Analysis of a Stock Exchange and Future Prediction Using LSTM

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Abstract:- **Stock Market Prediction (SMP) algorithms, main goal is to estimate the future trend of the market estimation of the monetary stocks of individual company. Machine learning and Deep learning technology have become the new trend for stock exchange prediction technologies, which make forecasts based on training on past trading data. To make predictions more accurate and simpler, Machine Learning itself uses various models. Machine learning and Deep learning technology have become the new trend for stock exchange prediction technologies, which make forecasts based on training on past trading data. To make predictions more accurate and simpler, Machine Learning itself uses various models. In this paper, we are using the Machine learning techniques to analyze the stock price over time, the daily return of the stock on average, the moving average of different stocks, risk in investing stocks at particular trends, and finally predict the future stock behavior using LSTM model. ML itself utilizes various models to make expectations simpler and genuine. This paper keen about the utilization of Regression and LSTM**
Based Machines figuring out how to anticipate stock qualities. To analyze the stock, we are choosing different sectors big players like from telecom sector "Verizon", from digital media "Netflix", from customer relationship management "Salesforce", and from ecommerce sector "Amazon" from these stock elements considered are close, open, high, low, and volume.

Keywords: Machine Learning, Deep Learning, LSTM

I. INTRODUCTION

A right prediction of stocks can prompt immense benefits for the merchant and the representative. Much of the time, it is drawn out that forecast is tumultuous as opposed to arbitrary, which implies it very well may be anticipated via cautiously examining the historical backdrop of separate securities exchange. AI is a proficient method to address such cycles.

It predicts a market esteem near the substantial worth, along these lines expanding the precision. Acquaintance of AI with the zone of stock expectation has spoken to numerous explores in view of productive and precise estimations [1][2].

A dataset is one of the most crucial components of AI. In light of the fact that even a little change in the data can result in a colossal change in the result, the dataset ought to be as exact as possible. The dataset used in this task comes from Yahoo Finance. Managed AI is used in this task. The five factors included in this dataset are open, close, low, high, and volume.

There are four distinct costs offered for a stock at discrete moments with almost direct names: open, close, low, and high. During a given time period, the amount of offers passed from one proprietor to the next is the volume. After that, the model is tested against the test information. LSTM and relapse models are locked in independently for this guess.

Relapse includes limiting mistakes and learning from mistakes This enhances the ability to recall last time's run information and results [3] [4]. In conclusion, the variance charts between a real and an anticipated cost are plotted (in celebration of a regression-based model) and a variance chart between the two (in the event of an LSTM-based model).

The basic research is a sort of speculation examination where the offer estimation of an organization is assessed by breaking down its business, income, benefits, and other financial elements. This technique is generally appropriate for long-haul gauging. Specialized investigation utilizes the authentic cost of trading stock to distinguish the cost of future.

The moving average is a calculation commonly used in specialized examinations. Accordingly, it tends to be understood as the weighted average of the past n data points. The strategy is suitable for transient estimations. Thirdly, time-arrangement information is examined. Calculations are divided into two main classes, respectively:

- Non-Linear Models
- Linear Models

ARMA, AR, ARIMA, and their variants [5] [6]. the most distinctive linear models. Using some predetermined conditions, these numerical models fit a univariate time arrangement. Models such as these have the primary drawback of not representing idle elements found in the information. These models do not recognize entomb conditions among stocks since they consider only univariate time arrangements. Additionally, the model distinguished for one arrangement won't good for the other.

Because of these reasons, it is unimaginable to expect to distinguish the examples or elements present in the information overall. Non-linear models include strategies like GARCH, [6] ARCH, TAR, and Deep learning calculations [7]. In [6] several selected companies listed in NIFTY 50 have been analyzed to determine the relationship between stock price and stock volume. The proposed work focuses on calculating stock value expectations by using profound learning methods [8].

Neuronal associations are non-direct capacity approximates that are capable of planning non-straight capacities. In view of the sort of utilization, different kinds of profound neural organization models are utilized. These incorporate Long Short-Term Memory (LSTM), multi-layer perceptron's (MLP), CNN (Convolutional Neural Network), Recursive Neural Networks (RNN), and so on.

They are experimented in different fields like image processing, NLP, time arrangement analysis and so on. Deep learning algorithms are equipped for recognizing covered-up designs and hidden elements in the information through a self-learning measure. On account of the financial exchange, the information produced is huge and is exceptionally non-direct. Such powerful information can only be displayed through models capable of decrypting and investigating secret examples and fundamental elements.

DL algorithms are equipped for distinguishing and misusing the associations and examples existing in information through a self-learning measure. In contrast to different algorithms, DL models can adequately demonstrate these sorts of information and can provide a good forecast by examining the co-operations and covered-up designs inside the information.

We can notice the use of different DL models for Multiple-variant time arrangement investigation. The primary endeavor to demonstrate a monetary time arrangement utilizing a NN model was presented in [9]. This work made an endeavor to show a neural organization model for deciphering the nonlinear consistencies in resource value developments for IBM.

Nonetheless, the extent of the research was restricted, however, it assisted in setting up proof against EMH. The proposed technique focuses around predicting stock price for International stocks recorded organizations.

The methodology we have embraced is a sliding window approach with information cover. Here we are attempting to acquire a summed-up model with the end goal of forecast which can utilize minute-wise information as info. This sort of demonstrating has applications in algorithmic exchanging where high-recurrence exchanging happens.

The paper is written as follows Section-2, Explains the Background study about algorithm. Section-3, Analysis of stocks and procedure Section-4, Results and Conclusion and Section-5, Future work.

II. BACKGROUND STUDY

In this background study, we are talking about the brief intuition about the algorithms like RNN and LSTM model also discussing about the statistical theories like Variance, standard deviation, moving average and correlation

A. Recurrent Neural Network (RNN)

RNN is one of the members of the Neural Network Architecture family. RNN architecture is a little different compared to the other networks, in that they use the previous run's output to feed the current run. In conventional NN, every input and output is self-governing of each other, except in states like when it is obliged to predict the next word in a paragraph or any sentence, the preceding information is required and therefore there is a necessity to memorize the preceding information.

So, RNN architecture brought into the light, which resolved this problem with the aid of a Hidden Layer. The most prominent feature of RNN is the Hidden layer, which recognizes some data about a series.

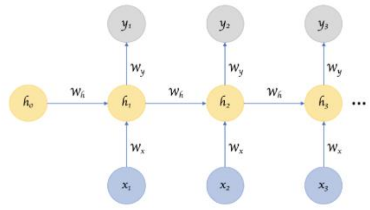


Fig. 1: A Recurrent Neural

1) Network, with a hidden state

In RNNs, all determinations are stored in a "memory." To deliver the results, it applies similar parameters to every contribution as it executes the same operations on every source of information or hidden layer. Contrary to other neural networks, this reduces the complexity of boundaries.

2) Long Short-Term Memory (LSTM)

LSTMs are a one of the special types of architecture of RNN, intelligent of detecting long-term dependences. These LSTM networks are developed by Schmid Huber and Hoch Reiter in 1997 also, were referred and promoted by various researchers in the accompanying work. They are being used on an exceedingly wide range of problems and work admirably.

It is explicitly intended that LSTMs maintain a distance from the drawn-out reliance argument. Their default behavior is to keep a log of data for extended periods of time, not to learn how to do it! Repeated neural networks are chains of neural networks that are rehashed continuously. This rehashing module is common in standard RNNs, for example, as a single tanh layer.

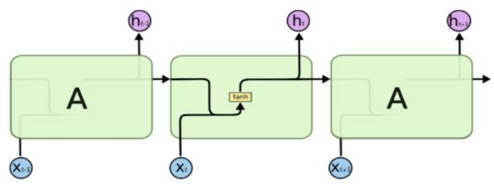


Fig. 2: The Recurrent module in a standard RNN contains a single layer

Like LSTMs, repeating modules have a chainlike structure as well, but they have a different structure. There are four layers, rather than just one, each interacting in a unique way

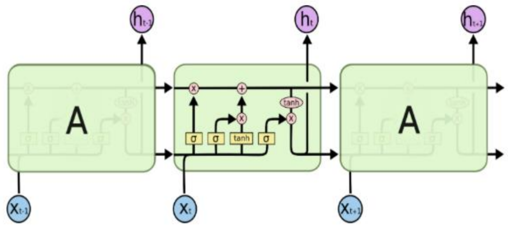


Fig. 3: The Recurrent module in an LSTM contains four connecting layers

Additionally, LSTMs have chain-like structures, yet there is an alternate design for rehashing. it has an extremely uncommon association results from four layers of NN, rather than just one. From one hub's yield to its contribution, each line in the chart represents a whole vector. Point wise activities are covered by pink circles, similar to vector expansion, while learned NN is covered by yellow boxes. Combining a line indicates that its substance is duplicated and transmitted to various location ns, while forking a line implies that its material is duplicated and transmitted to various locations.

The cell express provides an LSTM, the even line extending through the highest point on the graph. An analogy can be made between the state of a cell and the state of a transport line. A few minor partnerships run directly down the chain, with only a few more minor ones. This is incredibly simple because the data just flows along with it unaffected. In the LSTM, complex structures called doors are used to directly affect the phone state, removing or adding data. An alternative method of letting data through is through an entryway. Based on a sigmoid neural network layer and a pointwise increase activity, they create a probabilistic image.

3) *Statistics*

The covariance between the two factors describes their direct connection. When we say a factor is directly related to another or contrarily related to another, we mean it has a heading. The estimations of covariance can be any number between the two inverse vast qualities.

Additionally, notice that covariance just estimates how two factors change together, not the reliance of one variable on another. The estimation of covariance between 2 factors is accomplished by taking the summation of the result of the distinctions from the methods for the factors as follows:

$$Cov(x.y) = \frac{\Sigma(x-\bar{x})*(y_i-\bar{y})}{N} \text{......... (1)}$$

The upper and lower limits for the covariance rely upon the fluctuations of the factors in question. These differences, thusly, can change with the scaling of the factors. Indeed, even an adjustment in the units of estimation can change the covariance.

Accordingly, covariance is simply valuable to discover the bearing of the connection between two factors and not the size. The following are the plots which assist us with seeing how the covariance between two factors would glance in various areas.

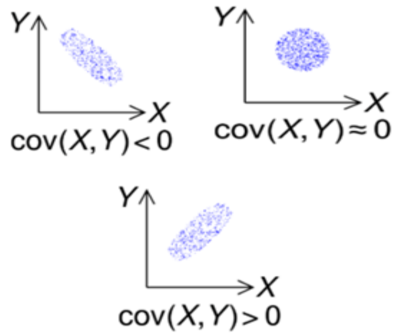


Fig4: Correlation

An investigation into connection between two factors is a method of examining the strength of a correlation between them using mathematical estimation. It is not just shows the sort of connection (regarding bearing) yet additionally how solid the relationship is.

Accordingly, we can say the connection esteems have normalized ideas, while the covariance esteems are not normalized and can't be utilized to look at how solid or feeble therelationship is on the grounds that the greatness has no immediate importance. It can expect values from - 1 to +1.

$$Correlation = \frac{Cov\ (x,y)}{\sigma x * \sigma y} \text{..........(2)}$$

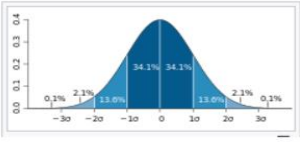
Where:

- Cov is the covariance
- σx is the standard deviation of X
- σy is the standard deviation of Y

To decide if the covariance of the two factors is enormous or little, we need to evaluate it comparative with the standard deviations of the two factors. To do so we need to standardize the covariance by separating it with the result of the standard deviations of the two factors, along these lines giving a relationship between the two factors. The principal after effect of a connection is known as the relationship coefficient.

4) *Standard Deviation*

In statistics, a standard deviation is a measure of the disparity or scattering of variables across a bunch of values. The low standard deviation indicates that quality values are generally near the mean, while the exclusive expectation deviation indicates that quality values are dispersed across a larger area. It basically gauges the outright fluctuation of an arbitrary variable.



$$\sigma = \sqrt{\frac{\sum(x_i - \mu)^2}{N}}$$

σ = population standard deviation
N = the size of the population
x_i = each value from the population
μ = the population mean

Fig. 5 : Standard Deviation

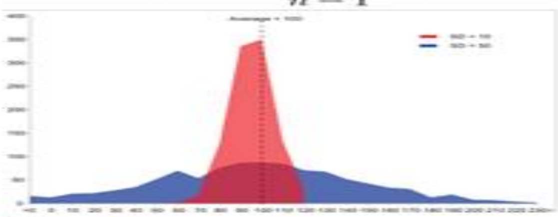
5) Moving Average

The moving Average (MA) is a straightforward specialized investigation device that smooth's out value information by making a continually refreshed normal cost. The normal is assumed control throughout a particular timeframe, similar to 10 days, 20 minutes, 30 weeks or any time span the broker picks.

6) Variance

Change is the assumption for the squared deviation of an irregular variable from its mean. Casually, it estimateshow far a bunch of numbers are fanned out from their normal worth.

$$S^2 = \frac{\sum(x_i - \bar{x})^2}{n-1}$$



S^2 = sample variance
x_i = the value of the one observation
$\bar{x}$ = the mean value of all observations
n = the number of observations

Fig. 6: Variance

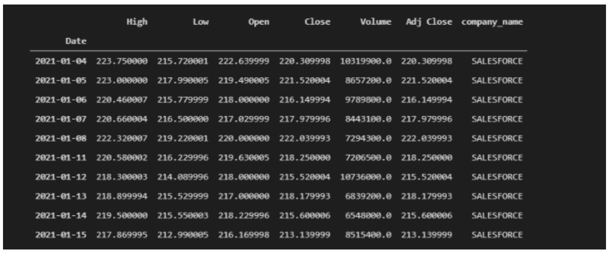
7) Heat map

A statistical reliance is a causal, if factual, relationship between two arbitrary variables or bi-variate information. In a broad sense correlation is any measurable affiliation, however, in like manner utilization, it frequently alludes to how close two factors are to have a straight relationship with one another. Natural instances of dependent phenomena incorporate the correlation between the actual heights of parent and their posterity and the correlation between the interest for a limited stock item and its cost. Correlation regarding the expectation free factor [10].

8) Dataset

In this research we are considering four internationally well-known organizations stock market data. All these organizations are in different sectors and we are directly importing the stock data from the links given below.

1. https://finance.yahoo.com/quote/NFLX/history
2. https://finance.yahoo.com/quote/VZ/history
3. https://finance.yahoo.com/quote/AMZN/history
4. https://finance.yahoo.com/quote/CRM/history



Date	High	Low	Open	Close	Volume	Adj Close	company_name
2021-01-04	223.750000	215.720001	222.639999	220.309998	10319900.0	220.309998	SALESFORCE
2021-01-05	223.000000	217.990005	219.490005	221.520004	8657200.0	221.520004	SALESFORCE
2021-01-06	220.460007	215.779999	218.000000	216.149994	9789800.0	216.149994	SALESFORCE
2021-01-07	220.660004	216.500000	217.029999	217.979996	8443100.0	217.979996	SALESFORCE
2021-01-08	222.320007	219.220001	220.000000	222.039993	7294300.0	222.039993	SALESFORCE
2021-01-11	220.580002	216.229996	219.630005	218.250000	7206500.0	218.250000	SALESFORCE
2021-01-12	218.300003	214.089996	218.000000	215.520004	10736000.0	215.520004	SALESFORCE
2021-01-13	218.899994	215.529999	217.000000	218.179993	6839200.0	218.179993	SALESFORCE
2021-01-14	219.500000	215.550003	218.229996	215.600006	6548000.0	215.600006	SALESFORCE
2021-01-15	217.869995	212.990005	216.169998	213.139999	8515400.0	213.139999	SALESFORCE

Fig7 : Sales force data

III. METHODOLOGY

Since there are numerous components that cannot appear to be taken care of, the stock market expectation appears to be a mind-boggling issue. Also, from the outset, it does not seem to be factual. Even so, through the use of legitimate AI procedures, past information can be linked to current knowledge to allow the machine to make appropriate inferences based on the past information.

The dataset is used for the investigation was gotten from Hurray Account. The dataset comprised around nine lakhs record's about the necessary stock costs and other significant variables. The informational collection comprises of the moment shrewd stock costs for every one of the associations. It incorporates data like time stamp, stock cost, day stamp, exchange id, and sold stock volume in every moment. For this research, we choose four distinct areas, Web based business area, Computerized Media, Client Connection The executives, and IT(Telecom) areas were taken for the examination. The information mirrored the stock costs at exact time spans for every day in a year.

With the end goal of recreation and investigation, the information for just one organization was thought of. All the information was accessible in a document of CSV design which was initially perused and changed into an information outline utilizing the Pandas library in Python. From this, the information for one specific organization was separated by isolating information based on the image processing.

Following this standardization of the information was got through the utilization of the scikit learn python library and the information were separated into test and train data sets into a 20:80 ratio. Despite the fact that AI as such has numerous models this paper centres around two of the most significant among them and made the expectations utilizing these. In this research we are gonna analyze different aspects of the stocks statistical analysis and finally use a deep learning model to predict the future trend of the stocks

i) *Change in stock price overtime*:

In this part, initially we used the libraries like pandas, numpy, matplotlib libraries to analyze the basic attributes of a stock. Using the pandas Data reader library to read the multiple stocks directly from the internet and time stamped it. Ex., shown in the figure: 5 above. The summary status of the particular data analyzed by using total count, mean, standard deviation at minimum, 25%, 50%, 75% and maximum of the all the parameters of each stock shown in below figure.

By using the below data of all the stocks, we take out the closing prices of all the time each and every stock plotted on the graph for visualization purpose. Generally, the closing price plays a role to decide how the market trend ends. It's not directly considered, the weighted average of the last 30 min of the stock trading hours.

Accordingly, the previous trading price refers to the last price at which the stock was purchased or sold before themarket closed for the day. So, we are using the closing data of all the years has shown in below figure: 7 and the total stock volume of all the stocks traded every day also plotted which is shown in figure:8.

	High	Low	Open	Close	Volume	Adj Close
count	253.000000	253.000000	253.000000	253.000000	2.530000e+02	253.000000
mean	461.309881	445.145022	453.117075	453.627549	6.897534e+06	453.627549
std	62.760471	62.221429	63.101240	62.442486	3.992562e+06	62.442486
min	322.899994	290.250000	302.399994	298.839996	1.144000e+06	298.839996
25%	420.239990	402.910004	410.309998	413.549988	4.408200e+06	413.549988
50%	486.299988	470.179993	478.869995	477.579987	5.770400e+06	477.579987
75%	507.730011	492.079987	500.000000	500.190002	7.881100e+06	500.190002
max	575.369995	541.000000	567.979980	556.549988	2.499140e+07	556.549988

	High	Low	Open	Close	Volume	Adj Close
count	253.000000	253.000000	253.000000	253.000000	2.530000e+02	253.000000
mean	58.187273	57.146680	57.652293	57.683953	1.681670e+07	56.232068
std	2.140882	2.550317	2.383945	2.313738	7.085050e+06	2.651980
min	51.910000	48.840000	49.360001	49.939999	5.763700e+06	47.833126
25%	56.939999	55.660000	56.220001	56.310001	1.246040e+07	54.601559
50%	58.360001	57.459999	57.910000	57.959999	1.537360e+07	56.386364
75%	59.750000	59.080002	59.459999	59.439999	1.856750e+07	58.181049
max	61.950001	61.270000	61.549999	61.740002	4.601380e+07	61.086052

	High	Low	Open	Close	Volume	Adj Close
count	253.000000	253.000000	253.000000	253.000000	2.530000e+02	253.000000
mean	2767.927819	2691.803003	2731.358894	2730.813078	4.938676e+06	2730.813078
std	535.807117	524.031861	534.217814	528.457920	1.971698e+06	528.457920
min	1759.449951	1626.030029	1641.510010	1676.609985	1.451900e+06	1676.609985
25%	2351.000000	2258.189941	2329.439941	2314.080078	3.514500e+06	2314.080078
50%	3069.550049	2970.000000	3018.530029	3008.729980	4.526600e+06	3008.729980
75%	3208.540039	3135.260010	3180.510010	3172.689941	5.789300e+06	3172.689941
max	3552.250000	3486.689941	3547.000000	3531.449951	1.556730e+07	3531.449951

	High	Low	Open	Close	Volume	Adj Close
count	253.000000	253.000000	253.000000	253.000000	2.530000e+02	253.000000
mean	205.602095	199.073676	202.619210	202.493439	7.629221e+06	202.493439
std	37.985012	37.415371	37.956009	37.522557	6.152695e+06	37.522557
min	133.419998	115.290001	125.540001	124.300003	2.785500e+06	124.300003
25%	178.199997	172.660004	175.559998	176.039993	4.448100e+06	176.039993
50%	194.990005	189.479996	192.000000	191.990005	5.864100e+06	191.990005
75%	242.520004	235.050003	237.389999	237.139999	8.515400e+06	237.139999
max	284.500000	270.579987	283.470001	281.250000	6.325340e+07	281.250000

Fig. 8: Netflix, Verizon, Amazon, Sales force stock statistical analysis

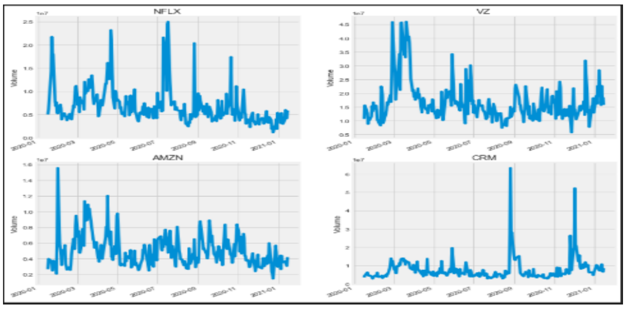


Fig. 9: Total volume traded each day

ii) Moving Average of the stock

Here we are finding out the moving average of the stock price. As it is a general guideline, when the stock price stays above the moving average the trend of the market goes up and it is considered as uptrend same way the stock price stays below the moving average the trend of the market goes down calls as a low trend.

However the moving averages can have different lengths, one moving average may indicates uptrend while other moving average indicates downtrend. The moving average can be calculated by different aspects. A five day simple moving average with recently closing prices and divides it by create a new average every day.

In the below histogram all the data like stock high, low open price, closing price, volume, and adj close averages shown in fig:9 Moving average of the stock prices for 10 days, 20 days and 50 days trend is plotted in the tight layout below figure: 10

Fig. 10: Moving average of adj close, close, open, high, low and volume of all the four stocks

iii) Correlation between different stocks closing prices

According to the correlation coefficient, the scale goes between - 1 and 1. With a correlation coefficient of 1, prices of two stocks move similarly, indicating that their prices move by the same amount consistently. The correlation coefficient of - 1 demonstrates a perfectly negative correlation indicating that the stock has consistently moved the opposite direction.

Correlation coefficients of 0 indicate there is no correlation between any two stocks and, as a result, no connection between those stocks. A correlation that is either optimally positive or optimally negative is strange.

Fig. 11: Moving average of 10%, 20%, and 50%

Stock brokers can utilize the correlation coefficient to choose resources with negative correlations for consideration in their portfolios. Correlation coefficients are calculated by taking the covariance of two factors and the standard deviation of each factor. Standard deviation terms refer to the scattering of information from the normal whereas covariance refers to the way in which two factors change simultaneously. In determining the correlation coefficient for the two standard deviations of the covariance, one can judge how much a portfolio will probably move. There are different ways to quantify risk analysis, the most primary way to use the information the daily percentage returns compared and expected return including the SD (standard Deviation) of the daily returns.

iv) Prediction of Stock market analysis using LSTM

LSTM is the high-level rendition of Recurrent Neural Network (RNN) where the data having a place with the past state endures. These are not the same as RNNs as they include long-haul conditions and RNNs work on discovering the connection between the new and the current data.

This demonstrates that the time period is generally more modest than that of LSTM. The principal reason behind utilizing this model in financial exchange expectation is that the forecasts rely upon a lot of information and are by and large subject to the drawn-out history of the market.

So, LSTM directs blunder by offering help to the RNNs through holding data for moreseasoned stages making the expectation more precise. In this manner substantiating itself as substantially more solid contrasted with different techniques.

Since the securities exchange includes the preparation of tremendous information, the angles concerning the weight lattice may turn out to be little and may debase the learning rate. LSTM keeps this from occurring. The LSTM comprises a recalling cell, input entryway, yield door, and neglects entryway. The cell recalls the incentive for long-haul proliferation and the entryways direct them. As part of this experiment, two sequential models are built with yield estimation of 128 and 64 by stacking two LSTM layers on top of one another. Two layers are contributed to the layer, one of which is layer '0' and one of which is layer '1'.

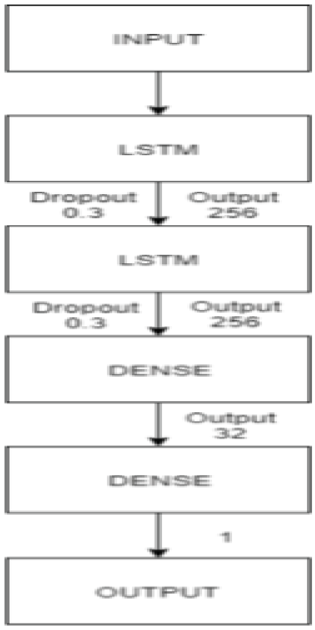


Fig. 12: LSTM Flow Chart

In order to not over-attack information in the preparation cycle, 0.3 out of all nodes will be frozen throughout the preparation interaction to reduce the dropout estimate from 0.3. A final thick layer is added in the centre where all neurons are tied together in the following layer resulting in 32 parameters contributing to the following core layer giving yield as 1. In order to maintain the error throughout all forms of interaction, a mean square cost function is employed and precision for the expectation is decided.

Fig. 13: Netflix data plot

```
Epoch 1/5
352/352 [==============================] - 9s 27ms/step - loss: 0.0014
Epoch 2/5
352/352 [==============================] - 9s 26ms/step - loss: 3.7858e-04
Epoch 3/5
352/352 [==============================] - 10s 28ms/step - loss: 3.3230e-04
Epoch 4/5
352/352 [==============================] - 10s 29ms/step - loss: 3.0606e-04
Epoch 5/5
352/352 [==============================] - 10s 29ms/step - loss: 2.6153e-04

: <tensorflow.python.keras.callbacks.History at 0x1c0bd2bf988>
```

Fig.14: Training parameters

IV. EXPERIMENTAL RESULTS

Over the Yahoo Finance dataset, the proposed system has been trained and tested. The data is split into training and testing sets, and after going through the different models, the following results are obtained:

```
# Get the root mean squared error (RMSE)
rmse = np.sqrt(np.mean(((predictions - y_test) ** 2)))
rmse
```

Fig.15: Root Mean Square Error

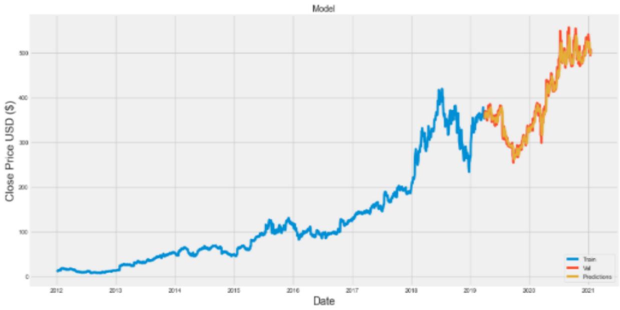


Fig.16: Prediction graph along with validation

In Fig: 16 and fig:17 shows the prediction graph and validation data table. In the prediction graph the trained which is shown in blue colour, the orange colour line which represents the prediction trend and red colour is a validation trend. A model based on LSTM has efficiency if the three color lines close to each other.

Several months after the prediction is made, the trend approaches reality [11]. A Train Score of (12.8953 RMSE) was obtained from the model. As the training process continues and the dataset size increases, the more accurate the system will become.

```
In [140]:  #Show the valid and predicted prices
           valid
Out[140]:
```

Date	Close	Predictions
2019-03-29	356.559998	356.994812
2019-04-01	366.959991	355.231812
2019-04-02	367.720001	357.176331
2019-04-03	369.750000	360.289642
2019-04-04	367.880005	363.677460
...	...	...
2021-01-11	499.100006	505.767120
2021-01-12	494.250000	501.670898
2021-01-13	507.790009	497.156891
2021-01-14	500.859985	497.508392
2021-01-15	497.980011	497.603363

455 rows × 2 columns

Fig.17: Predicted Prices

V. CONCLUSION AND FUTURE WORK

In this research, we investigated higher certainty and safety predictions of the stock exchange of a business through the use of machine learning. As a system for predicting stock prices, the innovative LSTM Model has been used as the principal advancement by the researchers. By generating positive results with the LSTM model, the technique has resulted in an improvement in the accuracy of prediction. This study has proven to be very encouraging and indicates more accurate predictions of the stock market can be made.

In future the research on stock exchange prediction will be continued using other networks like VGG-19 and GAN also using unsupervised learning along with sentimental analysis.

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