International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 03 | March - 2024 SJIF Rating: 8.176 ISSN: 2582-3930

# STOCK PRICE PREDICTION OF NIFTY 50

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***Abstract*—** In this project a forecasting system is presented which can predict the change in stock market value of Nifty Fifty index using the historical data of various factors influencing the stock value. Traditional stock market prediction models only factor in the trends of the historical data of the targeted stock value which is then fed to a time series algorithm to get a forecast. Since the real-world stock market is constantly being influenced by various factors, it is not possible to take all those factors into account and make the forecast, let alone using the target stock by itself. So, the objective of this project is to analyse and use the trends in the factors that majorly influence Nifty Fifty index like international stock indices and commodities that affect the economy addon Recurrent Neural Networks (RNN) which has the architecture that can retain the past information and use it in the prediction along with the observations at the current time step. This will allow the predictions to be more accurate and make it possible to make a better decision when investing in the Nifty Fifty index.

## 1. INTRODUCTION

The stock market is basically an aggregation of various buyers and sellers of stock. A stock (also known as shares more commonly) in general represents ownership claims on business by a particular individual or a group of people. The attempt to determine the future value of the stock market is known as a stock market prediction. The prediction is expected to be robust, accurate and efficient. The system must work according to the real-life scenarios and should be well suited to real-world settings.

The system is also expected to take into account all the variables that might affect the stock's value and performance. There are various methods and ways of implementing the prediction system like Fundamental Analysis, Technical Analysis, Machine Learning, Market Mimicry, and Time series aspect structuring. Predicting how the stock market will perform is one of the most difficult things to do. There are so many factors involved in the prediction – physical factors vs. phycological, rational and irrational behaviour, etc. All these aspects combine to make share prices volatile and very difficult to predict with a high degree of accuracy. In this project, we will work with historical data about the stock prices of a publicly listed company. We will implement a mix of machine learning algorithms to predict the future stock price of this company, starting with simple algorithms like averaging and linear regression, and then move on to advanced techniques like Auto ARIMA and LSTM.

***Keywords :*** Stock price prediction, Data Science, Predictive Modelling, Financial Data, National Stock Exchange, Machine Learning, Economic Indicators

## 2. RELATED WORKS

Predicting the stock price can be achieved using two methods. The first method is based on old models, such as the autoregressive integrated moving average (ARIMA) (Ilkka and Yli-Olli 1987) and the Cartesian autoregressive integrated moving average search algorithm (CARIMA) (Ostermark 1989). The second method is based on contemporary AI models, such as machine learning models (Parmar et al. 2018; Chen et al. 2021), artificial neural networks (Vijh et al. 2020), deep learning (Jiang 2021; Jing et al. 2021), fuzzy logic (Xie et al. 2021). Idrees et al. (2019), focusing on developing an effective ARIMA model for predicting the volatility of the Indian stock market based on time series data. Vaisla and Bhatt (2010) suggested the use of an analysis of the performance of the artificial neural network technique for stock market forecasting.

The projected time series was compared to the actual time series, which showed a mean percentage error of about 5% for both the NIFTY 50 and the Sensex, on average. Validation of the anticipated time series may be performed using a variety of tests. However, for the sake of validation, we employed the ADF and the Ljung–Box tests in this work. We believe that the ARIMA method is adequate for dealing with time-series data, but the drawbacks of choosing the variables were not studied, and the accuracy rate was not calculated for that model.

The NIFTY 50 is an index of 50 listed companies that act as a derivative of underlying stock within the portfolio called the NIFTY 50 index (Mondal et al. 2021). Kurani et al. (2023) have used an artificial neural network to forecast stock values in the financial industry. The authors also investigated the influence of various microeconomics variables and physical elements on the stock price of different financial sector stock values in the financial industry (Kurani et al. 2023). The proposed ANN model yields a maximum error rate of 16.13% for an Axis Bank stock. However, when the macroeconomics factors are boosted, it results in a decrease in the error rate (Jain et al. 2018). Implementing AI models in predicting the stock prices

gradually increases the model's learning ability. In their work, Dash et al. (2019) have made a comparisons between individual classifiers and various ensemble models. A total of 13 classifiers are ranked using the TOPSIS approach, including 7 original classifiers, i.e., radial basis function network, k-nearest neighbour (KNN), support vector machine (SVM), decision tree (DT), logistic regression (LR), naive Bayes (NB), and multilayer perceptron (MLP), as well as and 6 alternate models, i.e., accuracy (A), precision (P), recall (R), f-measures (F1), true positive, true negative, and G-mean. According to the findings, the TOPSIS-based base classifier is used for the CS ensemble to yield more accurate predictions than other ensemble models.

This technique also aids in picking the best-approaching classifiers for this model. Long et al. (2019) suggested a multi-filters neural network for the feature engineering of multivariate financial time series and classification-based prediction using a deep learning approach. Compared to RNN, CNN, and other machine learning models, the prediction result from the MFNN surpassed those of the best machine learning technique, with an accuracy of 55.5%, which was the most accurate prediction. Long et al. (2019) have advised using a particular network to harvest data from many sources (macroeconomic indicators, news, and market emotion) for better predictions. Vijh et al. (2020) have employed artificial neural network and random forest approaches to predict the closing price of five distinct company sectors. They predicted stock closing prices using the RMSE, MBA, and MAPE indicators. The estimated RMSE, MAPE, and MBE indicators in this research show that ANN outperforms RF in forecasting stock prices. In their study, Ananthi and Vijayakumar (2021) used the k-NN regression method to forecast market trends. The stock prices of numerous firms are evaluated, and a collection of technical indicators are projected. The results revealed a significant increase in

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accuracy between 75% and 95% compared to other machine learning techniques.

## 3. SYSTEM ARCHITECTURE

### 3.1 METHODOLOGY:

**DATASET:**

In our work Historical Dataset is used for training and testing and this has taken from Yahoo finance for the INFOSYS Ltd IT sector stock and NSE NIFTY50 index. For Training the dataset we used historical data of INFOSYS Ltd from NSE IT sector and NSE NIFTY 50 from Yahoo finance. The training dataset for the INFOSYS Ltd and NIFTY50 is from the period of 11 DEC 2007 TO 2017 DEC 11 and it contains the historical data set such as Date, Open, High, Low, Close. While training the data, the data has been separated into training and test set, so the training data has no acquaintance that test set exists during its training, but once the training is done, the test has been introduced to the RNN, so that it can make prediction for the future stock price. For feature scaling, the normalization has been applied, so that if there is a sigmoid function as the activation function in the output layer, it can be well accustomed. Therefore, to apply the normalization function:

$$x_{norm} = \frac{x - min(x)}{max(x) - min(x)}$$

To apply the normalization function, Min-MaxScaler class has been used to import from sklearn library. Now for creating a data structure for different time steps, for example- 60 times Steps, RNN is going to look at 60 stock prices before time t and based on the correlations and trends it is capturing, it will try to predict the next output i.e., the stock price at time t+1. By doing that we are appending the 60 previous stock prices for the current time t. So in the scope of this Financial Engineering problem, where we try to predict the trends of stock prices, predictors are the indicators, for now we have one indicator that is open Infosys Ltd. Stock price and we take 60 stock prices to predict the next one, that's the only indicator but to predict better results we need to add more indicators to predict the upward and downward trend of the stock market that is by using the reshape function which uses input shape which is the exact function expected by RNN in Keras, it contains the input in the form of 3D array which contains batch size, time steps and third one is corresponding to the indicators

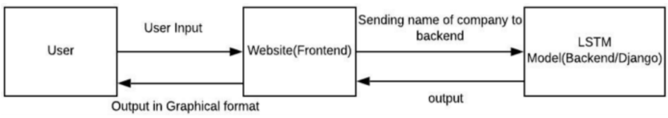


*Figure 5. Block Diagram of the proposed system*

The Long Short-Term Memory or LSTMs overcome the problem of Vanishing Gradient Descent because in Gradient Descent as we propagate the error through the network, it has to go through unravelled temporal loop and as it does that it Goes through the layers of neurons and are connected to themselves. In LSTM architecture, the memory line is at the top and the lower line represents the output i.e.,ht and xt-1 represents the previous block whereas Xt+1, represents the next block and similarly Xt represents the input. It is noticeable that output is coming from previous block is also impacting the result. It takes three inputs and has two outputs and all the values are vectors i.e., all the variables contain multiple values rather than the singular value.

The point wise-operation are controlled by layered operations sigma or sigmoid function and based on the output or decision of that, the valves is either closed or open. If it's open the memory flows through it freely. And as the decisions are made, the value which is another layer operation is either added to the memory or not added, so depending on the value that is decided in the point wise-operation. As point wise- operation contains the value either zero or one, the last point wise-operation is the output valve where it decides what part of the memory pipeline is going to be the output.

Though there are many variations in the LSTM's architecture, the basic functionalities are same. For testing, we chose data from NSE NIFTY 50 from Yahoo finance. Here, in the testing dataset we have extracted the daily opening and closing price of every stock and to predict the stock rate for the following year using different time steps and different number of LSTM, the result has been determined. Test datasets were considered from the period of 12 DEC 2017 TO 2018 DEC 12. The epoch size of input stock data was found that it performed error calculation for different epoch size that is the most accurate value that has been observed was using the epoch size of 100.

### 3.2 Mean Absolute Deviation:

It is used to measure variability in dataset. The mean absolute deviation is the mean distance between each data point and mean. By calculating how far away the data points are from the mean helps us get the absolute deviation values.

### 3.3 Mean Squared Error:

We measure the squares of the loss or error incurred. It is basically the square of the difference between the actual value and the forecasted value.

$$MAD = \frac{\sum_{t=1}^{n} |A_t - F_t|}{n} \qquad (2)$$

$$MSE = \frac{\sum_{t=1}^{n} (A_t - F_t)^2}{n} \qquad (3)$$

### 3.4 Mean Absolute Percentage Error:

When the loss or error has to be estimated in percentage terms then we use Mean absolute percentage error. It is evaluated is an unsigned percentage error that helps us assess the forecast accuracy

$$MAPE = \frac{\sum_{t=1}^{n} (A_t - F_t)/A_t}{n} \times 100 \qquad (4)$$

## 4. DEEP LEARNING:

When there is humongous amount of data there might be issues with predicting data with simple machine learning models, this is deep learning comes to the rescue. However, it might be a question for a lot of data enthusiasts as to when to we consider data as being big enough. Over a million samples is big enough. However, to test a model one may
not require huge set of data and some of the applications of deep learning involve speech recognition, image classification, natural language processing and many more. Ultimately, Deep learning is a part of Machine learning. Deep learning is a subset of machine learning and can use models used in it. However, with improved accuracies Recurrent Neural Network is a deep architecture of neural networks that

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learns from sequences, while dealing with sequential data we require a model known as Recurrent Neural Network. The same way as in the CNN processes its grid of values x such as an image, Recurrent Neural Network (RNN) is a neural network that is specialized for processing values x(1) … x(n) .The RNN can process any sequence irrespective of the length

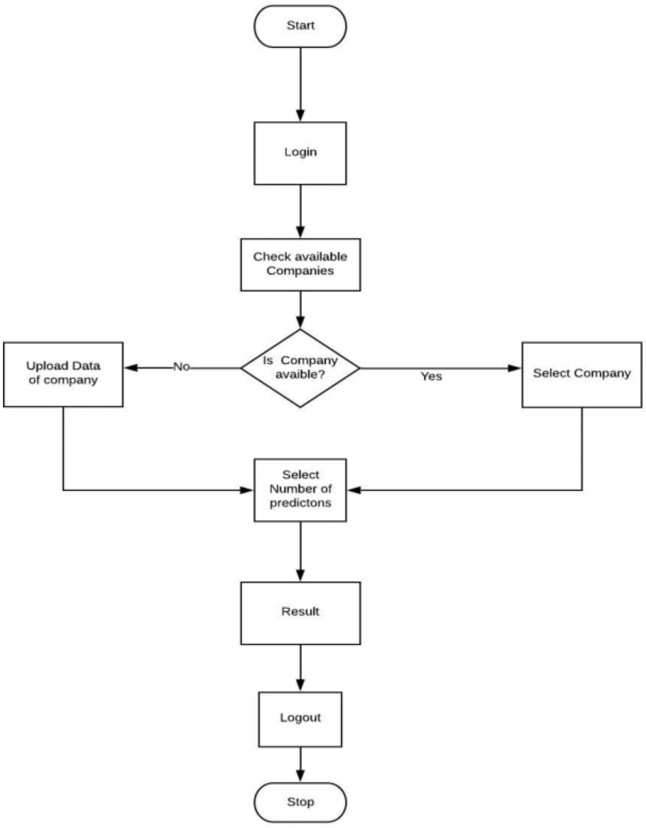


*Figure 6.Achitecture of system design*

## 5. RESULT AND DISCUSSION

In summary, when using LSTM models for stock market prediction, one can expect relatively high accuracy in short-term forecasts, with results influenced by data quality, market conditions, and model complexity. Back testing helps assess historical performance and risk management. Users should remember that predictions come with inherent uncertainties, and continuous model improvement is essential for adapting to evolving market dynamics. LSTM predictions serve as a valuable tool for informed decision-making but should be combined with sound investment strategies and risk mitigation measures.

## 6. CONCLUSION

Conclusion After researching through various papers related to Time series analysis , stock market prediction. We have concluded that predicting the stock market is really a challenging task and also involves a lot of factors including natural factors,
company's production or work. so it's impossible to predict accurately price of stock but A deep learning model can be developed that can predict the value of stocks based on previous values according to time or data which is just a mathematical model which can help us to see how market is going or we can take look of market direction i.e. trends. Various experiments have been conducted using different methodologies, the best results are seen in the methods that are based on neural networks. and used a method with less error

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