is collected and preprocessed. This typically includes tasks such as normalization, splitting into training and testing sets, and feature engineering, where additional relevant features may be created based on domain knowledge.

The DNN model is designed and configured. It typically consists of multiple layer of interconnected neurons. The number of layers and the number of neurons per layer can vary depending on the complexity of the problem and the available data. Common choices for activation functions in DNNs include ReLU (Rectified Linear Unit) or variants such as Leaky ReLU.

The prepared data is used to train the DNN model. During training, the model learns to map input features to the desired output, which in this case would be predicting future stock market movements or prices. The model parameters are updated iteratively using optimization algorithms such as gradient descent to minimize the prediction error.

Once the DNN model is trained, it can be used to make predictions on unseen or future data. Given the input features, the model predicts the future stock market behaviour based on the patterns it has learned during training.

It's important to note that stock market prediction is a highly challenging task due to its inherent complexity and the influence of various external factors. While DNNs can capture complex relationships in the data, they may still face limitations in accurately predicting stock market movements due to the presence of random fluctuations, unexpected events, and factors that cannot be captured solely through historical data.

RNN

Recurrent Neural Networks (RNNs) are commonly used in stock market prediction because they are designed to handle sequential or time-series data, making them well-suited for analyzing stock market trends and patterns. Here are some reasons why RNNs are used in stock market prediction:

Temporal Dependencies: Stock market data is inherently sequential, with each data point depending on previous data points. RNNs are capable of capturing temporal dependencies by maintaining an internal memory that can retain information from past observations. This enables the model to consider the historical context when predicting future stock prices or market movements.

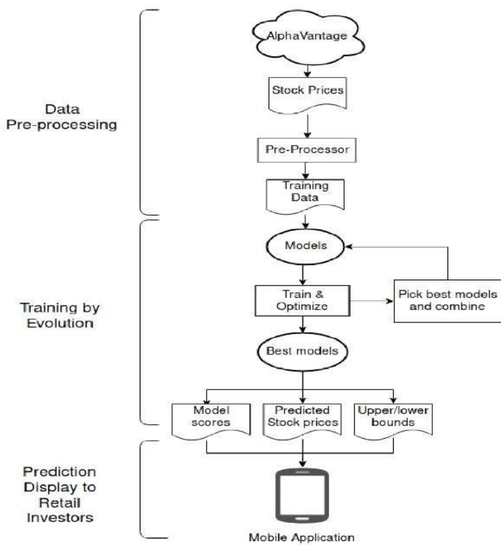
Variable-Length Input: Stock market data can have varying lengths of historical observations, and RNNs can handle inputs of different lengths. This flexibility allows RNNs to accommodate different time intervals, ranging from minutes to days or even longer.

Capturing Patterns: RNNs are effective in capturing patterns and trends in sequential data. By analyzing historical stock market data, RNNs can learn complex relationships and identify recurring patterns that may influence future price movements. This ability to learn from historical data and detect hidden patterns makes RNNs valuable for stock market prediction.

Long Short-Term Memory (LSTM): RNNs, particularly the LSTM variant, are commonly used in stock market prediction due to their ability to overcome the vanishing gradient problem. The LSTM architecture incorporates memory cells and gates that control the flow of information, allowing them to selectively remember or forget information over longer sequences. This helps in capturing long- term dependencies in the stock market data, which is crucial for accurate predictions.

Flexibility in Model Architecture: RNNs provide flexibility in designing the model architecture by stacking multiple layers of recurrent units. This allows for capturing different levels of temporal dependencies and modelling more complex relationships in the data. Additionally, RNNs can be combined with other neural network architectures, such as convolutional layers, to leverage both spatial and sequential information when predicting stock market behaviour.

III. METHODOLOGY



Data Pre-Processing

Data pre-processing refers to the steps and techniques applied to raw data to transform it into a format suitable for analysis or machine learning algorithms. It involves cleaning, transforming, and organizing the data to enhance its quality, structure, and usefulness. Data pre-processing is an important step in the overall data analysis pipeline, as it can significantly impact the accuracy and effectiveness of subsequent analysis or modelling tasks

Model Selection

Choose a suitable deep learning model for stock price prediction. RNNs, especially long short-term memory (LSTM) networks, are commonly used due to their ability to capture temporal dependencies in sequential data. Other models like convolutional neural networks (CNNs) or hybrid models combining CNNs and RNNs can also be explored.

Model Architecture

Design the architecture of the deep learning model. For example, an LSTM-based model may consist of input layers, LSTM layers with appropriate configurations, and output layers for prediction. The number of layers, the number of neurons per layer, and the choice of activation functions can be determined based on the complexity of the problem and available data.

Training

Train the deep learning model using the prepared training data. During training, the model learns to map input sequences of historical data to predict future stock prices. The model parameters are updated iteratively using optimization algorithms like stochastic gradient descent (SGD) or its variants to minimize the prediction error.

Evaluation

Evaluate the trained model using the testing set. Calculate appropriate evaluation metrics such as mean squared error (MSE), root mean squared error (RMSE), or mean absolute error (MAE) to assess the model's performance. Compare the predicted stock prices with the actual prices to measure the accuracy of the model.

Prediction

Once the model is trained and evaluated, it can be used to make predictions on unseen or future data. Given the input sequence of historical data, the model generates predictions for future stock prices.

IV. CONCLUSION

The project lays the foundation for democratizing machine learning technologies for retail investors, connecting predictions made by machine learning models to retail investors. It helps investors navigate through the stock markets with additional analysis and help them make more informed decisions. In conclusion, stock market prediction is a challenging and complex task that requires careful analysis, modelling, and evaluation. While various techniques and approaches can be employed, it's important to understand the limitations and uncertainties associated with predicting stock market behaviour.

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