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# Stock Price Prediction Using Machine Learning

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**ABSTRACT:** The project aims to provide retail investors mobile application to navigate through the stock market. This is achieved through the use of machine learning and mobile web technologies. Several stock price prediction approaches and models are developed including dense, feedforward neural networks, recurrent neural networks, simple linear regressions, and linear interpolations. Model architectures and hyperparameters are optimized and automatically searched by evolution algorithm. Promising results are found for trend prediction. The project serves as a foundation for democratizing machine learning technologies to the general public in the context of discovering investment opportunities. It paves the way for extending and testing out new models and developing AutoML in the financial context in the future. Stock prices are represented as time series data and neural networks are trained to learn the patterns from trends. In any country stock market is one of the most emerging sectors. Nowadays, many people are indirectly or directly related to this sector. Therefore, it becomes essential to know about market trends. Thus, with the development of the stock market, people are interested in forecasting stock price

KEYWORDS: Deep Learning, neural network, stock market, prediction

I.

# INTRODUCTION

Over the course of time, one will note that mankind has wanted to eliminate the suffering from his life. The presumption in society is that making more money brings security and luxury, so it is reasonable that there has been a lot of focus paid to trying to predicting the stock rates. Various strategies, hypotheses, and metrics, all with their own properties, have been attempted with differing degrees of effectiveness. Although it was attempted using a number of methods, no one was successful in solving the problem. The field of artificial intelligence researchers and investors alike are expecting that neural networks will help them figure out the underlying principles of consumer behaviour. A stock market is a public venue where shares of stock and derivative securities are exchanged at a given price. This is the type of market in which securities listed on a stock exchange can still trade. The corporation has a governing authority whose shares are traded on the stock exchange. It is often referred to as the secondary market because it takes place between two participants and influences the primary market. The Financial Exchange puts the two disparate people together to trade in their securities. Pricing in the stock market is determined by supply and demand. When stocks that are popular fall out of favor rise in price, on the market, but stocks that are being dumped on the market will decrease. Listed companies are described as any organization that has publicly filed shares that are traded on the stock exchange. Investors like to make the most money by buying and selling when their shares are at a point when they are both at their maximum.

# II. **RELATED WORK**

"Neural Network Technology for Stock Market Index Prediction"[1]. Stock market is characterized as dynamic, unpredictable and non-linear in nature. Predicting stock prices is a challenging task as it depends on various factors including but not limited to political conditions, global economy, company's financial reports and performance etc. Thus, to maximize the profit and minimize the losses, techniques to predict values of the stock in advance by analysing the trend over the last few years, could prove to be highly useful for making stock market movements. To obtain higher accuracy in the predicted price value new variables have been created using the existing variables. ANN is used for predicting the next day closing price of the stock and for a comparative analysis, RF is also implemented. The comparative analysis based on RMSE, MAPE and MBE values clearly indicate that ANN gives better prediction of stock prices as compared to RF. Results show that the best values obtained by ANN model gives RMSE (0.42), MAPE (0.77) and MBE (0.013). For future work, deep learning models could be developed which consider financial news articles along with financial parameters such as a closing price, traded volume, profit and loss statements etc., for possibly better results.

"Stock Closing Price Prediction using Machine Learning Techniques" [2] Stock market prediction is act of trying to determine future value of stock. As study of stock market subject is very vast and huge; hence, it is difficult to predict



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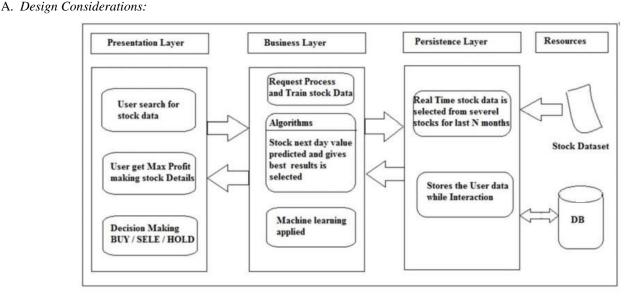
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accurate value of stock. So, in this work we will be using machine learning algorithms to predict the accurate value of stock. Linear Regression Model Basically regression based models are used in evaluation of continuous data. It is predictive modelling technique which is used to determine the relationship between independent and dependent variables as discussed in equation \. Random forest is one of the widely used model in prediction of stock. It works on the principle of decision tree. It is a type of ensemble learning. Proposed models are used to predict the accurate value of stock index from the given inputs as well as used to calculate the accuracy of each algorithm

"Application of Artificial Neural Network for stock market predictions".[3] Stock Market has started to attract more people from academics and business point of view which has increased. So this paper is mostly based on the approach of predicting the share price using Long Short Term Memory (LSTM) and Recurrent Neural Networks (RNN) to predict the stock price on NSE data using various factors such as current market price, price-earning ratio, base value and some miscellaneous events. methodology of data then model then predict and finally error calculation where there are few more works gone across this field using various other different methods using deep learning using text based method also using the numerical and both using RNN, LSTM and few other mechanism. the same cycle which is based on the company's various sector and trends can change change in this type of analysis sector but proper analysis will provide a greater profit so we have to use analytical strategies such as RNN, LSTM and Back propagation on the current information.

"Stock Closing Price Prediction using Machine Learning Techniques".[4] Researchers have found that, historical stock data and Search Engine Queries, social mood from user generated content in sources like Twitter, Web News has a predictive relationship to the future stock prices. The closed stock price return values of Dow 30 are the predicting variable in this research. DJI (Dow Jones Industrial Average Index) is used since it is a stable index. stock prediction involves with a time series, Recurrent Neural Network (RNN) is used. Initially various types of algorithms like LSTM (Long Short-Term Memory), ARIMA method were employed. Among those, LSTM showed comparatively best performances. LSTM network is a state-of-the-art RNN for the time series prediction at the time. Sentiment score (ts), Web news sentiment (ns), Google trends hits volume (gv), and closed stock price (c) were the input variables for the multivariate and univariate time series forecasting.

## III. **PROPOSED ALGORITHM**



#### Fig 1: System Architecture

## B. Description of the Proposed System:

The architecture of the system follows a client-server model, where the server and the client are loosely coupled. After relevant stock data are retrieved from the third-party data provider through the cloud, the backend pre-processes the data and builds the models. After that, predictions are made and the prediction results will be stored on another cloud, which can be retrieved from the web application. The advantages of the loosely coupled architecture include improved scalability and ease of collaboration. The workload for the cloud which serves the models and the one which serves the mobile application will be very different. One cloud serves the model prediction results, which are simple

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text files; another cloud serves the mobile application with a lot of rich user content such as images and large UI libraries. Having two clouds to adapt to two different demand patterns is more efficient, especially since cloud providers these days usually serve content on demand. Also, the separation allows different team members in the team to focus on different parts after agreeing on a common interface. It speeds up development as team members responsible for different parts of the system do not need to take care of the underlying implementation details. Also, it is easier to swap out different components, e.g. to replace the models the team could simply make changes to the backend, while the frontend remains unaffected



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mean 482.0343 468.4949 475.5134 475.1773 11,348,652.9921 468.1	
std 187.1424 183.2140 185.3756 185.2111 9,701,729.7369 189.4	
min 163,0000 152,6800 156,5600 156,5700 0,0000 148,4	
25% 279.1950 272.2575 274.8950 275.7550 5,978,261.5000 260.1	
50% 503.5250 490.0500 496.5000 496.6000 8,551,323.5000 489.0	
75% 621.8250 603.5375 613.1750 612.8375 12,812,866.2500 611.1	
max 866.9000 825.4500 848.4000 845.1000 120,541,914.0000 845.1	

Fig2 : Axis Bank Historic Price Visualization

Data	Dpen	High	Low	Close*	Adj Close**	Volume
May 20, 2022	18.82	18.83	18.39	18.70	18.70	6,019,100
May 19, 2022	18.36	18.83	18.22	18.63	18.63	9,392,800
May 18, 2022	19.32	19.39	18.76	18.78	18.78	10,672,000
May 17, 2022	19.42	19.62	19.40	19.61	19.61	7,184,600
May 16, 2022	19.13	19.18	18.90	18.94	18.94	11,057,600
May 13, 2022	19.30	19.51	19.19	19.45	19.45	14,033,200
May 12, 2022	19.16	19.65	19.12	19.53	19.53	13,434,100
May 11, 2022	19.59	19.77	19.38	19.41	19.41	8,503,200
May 10, 2022	20.02	20.12	19.52	19.76	19.76	18,342,600
May 09, 2022	20.04	20.14	19.76	19.82	19.82	14,538,200
May 06, 2022	19.96	20.00	19.71	19.85	19.85	6,614,900
May 05, 2022	20.60	20.79	20.11	20.31	20.31	9,577,100
May 04, 2022	20.10	20.66	20.04	20.61	20.61	7.519,400
May 03, 2022	20.19	20.29	20.13	20.22	20.22	7,716,800
May 02, 2022	19.88	20.22	19.84	20.15	20.15	15,073,900
Apr 29, 2022	20.24	20.30	19.87	19.87	19.87	12,324,800
Apr 28, 2022	20.41	20.66	20.35	20.50	20.50	24,229,100
Apr 27, 2022	19.99	20.32	19.99	20.12	20.12	9,754,100
Apr 26, 2022	20.25	20.38	20.06	20,12	20.12	13,027,100

Fig3 : Axis Bank Dataset

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Fig.4.Axis Bank 100 Days average Price



Fig.5. Axis Bank 100 Days vs 200 days average Price

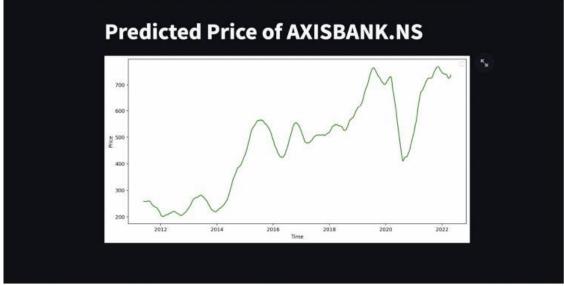


Fig.6 Axis Bank Predicted Price

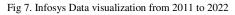
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INEX							
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count	High 2,857.0000	2,867.0000	2,857.0000	2,867.0000	2,867,0000	2,867.1	
mean	9.9673	9.8180	9.9032	9,9044	11,656,102.2323	8.1	
std	4.7749	4.6978	4.7369	4.7376	7,888,454.9235	5.0	
	4.8263	4,7413	4.7850	4.7712	1,068,400.0000	3.1	
25%	7.2506	7.1150	7,1775	7.1925	7,195,600.0000	5.8	
50%	8.4838	8.3200	8.4100	8.3988	9,813,600.0000	7.1	
	10.3725	10.2075	10.3000	10.2925	13,914,650.0000	9.6	
max	26.3900	25,5800	26.1500	26.2000	147,591,200.0000	26.5	



9 9873 9.8170 9.9072 9.9044 11,656,102.2323 8.5 4,7749 4,6978 4,7369 4,7376 7,888,454.9235 5.1 1, 4,8263 4,7413 4,7850 4,7712 1,068,400,0000 3.5 7,2506 7,1150 7,1775 7,1925 7,195,600,0000 5.4 9, 8,4833 6,3200 8,44300 8,3988 9,813,600,0000 7.1 9, 10,3725 10,2075 10,3000 10,2925 13,914,650,0000 9.4 30 26,3900 25,5800 26,1500 26,2000 147,591,200,0000 26,2								<u>0</u> + (		
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n       4.8263       4.7413       4.7850       4.7712       1,068,400.0000       3.7         %       7.2506       7.1150       7.1775       7.1925       7,195,600.0000       5.1         %       8.4530       8.3200       8.4130       8.3388       9,813,600.0000       9.1         %       10.3725       10.2075       10.3000       10.2925       13,914,650.0000       9.1         %       26.3900       25.5800       26.1500       26.2000       147,591,200.0000       26.2	mean	9.9873	9.8180	9.9032	9.9044	11,656,102.2323	8.5			L
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26.3900 25.5800 26.1500 26.2000 147,591,200.0000 26.2 NFY company chart	90%	8.4638	8.3200	8,4100	8.3955	9,813,600.0000	7.6			
NFY company chart	75%	10.3725	10.2075	10.3000	10.2925	13,914,650.0000	9.6			
and my my	max	26.3900	25.5800	26.1500	26.2000	147,591,200.0000	26.3			
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Fig 8:Infosys Price Char



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Fig 9:Infosys



Fig 10:Infosys



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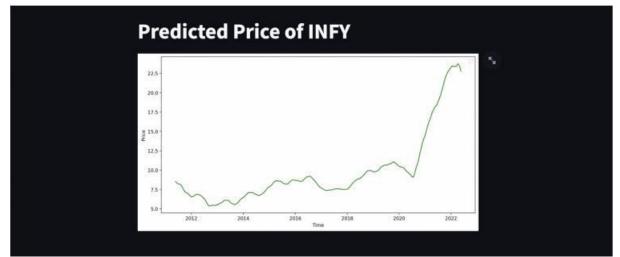


Fig 11:Infosys Predicted price

### V. CONCLUSION AND FUTURE WORK

Predicting financial time series is a tough work due to its low signal-noise ratio and there is too much noise in this kind of series. The neural network has many advantages in explaining the non-linear relationships in time series. In the future, we might consider combining linear and non-linear models to build a new model in stock predicting such as using an exponential smoothing method to fit the linear part in financial time series and using the neural network to fit the nonlinear part. In exponential smoothing, some specific neural network could also be used to estimate the coefficients. In financial time series, there might be lots of indicators which could influence the trend of the stock price. Selecting proper indicators is another problem researchers may face. Recently, unsupervised learning has been popular in deep learning. An appropriate model could be constructed by using an unsupervised learning method so that the model could extract vital information in many indicators to reduce the dimension in the inputs and reduce the parameters for training.

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