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Study and Analysis of Stock Market Prediction Techniques

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Abstract. The stock marketplace is a complex and demanding system in which people make more money or lose their entire savings. High-accuracy stock market forecasts offer higher returns for stock investors. Stock market data is generated in very large quantities and it changes rapidly every second. Making decisions in the stock market is a very challenging and difficult task of the financial stock market. The development of efficient models for forecasting decisions is very difficult due to the integration of stock market financial data and should have high accuracy. This study attempts to compare existing models for the stock market. Various machine learning methods such as Long Short Term Memory (LSTM), Convolution Neural Networks (CNN) and Convolution Neural Networks - Long Term Short Memory (CNN-LSTM) have been used for comparison. Models are estimated using conventional strategic measurements: MAE (Mean Absolute Error).

Keywords: Stock Market Prediction, LSTM, CNN, CNN-LSTM.

1. Introduction

Stock market forecasts are very crucial as they are used by many business people and the general public. People will either gain cash or lose all their financial savings in the stock market. Creating a specific model is difficult because it depends on more than one element, including news, social media information, fundamentals, company production, authorities bonds and the economics of the country. An inference model that has only one factor may not be accurate. There are many theories concerning the stock market that have been conceivable for years. Those principles try to explain whether the market can be defeated or try to explain the nature of the stock market. The market value of a stock consolidates all the information about that stock in that particular time frame. Traditional analysis is mainly based on finance and economics which uses basic and technical analytical methods. First, the fundamental analysis focuses on the underlying stock values and qualitatively analyzes external factors such as interest rates, exchange rates, inflation, industrial policy, the finances of listed companies, and international relations that affect stocks. Second, technical analysis largely focuses on the direction of the share price, trading volume, and the psychological expectations of investors that are largely focused on the stock.

Market using tools such as K-line charts or analyzing individual stock directions in a stock index. The above methods are the most commonly used methods for many companies and investors [4,5].

It is difficult to guarantee the accuracy of traditional fundamental analysis because the predictive results are highly dependent on the professional quality of the analysis and the influential factors are in a long-term cycle. Stock data features random walks in the financial time range. Due to the unfamiliar and high noise characteristics of the financial time series [6], only the accuracy of the use of the time series model is questioned.

There are certain limitations to clearly predicting stock price trends when using the linear time series forecast version or the neural network version. Currently, there is now a trend of economic improvement for time series deep learning [7], combining the advantages of different methods to enhance the hybrid approach.

Therefore, to make better use of the time range, a thorough examination of the characteristics of the record and the accuracy of the share price forecast can be improved. This paper mainly compares stock price forecasting approaches based on CNN, LSTM and CNN-LSTM.

The changing trend of stock prices is regularly referred to as the total turmoil within the financial sector [1]. Share prices suffer from a variety of internal and external factors, including the domestic and foreign financial environment, global conditions, enterprise prospects, financial information of indexed companies, and stock market performance [2, 3].

2. Literature Survey

The financial marketplace is noisy, non-parametric dynamic and there are mainly two types of forecasting techniques: Technical analysis technique and machine learning techniques [8].

The conventional econometric techniques or equations with parameters aren't appropriate for studying complicated large dimensional and noisy financial data. In the paper proposed by Aparna et al. [9], consideration of various parameters of various datasets as done, it was observed that Decision Boosted Tree was performing better when compared to SVM and logistic regression.

The paper proposed by Vijh et al. [10], dataset of five companies from 2009-2019 having new parameters for better prediction, such as High - Low , Open-Close, 7 day average stock price, 14 day average stock price, 21 days average stock price , last 7 days standard deviation was used. Comparative analysis basedon RMSE, MAPE and MBE results clearly shows that ANN provides better stock prediction when compared to RF.

The paper proposed by Hyeong et al.[11], the model performance was validated on both different time periods with several metrics like MSE, MAE and RMSE. By analyzing the testing results it was observed that Arima-Lstm hybid performs far better when compared to other financial models.

The paper proposed by Pushpendu et al.[12] it mainly focuses on application of Random Forestand LSTM to predict stock prices directional movements. It was observed that the LSTM outperforms random forests.

The paper proposed by Mehtabhorn et al. [13] it basically compares the various types of machine learning techniques and algorithm which is used in finance and stock market prediction.

The paper proposed by Wenjie Lu et al. [14], The CNN-LSTM model is used to predict the closing price of a stock price the next day.Experimental results show that CNN-LSTM have highest accuracy and best performance compared to CNN, RNN,LSTM< MLP and CNN_RNN.

The paper proposed by Nusrat Rouf et al. [15] comparisons of ANN, SVM, NB and DNN was carried out. SVM was the most popular technique used for SMP. It was observed that ANN and DNN performs more accurate and provides fasterprediction.

The paper proposed by Jingyi Shen et al. [16] used a comprehensive deep learning system. Prediction was carried on the datasets of Chinese stock market usingthe LSTM models. It was observed that the LSTM model achieved high prediction accuracy and outperformed the major models.

The paper proposed by D. Wei et al. [17], the prediction was performed on the datasets using various LSTM models. It was observed that Vanilla LSTM, Stacked LSTM and Bidirectional LSTM are the commonly used LSTM models. BI-LSTM was having greater accuracy and low error when compared to other models.

The Paper proposed by Sheng Chen and Hongxiang He et al. [18], CNN model was used formaking Stock prediction which was perform using conv 1d function to process 1d data in convolution layer. It wasobserved that if source data is sequential then the model is efficient and can even be used to make predictions.

The paper proposed by Wu et al. [19] with leading indicators prediction was performed on dataset using hybrid CNN- LSTM model. It was observed that CNN-LSTM model was achieving greater accuracy when compared with CNN and LSTM models.

The paper proposed by Xuan Jiet al. [20], MAE, RMSE and R-square values are calculated to evaluate the performance of various prediction models. It was observed that CNN-LSTM model out performs well when applied on various stock prices.

The paper proposed by Vanukuru, Kranthi et al. [21], the SVM model was used for predicting the stock index movements. It was observed that model generates higher profit as compared to selected benchmarks.

The paper proposed by A M Pranav et al. [22], the sentimental analysis was performed on stock prices to forecast stock price variations. It was observed that machine learning models were performing well on various datasets

3. Existing Machine Learning Models

A. Convolution Neural Network (CNN):

Sheng Chen [16], proposed a CNN model for creating stock prediction that use the conv1d function to process the 1D data in the convolution layer. CNN is a feedforward neural network that performs very well in image processing and natural language processing. If implemented correctly, it can even predict forecasting of the time series. The local perception and weight distribution of the CNN can significantly reduce parameter range thereby improving the performance of model learning.

The CNN as shown in Figure 1, particularly consists of a convolution layer as well as the pooling layer. Each convolution layer consist of various convolution kernel and its formula is shown in equation (1).

$$o_v = \tanh(v_i * k_w + v_b) \qquad (1)$$

where o_v is the output value after convolution, tanh is the activation function, v_i is the input vector, k_w is the convolution kernel weight, and v_b is the convolution kernel bias.

The CNN model extracts the features map with varying details across convolution layers of stock data. The stock data includes stock market performance of assets over the period of IPO (initial public offering - private companies offers its share to public in new stock issuance) introduction to current date. This is inherently temporally interdependent data which has been discovered in the EDA (Exploratory Data Analysis – the process of inspection of the dataset to find patterns, irregularity and structure hypothesis based on the comprehension of the stock dataset) phase. This temporal dependency is extracted as a 2D feature map by CNN which in turn is passed through dense layers to generate single continuous output that is target variable which is open price of the stock.

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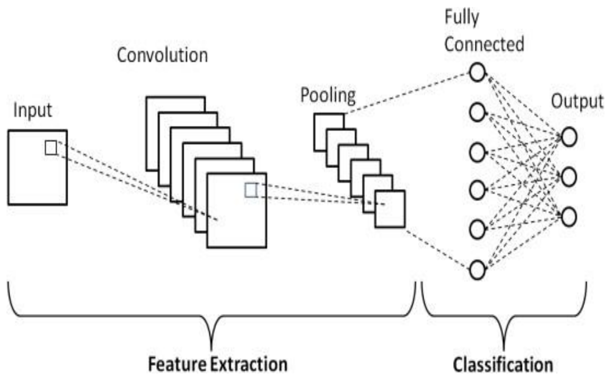

Figure 1. Convolution Neural Network (CNN)

B. Long Short term Memory (LSTM):

Xuan Ji [20], developed a new stock price forecasting model based on deep learning technology that uses Doc2Vec, SAE, wavelet transform, and LSTM mode. It mainly focuses on feature selection of stock financial features and text features (through social media like investors' comments and news published regarding stocks published by the companies).

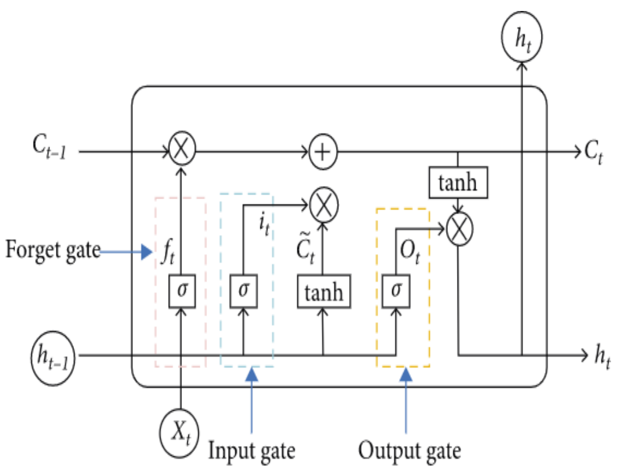

Figure 2. Long Short term Memory (LSTM) [14]

As shown in Figure 2, the LSTM memory cells consists of three parts: a forget gate, an input gate, and output gate. LSTM is used in analytical approach because LSTMs can store important information in the past and forget about other information. The input gate adds cell state information, the forget gate removes the information that is not needed in the model and the current gate selects the information that is displayed as an output. LSTMs combines the result of previous gate and the current gate and further, predicts the next state using the gain correlation.

LSTM is suited to extract long term dependencies in sequential data with temporal dependencies as it eliminates vanishing and exploding gradient in the backpropagation phase. The temporal dependency of stock market data is modelled by unfolding the data in time and passing through LSTM which predicts the output at next time step. The last price, volume and date provides input to the model and the open price is produced as the output of the target variable.

C. Convolution – Long Short term Memory Hybrid (CNN-LSTM):

The paper proposed by Wenjie Lu [14], states that a CNN-LSTM model is used to predict the closing price of the stocks of the next day. This method takes opening price, highest price, lowest price, closing price, volume, turnover, ups and downs, and changes in stock data as inputs, uses CNN to characterize the input data, and uses LSTM output to extract. It then learns the characteristic data and predict the closing price of the stock price the next day.

In CNN, it has the notions of listening to the maximum apparent features within side the line of sight, so its miles is extensively utilized in feature engineering. LSTM has the property of increasing overtime and is widely used in time series. The model structure diagram is shown in Figure 3. The CNN captures the spatial dependencies in the stock data inherent to the images. LSTM resolves the issue of vanishing or exploding gradient associated to the long term temporally dependent stock data. The combination of CNN and LSTM is tested in the predictive model. The CNN layers are used as initial layers which extracts the features in the sequential stock data andLSTM is then cascaded to incorporate long term dependency preservation in the features extracted by the CNN layers. At last, fully connected layers have been added to give the single continuous result.

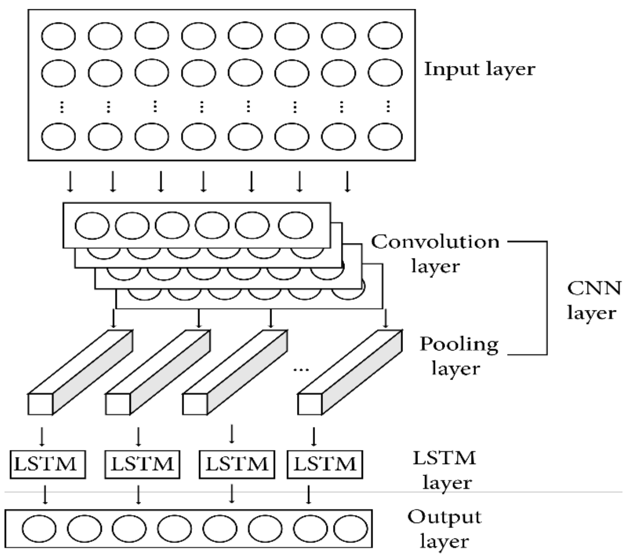

Figure 3. Convolution – Long Short term Memory Hybrid (CNN-LSTM) [14]

The models analyses the dataset in order to remove null values in the columns or replace them with mean or median values and also to detect the relationship between the parameters to determining the important parameters that affects the stock prices. The models handles thecategorical and date type data by identifying the columns/attributes datatypes. The date data type is handleby diffusing it into three components. This generates the report regarding the dataset which is returned to the models which is used for further processing. The dataset is divided into training dataset (80% of original dataset) and testing dataset (20% of original dataset). The trainingof the models is done on the training datasets whose performances (models predicted values on testing dataset)are compared to the testing datasets actual values. This is done by the models which returns the performance metriccalculated on the testing dataset.

PREDICTION WITH MACHINE LEARNING

Most approaches and procedures were tried to attempt to identify the inventory's future value. As the forecast of stock prices in finance and economics is an essential subject, the interests of researchers are becoming increasingly significant in developing a better predictive model which can predict a precise stock value.

FUNDAMENTAL ANALYSIS

Several academics utilize basic analysis and technological analysis approaches to achieve the aim of projecting stock revenues. These guidelines for stock exchange are based on macroeconomic data, ancient stock trading data. Fundamental approaches of analyzes acknowledge that inventory costs are based on their innate features and projected investment profit. Repeated analysts refer to financial statements, text analyses and reports for their data or key accounting signals. In this paper, the author presents the future income changes on the current year's profit change with fundamental signals. Here, one-year-ahead earning is represented as CSPS and designating year is represented as a funtion of t. Here t is the year for which the fundamental signal has been calculated in (1).

$$CSPS = EPS(t + 1) - EPS(t) \qquad (1)$$

Most scientists think that basic analytical procedures are useful for the long-term source. The best approach to understand the existing circumstances is to anticipate the future. It's thought that historical data can forecast future inventory returns [9].

ARIMA MODEL

Since the prediction of the stock prices in finance and in economy is an important issue, the attention of researchers rises to build a better forecast model capable of predicting correct stock prices. In 1970, Box and Jenkins proposed the integrated moving average autoregressive model (ARIMA). For time-series predictions, ARIMA models were studied. A linear combination of previous values and past mistakes in the ARIMA model [13] represents the future value of a variable. ARIMA models have demonstrated their efficient capacity to produce a short-term forecast and have continuously outperformed sophisticated structural models in the short-term [13] prediction. This model in financial time series is especially efficient and solid as the most common ANN techniques [15][17]. This model was recognized for its long range prediction. Predictive ARIMA model building phases involve model identification, diagnostic control and the [18] parameter evaluation. ARIMA models were utilized in [13] to construct a comprehensive short-term stock price prediction method. For the prediction of few studies linked to the ARIMA model [19][24]. The authors utilized the ARIMA model to set up a predictive stock price model with NYSE and NSE data.

ARTIFICIAL INTELLIGENCE AND DATA MINING

The Artificial Neural Network (ANN) model is recognized for its capacity to infer solutions from unknown input while learning patterns from it. To extract information from the data supplied, data mining techniques may be employed to separate knowledge from the data. As a result, a large number of researchers focused on advanced mathematics and science. The subject of artificial intelligence and data mining techniques has received excessive attention [25]. Multi-capacity neural networks have been frequently utilized for financial forecasts owing to its capacity to identify and predict variable reliability properly (1999, Vaughan and Vellido, Lisboa). The input value is concurrently inserted into a layer for each training sample to create the input layer. The IG (information gain) data mining analysis [9] was utilized to discover the entire set of excellent subjects that had a first period input value or variables.

The high is the highest stock price on a particular date. The low is the lowest stock price on a particular date. The last is the last price occurred for the last trade of a day. The close is the closing price of a stock is a price at which the stock closes at end of the trading hours in the stock market. The volume indicates how many are sold and bought in a given time duration.

The parameters settings for CNN model are convolution layer filters are 128, convolution layer kernel size is 3, convolution layer padding is same, learning rate is 0.001, loss function is mean absolute error, epochs is 25 and activation function is relu. The parameters settings for LSTM model are activation function is relu, learning rateis 0.001, loss function is mean absolute error, epochs is 15 and dropout is 0.2. The parameters settings for CNN- LSTM are convolution filters are 64, convolution layer kernel size is 3, convolution layer padding is same, batch size is 4, activation function relu, learning rate is 0.001, optimizer is adam, epochs is 15 and loss function is meanabsolute error.

The dataset is partitioned into 80% training dataset and 20% testing dataset. The mean absolute error (MAE) is calculated for the evaluation of the forecasting effect on CNN, LSTM and CNN-LSTM models.

BPNN

Some models were suggested and developed utilizing neural network techniques stated above, while writers of [26] performed an observatory survey on creating an alert system using neural back propagation networks to buy stocks or to sell alerters (BPNN). In the January 2004 to December 2005 timeframe, the system has been evaluated utilizing previous pricing figures of Hong Kong and Shanghai Banking method Corporation Holdings. The testing results revealed that the developed was able to accurately anticipate short-term pricing by around 74%.

NEURO-FUZZY MODEL

The 5-layer neuro-fuzzy model of Ching Long Su et al [27] is designed to display stock market components by utilizing specialist technical indicators. A number of data comprising four indicators were used to complete this model in prediction and forecasting: the stochastic oscilator (percentage K and percentage D), the adjusted volume moving average (VAMA), and easy moving (EMV) of TAIEX. M.H. The type-2 fuzzy rules based master framework for stock value prevision has been created by FazelZarandiet et al. [28]. The fluid logic system Type-2 allowed uncertainties to be modelled. The type2 fluid model suggested applied to the input variables the specialized and fundamental parameters. The model may be tested on prediction and forecasting of stock prices. The algorithm has succeeded in forecasting stock values from different industries via the tests. In real time trading the results were applied.

NEURAL-FUZZY INFERENCE SYSTEM

Weng Luen Ho et al [29] has suggested a predictor model financial trading system enabling the neural fuzzy inference system of Mamdani Takagi and Sugeno (eMTSFIS). The eMTSFIS model has human hippocampal mechanisms and processing capability. The system presented was based on the idea of average moveable divergence (MACD).

CHMM

Yin Song [30] has suggested a technique for analyzing the market behaviour. CHMM(Coupled hidden Markov model has proposed a new system development graph which would provide anomalies that could occur in connected behaviours. The results are applied to the actual inventory data and have proven the method to overcome both technical and business measures in terms of CHMM Markov basic model. A technique based on the Hidden Markov model was proposed by the authors Tao Xing and Yuan Sun [31] for predicting stock price movements. This document shows the hidden connection between the Markov Hidden. The approach for multiple variable fuzzy forecasting given by Shyi-Ming Chen and Yu-Chuan Chang [13] is implemented with fuzzy clusters and fluid rule interpolation techniques.

GENETIC FUZY SYSTEM AND ANN

In order to create an expert stock price forecasting system, some researchers have introduced genetic fuszy (GFS) and artificial neural networks (ANN). Specification of elements which impact stock prices is utilized step by step with regression analysis (SRA). They spread raw data to k clusters on the next level through the use of neural self-organization map (SOM) networks. Lastly, all the clusters have the capacity to adjust database to GFS models.

DECISION TREE

The financial time series prediction model has been established by developing and grouping fugitive inventory decision trees. For building a decision-making system, the forecasting model is coupled to the data collection process, a fuzzy decision tree (FDT), and genetic algorithms (GA). They used the decision tree classification method. As numerous factors affected the stock market, the results were ineffective for the suggested model. Within this study, a decision tree is utilized in prediction of stocks as a means of improving long-term and N short-term analysis by using some data processing techniques.

AUTO REGRESSIVE APPROACH

To anticipate stock prices, the authors [30] used a selfregressive approach. Because of its simplicity and widespread acceptance, the autoregression design is used. The Moore and Penrose technique is used to predict regression coefficients, and the prediction precision has also been investigated by comparing the values predicted with the actual values.

Convolutional Neural Network (CNN)

P. Patil et al. used graph theory and CNN to create a novel network that used temporal data from numerous equities, portraying the stock market as a complex web. In the meanwhile, stock and financial news indicators were used as inputs in the model. A model featured multiple CNN and bidirectional LSTM pipelines, given by J. Eapen and others. With the S&P500 large challenge data base, a single pipeline deep learning model and almost a factor of six may enhance the preview performance by 9% with a regressive vector maker support model.

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.

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.

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.

Reinforcement Learning

Reinforcing learning is a form of profound learning that focuses on how you respond to profits in a specific circumstance. The two essential components of strengthening learning are state and action. Increasing learning, which supplied buying, selling and holding probabilities as final output, defined the neural net structure, the reward and the behavior of the agents. Q. Kang proposed tackling portfolio management using an advanced Actor-Critical Asynchronous Advantage (A3C method) algorithm and created an independent deep enhancement learning model. This enhancement learning is based on a market reaction to the optimal timing of trading actions (choice of the best price, trading length, and order size).

Proposed Methodologies

In this Methodology we are using SVM and R Forest Classifier for accuracy of Prediction because this algorithm is easy to handle different kinds, various types of attributes.

Classification

Bracket is a case of supervised literacy wherein a hard and fast is anatomized and categorized consistent with a commonplace trait. From the values or data surpassed, the bracket draws some conclusions approximately the observed value (Ali Khan, 2016). But the bracket will essay to prognosticate one or similarly troubles for the equal, If further than one entry is handed. Some classifiers used then for inventory vaticination consist of Random wooded area Classifier.

R – forest classifier

It creates a fixed of choice timber, which produces an end result. Votes from the arbitrary subset of selection timber of choice trees and other hyperactive parameters comparable as the rating to determine the perfection of the arbitrary wood concept, max_features which incorporates the variety of capabilities (Venkatesh and Tyagi, 2011).

SVM classifier

The SVM Classifier is a kind of differencing classifier. SVM makes use of supervised literacy, which is categorized education facts. The affair are hyper planes that classify the new data set. They may be supervised literacy fashions that use the related literacy set of rules for bracket and retrogression. The parameters of the SVM classifier.

CONCLUSIONS

The stock market forecast is a challenge for future stock price forecasting. The stock exchange is too difficult to anticipate, given the changing nature of the stock. Every day stock prices change constantly. The stock market estimation has a strong stock client demand. Implementing at all times all rules derived is an important difficulty in order to estimate with high precision the future stock price. In this study we aim to explain the value of the stock market using around elf prediction models. The major objective of these models was to better explain or forecast the stock market value. These model predictions can aid investors make investing decisions to avoid financial hazards. If investors are able to anticipate the place to put their money, it will be safer and the stock market more stable. However, government officials must handle some concerns in order to prevent stock values from rising and falling inexorably owing to major increases. This article combines stock market news analyses with pricing in order to increase the precise behavior of the stock market. In order to better comprehend market interactions with the investors, we intend to shortly broaden our study on the dependability and compliance aspects of the stock market.

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