Stock Market Price and Cryptocurrency Price Prediction

Shiva Agarwal

Department of Computer Science and Engineering National Institute of Technology, Silchar Silchar, India shivaagarwal793@gmail.com

Abstract—Stock market price and cryptocurrency price prediction is a very challenging task. We are proposing dynamic algorithms which make use of LSTM and another time Series algorithm, i.e., prophet and we have various trained models on these two algorithms. We will make use of this dynamic algorithm which will self-evaluate different datasets and different pretrained models and will provide us with the best possible output for different test cases. For the longer duration, we are just focusing on up and down, but for the small duration, we are focusing on price-related accuracy. The main and challenging work is to deal with the dynamic dataset, so we require some dynamic algorithm for this.

Keywords—RNN, LSTM, CNN, LSTM, Artificial Intelligence, Machine Learning.

I. INTRODUCTION

Stock market price and cryptocurrency price prediction is a very challenging task. Making correct analysis of stock price is always being so much challenging to market experts. Also, for current generation machine learning and artificial intelligence algorithm, it is a very challenging task. When we look at how the stock market and cryptocurrency work, we have to understand the various concept of economics like demand and supply, market capitalization, stock or cryptocurrency open, close, high and low price, p/e ratio, people perception about that company, working model of different cryptocurrency and various other. Time series data can be difficult and frustrating to work with, and the various algorithms that generate models can be quite finicky and difficult to tune. After that, I have to select the top 50 Indian companies and top 2 cryptocurrencies to work with and make price predictions on them. The price variation of the stock market is a very dynamic system that has been very challenging and tough analysis from a number of disciplines. Coming to cryptocurrency, it is very volatile in nature, and also price variation is very high. We have seen that there are some specific trends that the market follows.

A. Background of Stock Market and its prediction

Firstly, we have to introduce Various terms which are related to the stock market. It is a challenging task. Not so easy, Various risks are involved. Keep the price monitoring of various stocks on; the understanding market cycle is truly challenging. Understand various market indicators like the P/E ratio. DOW feature, profits of the company, their advertisement budget, and various other things. It is truly a concept of demand and Supply.

B. Motivation

Growth of money, power of compounding, learning trends in the market, people perception for start-up, how the company grows. After completion of the project, we will have knowledge of trends in the market and machine learning or Naresh Babu Muppalaneni
Department of Computer Science and Engineering
National Institute of Technology, Silchar
Silchar, India
nareshmuppalaneni@gmail.com

forecasting algorithms that can predict the stock market and cryptocurrency for a longer duration of time.

C. Problem Statement

The issue existed for a long time to achieve high accuracy in the prediction of the market. We have seen that there exists no correct system for long-duration prediction. So, there is a huge gap in the current technique to correctly identify close, open, high, low, and volume prediction of stock and cryptocurrency. Also, this is accomplished by lack of availability of features, i.e., profit, loss, and tweets data which we need to make analysis. The price of stock and cryptocurrency is dynamic in nature, and dealing with this dynamic data is a challenging task.

D. Challenges

- As far as challenges are concerned, each researcher has worked on different data set. Hence, it is very difficult to predict how this is going to work on our data set.
- 2. Computation power, various machine learning models, have their different training time, some might do it early, and some might take a lot of time.
- 3. Major concern is with sudden changes of policies of the government, news, brand competitor tactics, malpractices inside the company, etc.

E. Our Contributions

Our major contributions in this paper are we have developed three models

- i) LSTM + Min Max scaler for short-term predictions of 7-30days.
- ii) LSTM+ Prophet + Log returns of closing price for long term and short term predictions
- iii) Auto ARIMA + Log Returns of Closing price for a more realistic approach

II. LITERATURE SURVEY

In 2014 The autoregressive integrated moving average (ARIMA) models were developed in Text for time series prediction. The author of this paper presents the challenging process of making a stock price prediction model by making use of the ARIMA model [1]. Taking stock data which is obtained from New York Stock Exchange (NYSE) and Nigeria Stock Exchange (NSE) are used with stock price prediction model developed. Results obtained stated that the ARIMA model has a strong potential for short-term prediction but for the long term, it has been found that accuracy has decreased. Hence it is not good for long-term prediction. Also, the accuracy claimed by the author is only 60 - 70%.

In [2], the authors used three different deep learning architectures, RNN, LSTM, and CNN, for the prediction of

share price and compared the error percentage of these three models, and also compared it with ARIMA. The authors work on three companies TCS, Infosys, and Cipla. The errors in the prediction of these models are listed in Table I.

TABLE I. ERROR PERCENTAGE

Indian Companies	RNN	LSTM	CNN	ARIMA
Infosys	3.81	4.17	2.35	32.91
TCS	7.64	7.81	8.95	22.16
Cipla	3.82	3.93	3.62	35.53

In [3], the authors explore the hypothesis that derived information from the news is most likely to have an adverse effect on the second-order characteristic of market volatility than on the asset values or their direction of motion. The authors carry out an extensive study and show findings in support of this knowledge. He constructed a Latent Dirichlet Allocation (LDA) model, which uses natural language processing features and reduction, though it proves to be a computationally high cost to train. Classification is achieved using a naïve Bayes algorithm, which proves well derived the simple assumption of feature independence. He is able to manage and obtain the accuracy of 40-60% and predicted closing price and volatility of stock using the model.

In [4], research was done for Crypto-Currency price prediction using Decision Tree and Regression. In the given work, it is made under consideration to predict the Bitcoin price correctly considering different findings that affect the Bitcoin price. It is finding the price trend on day-to-day

variation in the Bitcoin price while it gives information about Bitcoin price. For the dataset of bitcoin, he has claimed accuracy for a short period of time 95.88 for the decision tree and 97.59 for regression.

In 2020, Ali Mohammad Tarif and S M Raju [5] used the knowledge of sentiment analysis they classify the data into three major sentiments, namely positive, neutral and negative, and uses the machine learning model LSTM and ARIMA and predicted or forecast that on that particular day whether the price of bitcoin prices will fall or goes up.

In 2018 M, Hiransha & Gopalakrishnan, E. A & Menon, Vijay & Kp, Soman [6] develop a model for NSE Stock Market Prediction Using RNN, LSTM, CNN, and MPL with Accuracy ranging between 85-91%.

In 2019 A. Sachdeva, G. Jethwani, C. Manjunath, M. Balamurugan, and A. V. N. Krishna [7] made a deep learning model using Recurrent Neural Network for predicting variation in the National Stock Exchange of the stock market index, i.e., NIFTY 50 and predicted Infosys stock market data with an accuracy of 97% and for others, he was able to make a prediction with 90% accuracy.

In 2020 sidra mehtab, jaydip sen, and Abhishek Dutta [8] worked on the dataset of nifty 50 from December 29, 2014, till July 31, 2020, using the LSTM model. His team uses python, TensorFlow 2.3.0 & Keras 2.4.3 frameworks. For a short period of time, all his teammates manage to get a very good accuracy of 90%.

TABLE II. COMPARATIVE STUDY FOR DIFFERENT MACHINE LEARNING MODELS ON DIFFERENT DATASET

Year	Author	Model used	Dataset used	Accuracy achieved
2014	A. A. Ariyo, A. O. Adewumi	ARIMA	New York Stock Exchange	60-70%
	& C. K. Ayo		(NYSE)	
	·		Nigeria Stock Exchange (NSE)	
2017	Selvin, Sreelekshmy, Ravi,	RNN	Infosys	RNN 90%
	Vinayakumar,	LSTM	TCS	LSTM 91%
	Gopalakrishnan, E. A	CNN	Cipla	CNN 90%
	Menon, Vijay & Kp, Soman	ARIMA		ARIMA 61%
2018	Atkins, Adam & Niranjan,	Latent Dirichlet Allocation	Stock Twits, Google Trends of	Predicted market volatility
	Mahesan & Gerding	(LDA)	Goldman Sachs, and J. P.	40-60%
			Morgan	
2020	Ali Mohammad Tarif and S	Sentiment analysis using ARIMA,	BITCOIN	Predicted bitcoin volatility
	M Raju	LSTM		50-65%

TABLE III. COMPARATIVE STUDY ON NIFTY 50 INDIAN DATA SET

Year	Author	Model used	Dataset used	Accuracy achieved
2017	Selvin, Sreelekshmy, Ravi, Vinayakumar,	RNN	Companies of nifty 50	RNN 90%
	Gopalakrishnan, E. A Menon, Vijay & Kp,	LSTM	Infosys	LSTM 91%
	Soman	CNN	TCS	CNN 90%
		ARIMA	Cipla	ARIMA 61%
2018	M, Hiransha & Gopalakrishnan, E. A &	RNN	Companies of nifty 50	RNN 89%
	Menon, Vijay	LSTM		LSTM 90%
		CNN		CNN 89%
		MPL		MPL 90%
2019	A. Sachdeva, G. Jethwani, C. Manjunath, M.	RNN	Nifty 50	90%
	Balamurugan & A. V. N. Krishna			
2020	Sidra mehtab, jaydip sen and abhishek dutta	LSTM	Nifty 50	90%

The outcomes of our literature survey is tabulated as comparative results of various machine learning models on different datasets in the Table II and comparative results on Nifty 50 dataset are tabulated in Table III.

Stock market research by using backpropagation and recurrent neural networks are giving the prominent results[9-10].

III. METHODOLOGY

To design a better accuracy system for long-duration prediction.

More number features

- Stock: profit
- cryptocurrency: tweets

Dynamic data structure.

Development of Automatic dynamic Algorithm. These all will be very crucial and make the accuracy of the system record high.

LSTM (Long short-term memory)

LSTM is an artificial recurrent neural network (RNN) architecture[11] used in the field of deep learning. See in fig 1, which shows how LSTM models work. We can see

- $x^{(n)}$ Shows the n input to the model.
- $o^{(n)}$ Shows the n output of the model.

LSTM unit is composed of a cell, an input gate, an output gate, and a forget gate. In LSTM - RNN, hidden layers are replaced by LSTM Cell add another connection 'C' which is called cell state.

Each LSTM has a cell state(C_t) - to read from it, write from it, reset the cell through an explicit gate mechanism

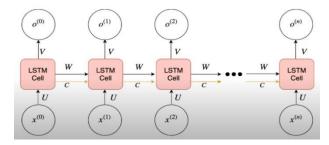


Fig. 1. LSTM Model representation

As shown in Fig 2, there are three gates [12]

1. **Input Gate-** check is cell updated? See Eq 1 for input gate.

$$i^{(t)} = \sigma(W^{i}[h^{(t-1)}, x^{(t)}] + b^{i})$$
 (1)

2. Forget Gate- Is memory set to zero? See Eq 2 for Forget gate.

$$f^{(t)} = \sigma(W^f[h^{(t-1)}, x^{(t)}] + b^f)$$
 (2)

3. Output Gate- Is current information visible? SeeEq 3 for Output gate.

$$o(t) = \sigma(W^{o}[h^{(t-1)}, x^{(t)}] + b^{o})$$
 (3)

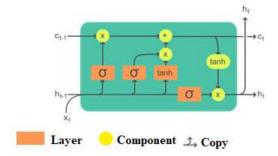


Fig. 2. LSTM model with all input, forget, and output gates.

Facebook prophet model is one of the time series models we have to work on it too. It is open source available on Github[12]. We have to develop the model on the basis of it. It has four things.

- Growth represented by g(t)
- 2. Seasonality represented by s(t)
- 3. Holidays represented by h(t)
- 4. The error which is represented by e_t

Finally, we are talking about an output function that is represented by y(t) as in Eq 4.

$$y(t) = g(t) + s(t) + h(t) + e_t$$
 (4)

Now we propose a dynamic algorithm, and we have the various trained model on these two algorithms. We will make use of this dynamic algorithm which will self-evaluate different datasets and different pre-trained models and will provide us with the best possible output. For a longer duration[12], we are just focusing on up and down, but for a small duration, we are focusing on price related accuracy.

Now we are coming to dataset part. We have used yahoo finance. Table IV. Is having 50 companies and one of cryptocurrency.

TABLE IV. DATASET- NIFTY-50 AND BITCOIN

S.no	symbol	Company name	industry involved
1	ADANIPORTS.NS	ADANI PORTS & SEZ	MISCELLANEOUS
2	ASIANPAINT.NS	ASIAN PAINTS	PAINTS
3	AXISBANK.NS	AXIS BANK	BANKING
4	BAJAJ-AUTO.NS	BAJAJ AUTO	AUTO
5	BAJFINANCE.NS	BAJAJ FINANCE	FINANCE
6	BAJAJFINSV.NS	BAJAJ FINSERV	FINANCE
7	BHARTIARTL.NS	BHARTI AIRTEL	TELECOM
8	BPCL.NS	BPCL	ENERGY
9	BRITANNIA.NS	BRITANNIA	FOOD BEVERAGES
10	CIPLA.NS	CIPLA	PHARMA
11	COALINDIA.NS	COAL INDIA	MINING
12	DIVISLAB.BO	DIVIS LABORATORIES	PHARMA
13	DRREDDY.NS	DR. REDDYS LAB	PHARMA
14	EICHERMOT.NS	EICHER MOTOR	AUTO
15	GRASIM.NS	GRASIM	TEXTILES
16	HCLTECH.BO	HCL TECHNOLOGIES	SOFTWARE
17	HDB	HDFC	FIN. INSTITUTIONS

18	HDFCBANK.NS	HDFC BANK	BANKING
19	HDFCLIFE.NS	HDFC-LIFE INSURANCE	INSURANCE
20	HEROMOTOCO.NS	HERO MOTOCORP	AUTO
21	HINDALCO.NS	HINDALCO	ALUMINIUM
22	HINDUNILVR.NS	HUL	FMCG
23	ICICIBANK.NS	ICICI BANK	BANKING
24	INDUSINDBK.NS	INDUSIND BANK	BANKING
25	INFY.NS	INFOSYS	SOFTWARE
26	IOC.NS	IOC	OIL & GAS
27	ITC.NS	ITC	FMCG
28	JSWSTEEL.NS	JSW STEEL	STEEL
29	KOTAKBANK.NS	KOTAK MAHINDRA BANK	BANKING
30	LT.NS	L&T	ENGINEERING
31	M&M.NS	M&M	AUTO
32	MARUTI.NS	MARUTI SUZUKI	AUTO
33	NESTLEIND.NS	NESTLE	FOOD BEVERAGES
34	NTPC.NS	NTPC	POWER
35	ONGC.NS	ONGC	ENERGY
36	POWERGRID.NS	POWER GRID	POWER
37	RELIANCE.NS	RELIANCE IND.	ENERGY
38	SBIN.NS	SBI	BANKING
39	SBILIFE.NS	SBI LIFE INSURANCE	INSURANCE
40	SHREECEM.NS	SHREE CEMENT	CEMENT
41	SUNPHARMA.NS	SUN PHARMA	PHARMA
42	TATACONSUM.NS	TATA CONSUMER	FOOD BEVERAGES
43	TATAMOTORS.NS	TATA MOTORS	AUTO
44	TATASTEEL.NS	TATA STEEL	STEEL
45	TCS.NS	TCS	SOFTWARE
46	TECHM.NS	TECH MAHINDRA	SOFTWARE
47	TITAN.NS	TITAN	CONSUMER DURABLES
48	ULTRACEMCO.NS	ULTRATECH CEMENT	CEMENT
49	UPL.NS	UPL	CHEMICALS
50	WIPRO.NS	WIPRO	SOFTWARE
51	BTC-INR	Bitcoin	cryptocurrency

We have to build a dataset from Yahoo finance and Tiingo. The dataset has the following attributes.

Date – Shows what is the date on that day

Open – Shows at what price stock is open on that particular day.

Close – Shows at what price Stock closed on that day.

Adj Close – Stands for adjusted close and Shows the close price – dividend given on the stock.

High – This shows what the maximum price stock touched on that particular day was.

Volume – This shows how much stock quantity is traded on that particular day.

We have removed 'Adj Close' from our dataset and made an index on the number. And we can make the choice of any feature, but here we chose 'close' as our feature. Now with the required data, we make them split into training and testing parts. We, for our convenience, choose training 70% and testing 30%. Now we use a min-max scaler to scale down the close feature between 0 and 1. Then we make use of fit transform so that we can pass it for training. Here we use four-layer and at last one dense layer to combine all the layers. We use LSTM from keras.model and finish our training. Using matplotlib.pyplot we can see our predicted model. For this predicted model, we represented original data with the blue line and predicted data as red.

As shown in Fig 3, we can see the Four-layer LSTM model For Price Prediction, and at last, we use a dense layer to combine all four-layer. We can also see the use of a min-max scaler on the close price of the stock.



Fig. 3. Four-layer LSTM model For Price Prediction

The formula for log returns calculation is shown in Eq 5.

$$R_{log} = \frac{ln(\frac{v_f}{v_i})}{t} \tag{5}$$

Here,

R_{log} shows log returns

V_f shows final close price After 't' time

V_i shows the initial close price at staring

t shows the time duration

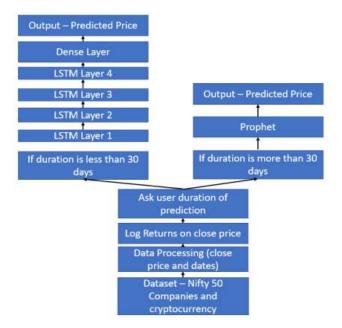


Fig. 4. Using two machine learning algorithms on the basis of the duration of the prediction

Fig 4. using two machine learning algorithms on the basis of duration of prediction, we have made a mixture and let the user decide whether he has to go for a longer duration or shorter duration, basis of which we shift our machine learning model. We have to work on prophet. We are using mixture of time series and machine learning algorithms, i.e., LSTM. For a longer duration of time, we are shifting our model to Prophet, and for a Short duration, accuracy matters where we are using LSTM.

As you see in fig 5. As we see, some model is required, which should be dynamic to deal with dynamic data. As we see, data in the stock market is constantly changing basis of which our model should also be dynamic, i.e., adjust and select best model as per different company and different volatility of different company. See the process and steps by which we are performing such modification as stated in fig 5.



Fig. 5. Auto ARIMA to deals with Dynamic Data

We make the sum of all root mean square errors obtained on it as shown in Eq 6.

$$R(n) = R_1 + R_2 + ... + R_n$$
 (6)

For Finding Accuracy, we take the mean of all root mean square errors.

IV. RESULTS AND DISCUSSION

We have to start from where we have left. In the methodology section, we have discussed three ways of the algorithm.

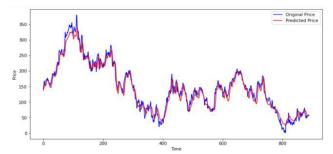


Fig. 6. Graph Between the original and predicted price of any given stock

In Fig 6. we have plotted the graph and formed a conclusion that accuracy of the system using the LSTM model with the use of min-max scalar we have achieved the accuracy of 92 percent, our error find was eight percent in our system. We have further mode work on the dynamic algorithm, so that this can be refined and we can move toward better accuracy. This accuracy depends on various factors like the dataset used and the training layer of our LSTM model. Next, we have to look at long-term predictions using prophet. We are using mixture of time series [13] and machine learning algorithms, i.e., LSTM. For a longer duration of time, we are shifting our model to Prophet, and for a short duration, accuracy matters where we are using LSTM. So, this will make out model double verifiable and make prediction accuracy much higher.

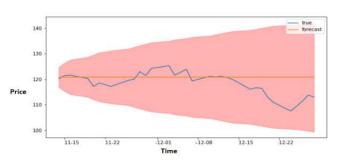


Fig. 7. Using Auto-ARIMA model to predict price

The above fig 7. Shows forecast price with orange line and true price with the blue line. The pink border shows how much variation can be their on-closing price.

TABLE V. COMPARION OF RESULT

Author	Model used	Accuracy
Mehtab S.	LSTM	90%
et al [8]		
Our First	Min-max Scalar + vanilla	92.5%
model	LSTM[15]	
Our second	Log Returns of Stock +	95%
model	vanilla LSTM + Prophet[12]	
Our third	Log returns of Stock +	94%
Model	AUTO-ARIMA model	

In Table V, we have provided a comparative analysis of our proposed three models with the existing model developed by Mehtab S. et al[8].

For accuracy checking, RMSE (Root mean square error) [14] as shown in Eq 7 is used.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} |y(i) - y'(i)|^2}{N}}$$
 (7) We have used the above formula to calculate errors in our

We have used the above formula to calculate errors in our different models. We have taken the mean for all RSME and calculated the new RSME, which will be given us the final error. Hence the accuracy can find out by subtracting RSME by 100, which will give us final accuracy.

V. CONCLUSION

We are looking forward to the various work and modifications; hence, we modified it by using Min-max Scalar and vanilla LSTM, which is a time series model and marked an accuracy of 92.5%. Then we jumped to our last model, which makes use of Log Return and vanilla LSTM, and Prophet. This time we make changes in the accuracy calculation method and define accuracy on the basis of manual method and hence reliable and achieved 95% accuracy. Take reference from Table V. We have developed each model for a separate purpose, and we don't advise any investment for the short term or long term. First, make a detailed assessment of the fundamentals of the company before making any investment. Now coming to details, the first model was developed to make a prediction for a very short duration, like 7-30 days. As LSTM model requires a previous closing price hence not suitable for long-term investment.

The second model takes the input of log return basis, of which we make a prediction of returns of stock price. As we see, we have to make the decision and make divergence on the basis of days required for prediction. Hence this model is used for a longer duration of prediction as it involves trend, growth, and Seasonality component.

Coming to our last model and why we develop this model, the reason is dynamic data and dynamic algorithm. Moving to realism, what we see we will never have next day data for the day after prediction. Our model develops and is tested on realistic data. It has produced good results.

The future scope of this project can be making use of tweets, news, and several other market feature to optimize the model too much higher accuracy.

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