Stock Market Direction Prediction Using Deep Learning

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***Abstract*—The advent of trading technology has made stock trading accessible to a larger number of people. This has made stock trading one of the best sources of income for a large part of the younger population. This stock trading is highly dependent on the accurate and reliable prediction of the stocks that are being traded. Reliable prediction helps the individual or a firm achieve better trading profits. Manual prediction and trading systems have their disadvantages of being tedious and inaccurate, an automated system of prediction can be implemented using the machine learning technique. This study investigates the ability of deep learning modalities of machine learning to predict stock market direction prediction. This study implements the Deep Long Short-Term Memory (LSTM) model. The implemented models are evaluated based on the Root Mean Squared Error (RMSE) as evaluation metric.**

***Index Terms*—Artificial Intelligence, Prediction System, Deep Learning, Long Short Term Memory (LSTM), Root Mean Squared Error (RMSE).**

I. Introduction

The stock market has been an important mode of wealth generation for both the companies and the traders. Owing to this, a large amount of research is being conducted in the field with the assumption that the information available about the past of a stock can be utilized for future returns (Kolarik & Rudorfer, 1994). The traders try to analyze this underlying predictability of information to achieve higher gains. However, stock prices are dependent on various factors ranging from Government decisions and regulations, industry-specific growth reports, and also the company-specific quarterly reports etc. (Qui & Song, 2016; Lakshminarayanan & McCrae, 2019). Recent advancement in technologies have made the stock markets being traded over internet and has caused a large population across the globe to trade stock at the convenience of their homes and offices (Qui & Song, 2016). With such a large number of transactions being happening around the world each second, the stock prices tend to change instantaneously. This is attributed to the news that arrives at the markets almost randomly. This nature of the behavior of stock market is called 'random walk' model which states that the next best prediction for a stock price is its current price. Efficient stock market also means that the entities that are affecting a stock price has already affected it even before the traders can place the trade (Fama, 1970). However, this is true only for efficient markets, which is an ideal situationPredicting stock prices beforehand involves modelling the stock prices based on its past values. This becomes a problem of time-series forecasting. There are algorithms that are developed for time-series forecasting. They are Autoregressive (AR), Autoregressive Moving Average (ARMA), Autoregressive Moving Average (ARIMA), and Seasonal ARIMA (SARIMA). The major drawback these algorithms face is their accuracy in prediction. Various studies in the past have shown that these models are highly inaccurate (Sharma & Bhalla, 2021). Another drawback that these algorithms suffer from is the stationarity of the time series. These algorithms are required to have stationary time series in order to make reliable predictions. To avoid the drawbacks associated with these algorithms, machine learning techniques are being incorporated in stock market predictions. Machine learning algorithms are preferable over the conventional techniques firstly because they do not suffer from the drawback associated with the conventional techniques, and second, models built using the machine learning techniques can be automated and can be implemented in all sorts of devices (Shen & Shafiq, 2020).

A. motivation

The motivation to undertake this study is that the stock market has become a major source of parallel income for working class, housewives, and students as well. Developing a system of stock price prediction can help the parties involved achieve higher gains with their existing investments. An automated system of stock price prediction can also help large trading firms to trade in multiple markets across the globe in real time and achieve higher returns.

B. research question

This qualitative research aims to find answer to the following research question. "How can a system of stock prices prediction be developed to ensure profits to the traders?" Seeking answer to this question also generates separate sub questions. These are listed below. 1. What kind of role should a supervised machine learning model be able to perform in predicting stock prices? 2. Will the individual models be enough to establish a model of automated prediction?

C. objectives

To fulfil the aim of the research, following objectives must be satisfied. 1. Identifying a dataset that will be used for the study. 2. Identify the supervised machine learning models that are capable of predicting future values. 3. Identify the necessary constraints in developing a system of automated stock prices prediction.

II. LITERATURE

Stock market direction is important as it helps in presenting the direction that leads to the necessary opportunity to be taken into account if the markets are subjected to rise. It will be holding accountability to the individuals' stock prices, which are subjectively to rise up and further associate with bringing a clearer identification on the decisions that are to be made focusing on the information needed. The stock market direction prediction has been associated with multiple standard applications and activities, which relates to significantly stronger understanding established on the associated market direction. The ratio is further computed by categorizing the number division through putting up options holding critical accountability for trading standards as needed. The current literature review would be discussing through the literatures that already exist in regards to deep learning process. The literature would be drawing out accountability to the existing research strategies essential in managing through the constructive development of the market prediction process as applied and followed in the organization.

A. Deep learning

Deep learning models are based on objective functions that are effective in holding accountability to the process of objective function in a manner that addresses the design revealing through the purpose of the model as needed. It will be drawing accountability to the overall understanding and is aligned on the prospect of learning models relating to the critical management of the different types of reward-based model and multi-objective optimization processes. It is further associated with drawing and undertaking the necessary data needed to conduct the act of prediction or any other data undertaking activities. Deep learning models are subjected to the presence of large model complexity, which will be effective in holding accountability to the artificial neural networks, and associated with the presentation of the ANN characteristics, which is efficiently controllable. The prospect of managing through deep learning activity is widely regulated with multiple adjustments established on the different types of network layers holding numerous connections as well as layer size (Vinayakumar et al. 2019). The application of deep learning is identified to be categorically easy in bringing a subjective understanding on the level of accuracy that is being established over the larger data volume that needs to be assessed. Deep learning models hold the presence of feature learning ability where the performance of the model is widely based on the reliability established over the neural networks (Lee et al. 2019). This allows an automatic clearing process while efficiently featuring on the representations using non-linear transformation carried out through the primitive data features as needed. deep cleaning can be effective drawing using salient features that are efficient in targeting the overall tasks without needing the requirement of model designs to be able to obtain the special domain knowledge strategically. The third option for the process of deep learning model to be successful is the end-to-end learning process that does not hold significant understanding in the machine-learning model or the categorisation relating to the multistep features as well as solutions to be pressed (Vinayakumar et al. 2019). It will be corresponding to the learning features while holding efficient categorization on the modelling structure and ensemble through the same. The hardware usage for deep learning will be effective in bringing clear accountability to the standards of development that must be undertaken to manage through the prospects for deep learning models and development as needed. The overall accountability to be associated with the computational efficiency has been effective in managing through the progress needed while holding accountability to the graphics processing unit process. It will be relying on the overall understanding to be established on the accelerated computation system relatively applied on the different types of activities that are needed with a better parallelism system.

B. Stock market direction prediction

The stock market direction prediction refers to the application of different types of tools and techniques that provides an accurate index of the direction that the stock is proceeding, referring to the trends that are occurring in the stock. It will be corresponding to the management standards that are a necessity in drawing accountability to the process of return that must be obtained holding specific investing portfolios that have been established by the company and the stock management agencies (Gunduz et al. 2017). It is important to note that there are multiple standards and options available to ensure effective prediction of the stock market direction. These processes are focused on identification and management of the indicators that are relatable to the Put-Call Ratio (PCR). This ratio is significant, as it will be holding a clear management on the overall standard indicators that is being used on a wider note gauging the market direction that significantly demonstrates a simple ratio that must be followed to hold accountability to the division of the trading put options that are available. There are a significant number of PCR values, which are effectively present and readily available in different formats holding accountability to the option of exchange matters. These are coercively based on the overall PCR values holding accountability to the equity-only PCR and the index-only PCR values. It is categorically essential in holding clear identification of the PCR containing referring to the options data and the exclusion of the overall equities options that are present. The emergence of machine learning and artificial intelligence algorithms has been effective in taking down the computational demanding process that must be taken into account into the mathematical models of stock price direction prediction process. It is widely efficient in drawing clear accountability to the standards of development holding cellar application for the neural network system that is based on the Bayesian networks, along with the support vector machine system. It is important to note that there have been multiple predominantly methods that are present and applied in the stock market process which collectively brings a more strategic identification of the approaches that are successfully based on the SVM application. Apart from the machine learning models and other various techniques that are followed to determine the stock market direction, prediction can be further recognised through the application of the different types of tools. These tools are efficient in resigning through the stock trends, the moving averages, relative strength index, Fibonacci retracement, and support and retracement. Identifying through the stock trend will be based on the parameters that confirm where the stock is a trade pick or not (Zhong and Enke, 2019). This will be holding accountability to the technical analysis undertaken over the software present relating to a clear management and identification of the moving convergence as well as divergence present. It is important to note that the overall understanding established on the Fibonacci retracement and the candlestick price chart application identifies it to be more efficient in presenting a clear sound daunting over the associated management of the software available in the current times. Moving averages are subjected to the development of an understanding which is clearly defined through the multiple categorization on the sensex that is being developed in a given duration of time. It is important to note that the establishment of the relative strength index relates to the development of clearer RSI, which further compares with the alginates that must be associated with losses occurring holding accountability to the asset that is being overseen on a categorical manner. It is important to note that the scope of holding clear accountability to the prediction process is further resurfaced with the identifier standards of development.

C. Application of deep learning in stock market direction prediction

The application of the deep clearing process or method in the stock market direction prediction has been categorically associated with the exploited models for the short-term stock market price trend. This trend process is significantly associated with the different types of support vector machines holding accountability to the multilayer perception within the artificial neural network significantly developed. The scope of drawing accountability of the machine learning models are subjected to the different types of performance that must be drawn over the training significant associated with the selected RFE. It is important to note that the LR algorithm will be holding lesser cost training in comparison to the other algorithms that are present. It will be holding categorical knowledge on the different types of activities that must be considered to bring significant management of the result structure that is to be associated with the data classifier standards. The rate of accuracy is subjected to the standards of development, which must be categorized with the prediction system that is being stimulated with multiple investments being undertaken while processing through the different types of simulated invested tests undertaken. The application of the deep cleaning method is categorically associated with the management of the PCA effectiveness, which holds major accountability to the training procedure that has been proposed to the LSTM model as well. It is important to note that the overall significance that has been established using the model training process refers to the features of holding a set of five principal components that must be significantly improved through the training efficiently which is efficiently needed to be taken into account (Shen and Shafiq, 2020). This further relates to the understanding that the application of the deep learning model to associate with the development of the stock market direction prediction system is significantly associated with the proposed fine-tuned as well as customized deep learning prediction system necessity.

D. Price prediction by using machine learning

Stock market return related accurate prediction connects with the computational capabilities, programmed methods and considers prediction processes that can prove to be effective to maintain the better prediction plan for the stock prices. The technical analysis processes with the understanding about volume traded, opening price possibilities and considering adjacent values which is highly effective to consider in this prospect that develops and processes with standard economic directions through financial action get accessed. Advanced intelligent techniques with the proposed support plan and evaluations cater the ideas about better efficiency support and maintain the idea regarding supportive economic directions. Variety of efficient data and maintaining proper patterns and complex data sets can be mitigated by engaging with the strong machine learning approaches. Ensemble learning is associated with the different types of machine learning that connect with classical algorithms and present the ideas about different linear models like Autoregressive Integrated Moving Average and Autoregressive Moving Average that support stock market prediction while managing enhanced processes in the machine learning system.

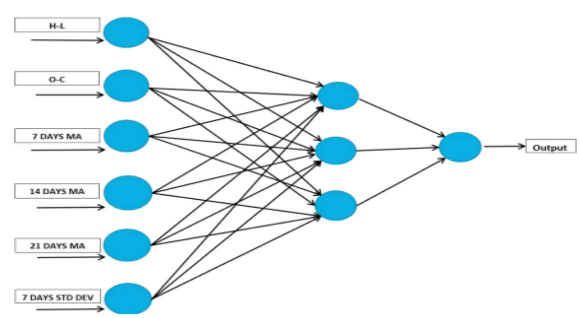

Fig. 1.

The machine learning technique followed by Artificial Neural Network (ANN) helps to cater the ideas about promising result specific approaches and it is capable of finding out specific data about the entire system. The forecasting processes through effective operational processes connect with the output segment that is the regression of individual decision trees. ANN is highly capable of finding some hidden features and maintaining self-learning processes so that dataset related input and output systems. Vijh et al. (2020) has used different new indicators that support and maintain the necessary ideas regarding standard action specific directions and maintain coordinated support plan that connects with proper volume and data-set practices so that helpful projections and necessary variable specific ideas can be coordinated and supported. ANN provides major support towards intelligent data mining techniques and processes with fundamental trends that find effective capabilities to channelize most effective action methods to access different output layers and its functions.

III. Methodology

This section discusses the methodology that has been implemented in the study. Following figure 2 depicts the modules involved in the methodology.

Fig. 2.

This study follows the CRISP-DM methodology to mine and analyze the data. CRISP-DM is a data mining methodology that is used by various organizations across the world (Schröer, et al., 2021). Following figure 5 depicts the CRISP-DM architecture. This study aims to apply the CRISP-DM up until the Evaluation phase as the deployment of the methodology will be discussed in future work in subsequent sections. Phases of the CRISP-DM study are discussed below. CRISP-DM Phases: Following are the phases involved in the

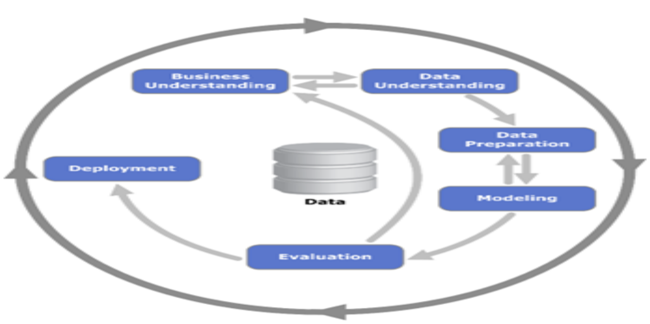

Fig. 3.

CRISP-DM Methodology. The phases relating to the study are discussed below.

A. Data Understanding

The dataset under the study contains time series of stock closing prices for Apple containing more than 63 samples. Figure 4 below depicts the Apple closing prices.

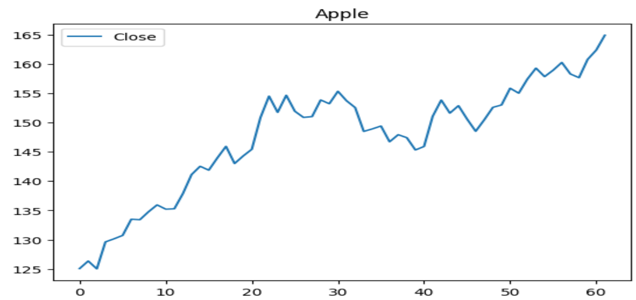

Fig. 4.

B. Data Preparation

This phase of the methodology deals with the preparation of the data for processing. This study involves two operations in this phase. They are data normalization and data splitting.

IV. . Modeling

This phase of the CRISP-DM involves identifying and implementing suitable models for the prediction. This study makes use of sequential models of regression for predicting the stock prices of the shares.

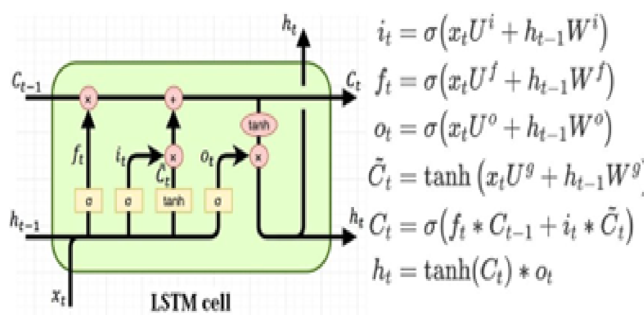

Fig. 5.

V. Data Analytics and Insights

This section of the study discusses the data analytics and insights through the results obtained for the implemented methodology. This section discusses the dataset in detail, insights into the dataset, and vital information about it. The data analytics for the study is conducted using the Python programming language using the Jupyter computation framework.

A. The Dataset

The dataset consists of 5 columns as depicted in figure 6 below. These columns act as attributes for study. Figure 9 below displays the last five rows of the dataset. The figure shows the date, Close, Volume, Open, High, and Low attributes. This study works on the ‘close’ attribute of the dataset for prediction purposes. The values in the figure belong to the closing prices of Apple stock.

	Date	Open	High	Low	Close	Adj Close	Volume
0	2023-01-03	130.279999	130.899994	124.169998	125.070000	124.879326	112117500
1	2023-01-04	126.889999	128.660004	125.080002	126.360001	126.167366	89113600
2	2023-01-05	127.129997	127.769997	124.760002	125.019997	124.829399	80962700
3	2023-01-06	126.010002	130.289993	124.889999	129.619995	129.422394	87754700
4	2023-01-09	130.470001	133.410004	129.889999	130.149994	129.951584	70790800

Fig. 6.

Figure 7 below illustrates the Apple closing prices. The highest value of the price can be seen to be around 165. The number of values is 63.

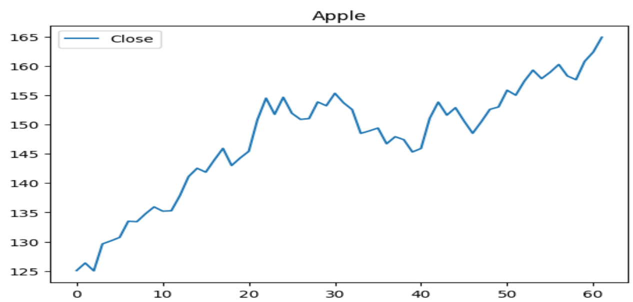

Fig. 7.

Autocorrelation of a time series data analyses the similarity of the time series with the lagged version of itself. It helps identify important information about the time series. It helps in measuring the relationship of the current values of the time series with its past values. Figure 8 below depicts the autocorrelation of the Apple stock closing prices with a lag of 5-time steps. Autocorrelation helps to identify the predictability of a time series. From the figure, the diagonal cluster of values indicates that the time series is highly auto correlated which means that the series is predictable.

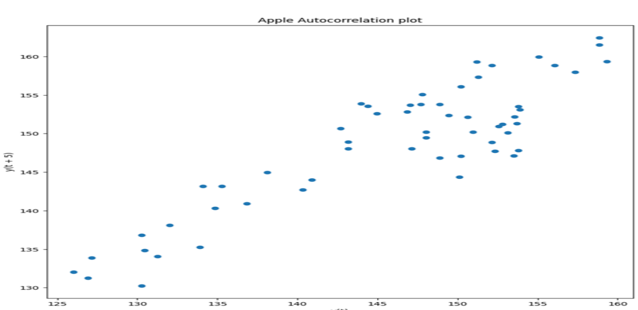

Fig. 8.

B. Data Preparation

In the first phase of data preparation, data present in the dataset is normalized between 0 and 1 using the Min-Max normalization. The data takes values as shown in figure 9 below.

```
[array([0.00125384, 0.03360091, 0.        , 0.115346  , 0.12863584,
       0.14317952, 0.21238738, 0.21038133, 0.24423267, 0.27382161,
       0.25551682, 0.25702126, 0.32221662, 0.40346051, 0.43906728,
       0.42226693, 0.47492506, 0.52432291, 0.45085267, 0.48319953,
       0.51178529, 0.64694112, 0.73921778, 0.6697593 , 0.74297892,
       0.67452365, 0.64819458, 0.65170511, 0.72291904, 0.70661991])]
[0.7600302728207331]
```

Fig. 9.

C. modeling

The modeling phase of the study trains the models on the training part of the data after normalization. This study involves the implementation of LSTM, Decision Tree Regression, Linear Regression, and Ensemble of Models for prediction. Their implementation is discussed below.

The LSTM model of neural networks involves implementing layers of the neural network. The following figure 10 illustrates the implementation of the LSTM model for prediction. The model is implemented using the Keras library available for Python. The Sequential() function of the Keras initializes a sequential neural network (i.e. an RNN). The type of RNN required is implemented by adding the particular hidden layer in the model. The LSTM layer as shown in the figure is added to the model with 128 hidden neurons. To implement stacked LSTM layers, the return_sequences attribute of the LSTM layer is set to True which returns 3D input to the next LSTM layer. The deep architecture of the LSTM is achieved by adding a 'Dense' layer to the model. The model in the study assumes 25 neurons in the hidden dense layer. The final layer of the model is the output layer.

```
# Build the LSTM model
model = Sequential()
model.add(LSTM(128, return_sequences=True, input_shape= (x_train.shape[1], 1)))
model.add(LSTM(64, return_sequences=False))
model.add(Dense(25))
model.add(Dense(1))

# Compile the model
model.compile(optimizer='adam', loss='mean_squared_error')

# Train the model
model.fit(x_train, y_train, batch_size=1, epochs=1)
```

Fig. 10.

The initialized model is compiled using the 'adam' optimizer with the loss metric of 'mean_squared_error'. The model is trained with the batch_size of 1 and epochs=1 using the fit() function.

D. evaluation

The models that have been implemented in the study are evaluated based on their predictions.

Figure 11 below shows the prediction of the next 30 samples for the Apple stock using the LSTM model.

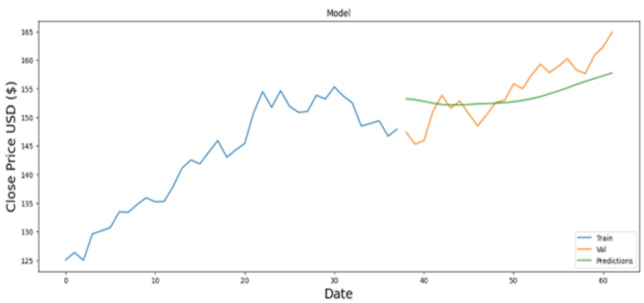

Fig. 11.

VI. Conclusion and Discussion

Predictive analytics is an important field of data analytics that deals with the prediction of the future occurrences of the data based on the historical data available. This helps in designing important systems across various domains. One such domain is the financial domain. The most important field of this domain is stock price prediction. Although many systems such as Autoregressive (AR), Autoregressive Moving Average (ARMA), and Autoregressive Integrated Moving Average (ARIMA) have been used for the prediction of stock prices, they, however, are not accurate and suffer from many disadvantages. One of the main disadvantages is that they are computationally expensive models for predictions. They also need to have a stationary time series. The prediction itself is, however, not an easy task to achieve in financial markets as they are dependent on various factors. Today's markets are getting more and more connected to each other an event in one market can considerably affect another. This makes predicting stock prices all the more difficult. The manual prediction has its disadvantages as it can become more labor intensive and slow. In the current financial world's fast-paced economy, this is highly disadvantageous. To ensure better stock price predictions at a higher speed, machine learning modalities are being implemented as shown by various research. Being highly accurate, machine learning models are finding their uses in applications across multiple domains. Considering their, business scopes, they are being highly studied in the financial sector. This study has implemented machine learning techniques to learn and predict the trend in stock market prices of Apple. The implemented Long Short Term Memory (LSTM) model is evaluated based on the root mean squared error (RMSE) metric. The results show that the LSTM achieved the RMSE of 4.03. The RMSE obtained for the LSTM has been found to be the lowest. With such a small RMSE, it can be concluded that the LSTM is able to reliably predict the future values of the stock prices. The high accuracy of LSTM can be attributed to the sequential nature of the model. Because of the presence of the memory units, the model itself improved upon the result subsequently achieving the best results. In conclusion, it can be said that a system of stock market prediction can be implemented using the powerful model of LSTM.

VII. Future Work

This section of the study discusses the future prospects of the research undertaken. As this study involved 5 of the 6 steps in CRISP-DM methodology, the future work of the study can be to implement the 6th step of the CRISP-DM i.e., the deployment phase. The implemented model of the prediction i.e., the LSTM model can be deployed to predict the stock prices. These predictions can help the investors and traders in the stock market to achieve better monetary results. The developed model can be tested across a variety of stocks to confirm its reliability and accuracy. Including larger data in learning yields better accuracy results in the case of supervised machine learning models such as LSTM. Hence the knowledge attained by the model by studying all the stocks of the share market can help implement the most reliable model for stock price predictions.

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