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Divination of stock market exploration using long short-term memory (LSTM)

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Abstract In this modern era, there is a significant rise in stock market price which attracts the shareholders of the company. The shareholders, as well as the investor, show a great interest in the analysis and prediction of the stock market which eventually makes the investors and other speculators to invest some good fortune in the company. A good prognosis may result in meaningful benefits. In today's life, more optimized models and different outlooks and analyzing trends were created over time. The analyzing framework used in this work is Long Short-Term Memory (LSTM) which is a part of Recurrent Neural Network (RNN) for long term dependencies. With the use of these algorithms with proper parameters precise results can be obtained. This can be achieved by collecting a dataset that consists of stock market data with all the opening and closing prices of stock having to be measured with several hidden layers and different units. With the result of this method, a more accurate prediction of the stock market is possible with historical datasets.

Keywords: long short-term memory, recurrent neural network, market prediction, artificial neural networks, support vector machines

1. Introduction

The stock market does have the character of being volatile, unreliable, and unpredictable. It is a chaotic environment with an enormous amount of continuously changing data, which makes it difficult to accurately predict the future and take successful action based on such predictions (Kirubakaran et al 2022). It is one of the most challenging careers in time series forecasting. The primary goal of this project is to explore and apply deep learning techniques to the stock market to forecast stock behaviors and then act on those predictions to reduce potential investment risk and generate profits (Palaniappan et al 2020). The goal can be achieved by using transfer learning to benefit from previously developed neural network models (Palaniappan et al 2018). The predictions are then tested against actual historical stock price data (Cui et al 2021). Having followed extensive research, it was determined that Python would be the perfect programming language to be used for the implementation due to its adaptability, accessibility to pre-built models, and availability of open-source libraries that could assist us in achieving the goal and potentially improve the outcomes (Balaji et al 2022). The LSTM model, which stands for Long Short-Term Memory, is without a doubt the finest model for time series forecasting (the one that yields the greatest results) (Kirubakaran et al 2022). It beats a standard deep neural network in terms of performance due to the requirement of a memory component for time series predictions (Rahaman et al 2022).

2. Existing system

In the current system (Bijolin et al 2022), the SVM algorithm and the Back Propagation method were employed, and no other method will do the back-out procedure. As a result, unneeded data were processed, wasting time and memory. SVM and Backpropagation are less successful in predicting future stock values due to the processing time for undesired data. The existing system's use of SVM and the Backpropagation method is ineffective when dealing with non-linear data. As a result, LSTM (Long Short-Term Memory) was used in our suggested future stock price prediction since it delivers a more accurate value for the next day than SVM nd the Backpropagation method (Roshni et al 2022).

Tej et al (2022) investigates the usage of the prediction system in practical contexts as well as challenges related to the correctness of the overall values provided. Backpropagation produces output as the ultimately expected rate arrives. The suggested system may generate a prediction list of stock prices as well as a graph of the prediction table so that the user can see the final expected result. The effective forecast of the stock will serve as a wonderful asset for financial markets and institutions and will bring real-world answers to stock investors' difficulties.

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In the old days, the stock market and its predictions were done using some basic methods and analysis which includes past results and statistical analysis of it. But with Genetic Algorithm (GA) or Artificial Neural Networks (ANN). The problem with using the ANN algorithm is when the dataset is too large or small it makes the convergence value very slow resulting in complexity and not an optimized method for prediction. There is another way to approach stock market prediction is to reduce the dimensionality of the dataset which means reducing and terminating the unwanted data present in the dataset. But this method is not applicable for the long term because it eventually fails because of new parameters being added up day to day, so it is not suitable for stock predictions.

3. Literature survey

Ding et al (2020) suggest the stock market has good fortune for investors as well as investment companies. Statistical methods and Artificial Intelligence methods are the two methods used in prediction. They use statistical methods such as the logistic regression model, and the ARCH model. Artificial intelligence techniques include backpropagation and multi-layer perceptrons. But the problem here is this can only predict a single value whereas stock data has huge and multiple data so that cannot be predicted using this method. So to overcome this problem the LSTM model is created. It has a prediction accuracy of 95%. In this method, the support vector machine's parameters are optimized using the particle swarm optimization technique, which can accurately forecast stock value. So, it gives a better-optimized value of stock data and it is mainly used for predicting time series data.

Yanga et al (2019) have suggested that it is very hard to solve long-time dependencies because of the errors the LSTM model brings with the increase of time series length. They have used the RNN mechanism to monitor and prophesy the historical data of traffic flow. The traffic flow falls into two different categories as parametric approach and nonparametric approach. Parametric approaches work with empirical data which has a kinetic-wave approach and the cellular automata model which helps to get higher prediction accuracy. With the evolution of LSTM, an enhanced version helps to give high-impact features and also it mitigates the inability to understand extraordinarily lengthy sequences.

Qing et al (2018) proposed the theory of solar radiance diagnosis that makes the cost-effective and provides high power quality for the electrical grids. This mainly works by not indulging in power system meters rather it works on projecting and monitoring the weather. In this model, they have used the persistence algorithm and backpropagation algorithm (BBPN) for solar irradiance prediction. By the use of standard prediction methods such as Root Mean Square Error (RMSE), they have obtained an accuracy of 18.34% with BBPN, but with the help LSTM algorithm they have a high prediction of about 42.9% without using BBPN. To make an economic profit from the PV power generation in case any error occurs in this system then the power system gives a negative impact on the system. A good control algorithm is needed to deliver the photovoltaic system a big economic perk.

Khairdoost et al (2020) created a model for the modern Advanced Driver Assistance System (ADAS) which is used for analyzing and estimating the driving experience by improving the driver's awareness and potentially decreasing the accident and other hazardous travel conditions. They previously developed a model which includes basic driver actions and lane changes that has a reflex time of 3.6 seconds in real time. When implementing the LSTM algorithm with the strategy using actual data from the previous model and also including some other extra movies such as the IOHMM system, basic driving maneuvers, and lane changes surprisingly with the usage of the same set of data the F1 score has been boosted by 4 which elevates the total score to 84%.

Iqbal et al (2021) suggested a model to analyze and predict the number of patients being affected by the virus. The author has taken the data from Pakistan starting from (March 2020 to May 2020). Since it's a time series data that has a very large volume of data, the LSTM algorithm is the best way to predict and classify the tasks. They have proposed an optimized model to get an actual patient count. They will gather data like upcoming cases, deaths, and cured patients being subjected to this particular model. Around 24 days of data are being implemented in it. Since it is a time series data with a huge volume, LSTM is one of the best ways to showcase an accurate result. The data are divided into training and testing data. It is one of the best ways to convert time-series data into a simpler structure.

Xue et al (2021) introduce an automatic trajectory clustering element in the computationally efficient source/destination clustering pedestrian trajectory prediction issue. In the ensuing trajectory prediction method, they acquire several RCs using trajectory clustering that captures various trajectory patterns. They used a procedure called PoPPL, which they refer to as the "prediction of pedestrian paths by LSTM". In the initial stage of PoPPL, a bidirectional LSTM network is trained using the clustered RCs. The RCs to which each observed trajectory would probably belong are predicted by this network. For the second stage, three distinct sub-LSTM designs are suggested to produce trajectories. PoPPL can produce several prediction outcomes corresponding to various RCs using a two-stage LSTM-based prediction procedure.

Munir et al (2021) suggested DP-AGL, a new framework that uses attention-based GRU-LSTM to forecast software flaws. The Gated Recurrent Unit (GRU) is an enhanced version of the LSTM. They use Clang to transform the source code into an AST before adding 32-level matrix features and tags for each statement. The number of unary operators or operands used in each phrase acts as the feature in Clang. Each sentence is labeled, after which a three-dimensional vector is created, used as an autonomous learning model, and finally, a GRU with an LSTM is employed. To improve the accuracy and feature, additionally, they used an attention mechanism. Under typical circumstances, their well-trained DP-AGL has risen by 1% in the recall, 4% in precision, 5% in accuracy, and 2% in F1 measurement respectively when compared with the evaluation method.

Nirmala et al (2022) suggested implementing a recurrent neural network (RNN) with LSTM to predict crude oil prices. This will aid in the timely purchase of crude oil by the general public. The greatest option for this type of prediction is time series analysis because he analyzed the past performance of crude oil prices to forecast future prices. One of the best models for handling time-series-based sequential data is RNN. LSTM is one of the RNN architectures. When compared to other traditional networks, he predicts the crude oil price with greater accuracy using LSTM because LSTM only focuses on storing past data and prediction, which is more approximative and encouraging.

Kajabad et al (2020) used LSTM to predict electric consumption. An LSTM network is provided for nonlinear dynamic modeling in order to predict events in the setting of changing electric demand. First, to train the model, they transform a series of univariate observations into supervised learning. Second, the prediction data serves as the basis for forecasting the next time steps, with the 5, 10, and 20-time steps being forecasted using the Walk-forward cross-validation method, accordingly. When compared with other models, they were able to get a good result.

Kim et al (2021) suggested the LSTM method to forecast the coming economic effects of COVID-19 spread. Because It's important to accurately forecast the economic effects of the COVID-19 pandemic to reduce worry and uncertainty about the socioeconomic harm that will result from it. This work has built an epidemic illness transmission model and economic scenario prediction model based on past incidences of epidemics and economic trends. First, they used this model to assure 77% accuracy in forecasting inflation rates. Second, they used this model to forecast the economic effects of COVID-19 for the next 1 year.

4. Proposed work

In the proposed system we are trying to find the most accurate and exact result of the stock prediction. To make investors invest in the stock market as well as to sell their stock at the proper timing, we need a good prediction algorithm to do. The best algorithm currently which is more accurate and optimized is Long Short-Term Memory (LSTM). Which is one of the algorithms in Recurrent Neural Networks (RNN). LSTM can process very huge data, not only a single value more than that it can process and predict it. It is more accurate and optimized than ANN and Genetic Algorithms. LSTM is used for predicting time series data which will have data over a month or many days. It can easily process the data associated with that. Since it can process and predict the data. We can use it for forecasting and analyzing the stock market since the stock uses time series data. LSTM has a memory cell that can properly handle data that is irrelevant to process it correctly. It can also store them and gives us a clean virtualization of the processed data even in tabular format.

4.1. Getting datasets

We get the dataset from Kaggle which is from NIFTY-50 Stock Market Data (2000 - 2021) which consists of Asian paints, ITC, and Cipla that has the data of 21 years. The data is simply a file that consists of a huge number of records and fields embedded in it. Fields refer to specific categories of data. We have to use the pandas function and CSV file to import the dataset so that it can be fetched by the code. Using google collab we can easily collect the required data and its parameters from the dataset with the use of a CSV file.

Code Snippet:

```
import pandas as pd

print (‘Read data’)

df=pd.read_csv(‘dataset\ASIANPAINTS.csv’)

data=df.values

print(data)
```

The reason for choosing the Nifty 50 dataset is because of its widely followed index in the Indian stock market and provides a comprehensive overview of the performance of India's top companies across various sectors such as financials, energy, information technology, and consumer goods. The dataset can be used to analyze trends in the Indian stock market, identify investment opportunities, and make informed decisions about investing in Indian equities. Additionally, as the Nifty 50 represents the performance of some of India's largest and most established companies, it can be used as a benchmark for evaluating the performance of individual stocks or portfolios in the Indian market.

Asian Paints, Cipla, and ITC are all well-known, large-cap corporations in the Indian market with sizable market capitalizations. Making educated judgements regarding investing in large-cap stocks may be facilitated by analysing the performance of large-cap firms, which can offer insights into the general market mood. Figure 1 represents the data that is read from the Asian Paint dataset using python. These companies have established businesses with a history of reliable success in their specialised fields. It is possible to get understanding of the company-specific elements that contribute to success, such as product innovation, marketing plan, and financial management, by analysing their financials and market trends. For investors wanting to make investments in these businesses or businesses in related industries, this information may be helpful.

```
               Symbol Series  Prev Close    Open     High      Low    Last  \
Date
2000-03-01  ASIANPAINT     EQ      361.20   370.0   390.00   370.00   385.0
2000-04-01  ASIANPAINT     EQ      381.65   380.0   392.00   375.00   390.0
2000-05-01  ASIANPAINT     EQ      385.55   371.5   390.00   371.50   383.0
2000-06-01  ASIANPAINT     EQ      383.00   384.9   384.90   374.50   375.1
2000-07-01  ASIANPAINT     EQ      377.50   376.0   390.00   370.00   389.0
...                ...    ...         ...     ...      ...      ...     ...
2021-04-26  ASIANPAINT     EQ     2517.95  2530.0  2575.00  2530.00  2558.0
2021-04-27  ASIANPAINT     EQ     2557.90  2545.0  2579.90  2534.00  2571.0
2021-04-28  ASIANPAINT     EQ     2574.35  2588.0  2620.25  2575.00  2612.0
2021-04-29  ASIANPAINT     EQ     2614.55  2630.0  2642.00  2570.00  2613.0
2021-04-30  ASIANPAINT     EQ     2613.45  2595.0  2605.80  2524.05  2529.0
```

Figure 1 Data read from the CSV file using pandas.

4.2. Loading Dataset

We know that datasets play an important role in deep learning; they are the starting point for training machine learning models. We must have sufficient data to train the machine to deal with the issue. Some challenges require the compilation of a dataset that offers context and trains us on how to behave in response to real-time inputs. Every day, these datasets might be retrieved from the internet. A data set is frequently composed of a single statistical data matrix, in which every column represents a distinct variable and each row refers to a specific dataset member. Certain conditions must be met by the dataset. It should represent data in a table or CSV file format and be arranged as a series of tables. A well-organized table should result in a meaningful dataset. If you choose a format other than CSV, you must use additional tools to process the dataset. To separate data in a CSV file, use a comma. A CSV file includes one or more fields, separating them by commas. Our dataset includes the following values: date, open, high, low, and close. Figure 2, Figure 3 and Figure 4 represents the sample datas with price of the stocks during opening time, closing time and many other parameters that is read from the Asian Paint, ITC and CIPLA datasets respectively.

	A	B	C	D	E	F	G	H	I
1	Date	Symbol	Series	Prev Close	Open	High	Low	Last	Close
2	03-01-2000	ASIANPAINT	EQ	361.2	370	390	370	385	381.65
3	04-01-2000	ASIANPAINT	EQ	381.65	380	392	375	390	385.55
4	05-01-2000	ASIANPAINT	EQ	385.55	371.5	390	371.5	383	383
5	06-01-2000	ASIANPAINT	EQ	383	384.9	384.9	374.5	375.1	377.5
6	07-01-2000	ASIANPAINT	EQ	377.5	376	390	370	389	385.7

Figure 2 ASIANPAINT Dataset.

	A	B	C	D	E	F	G	H	I
1	Date	Symbol	Series	Prev Close	Open	High	Low	Last	Close
2	03-01-2000	ITC	EQ	656	694	708.5	675	708.5	708.5
3	04-01-2000	ITC	EQ	708.5	714	729	694.3	710.65	712.35
4	05-01-2000	ITC	EQ	712.35	716.25	758.9	660	731	726.2
5	06-01-2000	ITC	EQ	726.2	741	784.3	741	784.3	784.3
6	07-01-2000	ITC	EQ	784.3	832.4	847.05	824	847.05	847.05

Figure 3 ITC Dataset.

	A	B	C	D	E	F	G	H	I
1	Date	Symbol	Series	Prev Close	Open	High	Low	Last	Close
2	03-01-2000	CIPLA	EQ	1349.4	1410	1457.35	1380.05	1457.35	1457.35
3	04-01-2000	CIPLA	EQ	1457.35	1537	1537	1430	1466.05	1465.25
4	05-01-2000	CIPLA	EQ	1465.25	1474	1474	1365	1441	1435.05
5	06-01-2000	CIPLA	EQ	1435.05	1434	1435	1349	1365	1355.85
6	07-01-2000	CIPLA	EQ	1355.85	1370	1389.9	1247.4	1247.4	1247.55

Figure 4 CIPLA Dataset.

4.3. Data Preprocessing

Figure 5 represents the steps involved in preprocessing the datasets of Asian Paint, ITC and Cipla. The dataset consists of raw data that was generated in real-time. This data must be preprocessed before it can be used. Data preprocessing is the process of transforming raw data into a format that machine learning can process efficiently. The collection includes a variety of values in various forms. The dataset contains duplicate or null values, resulting in some inaccuracies. Because all these data were acquired from several sources, they must be prepared in the same format. As a result, we must remove noisy data, incorrect format, and null values from the data. Panda's tabular data may be utilized to clean up information.

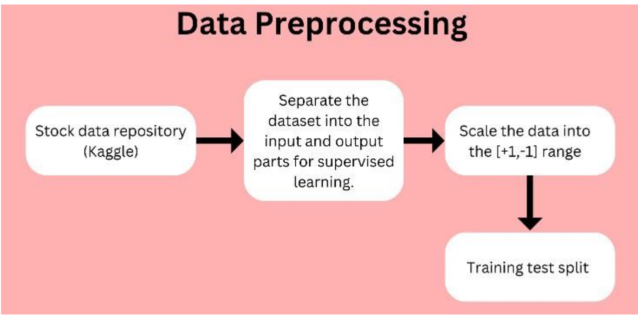

Figure 5 Data Preprocessing of LSTM.

4.4. Feature Scaling

Feature scaling is a method for uniformly distributing the independent features in the data over a predetermined range. It happens during the pre-processing of data. Feature scaling in machine learning is one of the most important steps in the pre-processing of data before creating a machine learning model. Scaling can contrast a weak machine-learning model and a better machine-learning model. Normalization and Standardization are the two methods of feature scaling that are most commonly used. Utilizing Normalization, we can connect the values of two numbers, between [0,1] and [-1,1]. Our data are rendered unitless by standardization, which changes them to have a mean of 0 and a variance of 1. We are using the scaling method because the machine learning algorithm uses numbers but has no idea what that number represents. In machine learning, the distances between the data are calculated by feature scaling. If the scale is not used, then the character with a higher value range takes precedence when calculating the distances. The relative scales of features are important to the Machine Learning algorithm. Scaling is a must in many algorithms when we want to get faster convergence, like in neural networks. Figure 6 represents the feature scaling of LSTM algorithm.

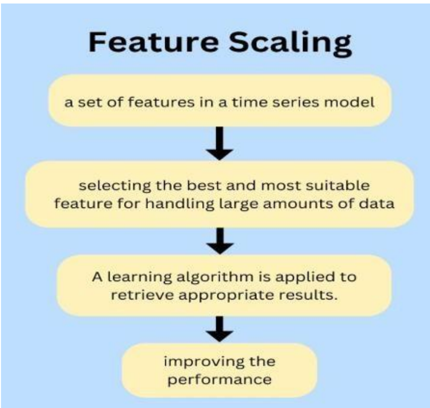

Figure 6 Feature Scaling of LSTM.

4.5. LSTM Architecture

LSTM stands for Long Short-Term Memory which is a special kind of Deep Recurrent Neural Network. It uses time series data which consists of a memory cell that can read, write and delete data or information in its memory depending on its use. It decides what to store or delete in the memory cell. The physical structure of LSTM memory cell is represented in Figure 7. It has an internal cell state that is used to describe the information and tells what to be reserved from the previous LSTM unit. The LSTM architecture has three main gates which are very efficient and used to predict values more precisely.

The input gate determines which data or information should be sent to the internal cell state. And also based on the input it is provided It stores the values in the cell. It also finds the mistakes of its predecessor and learns from them making the next module more efficient. And also, the tan function with the input and the hidden values combined gives us the output value.

Forget Gate measures how much data should be forgotten from the previous units. It determines what should be removed from the cell parts. This gate performs when there is a huge amount of unwanted data and eliminates it.

The output gate is the last gate in the model which gives the output value from the model. The cell's input value determines its output. The component transfers information from one cell to the next cell. It generates output from the current internal cell state. And it also decides what output values should be stored. The hidden data and the input data will be passed to the functions which process the data from the input values and gives an optimized output.

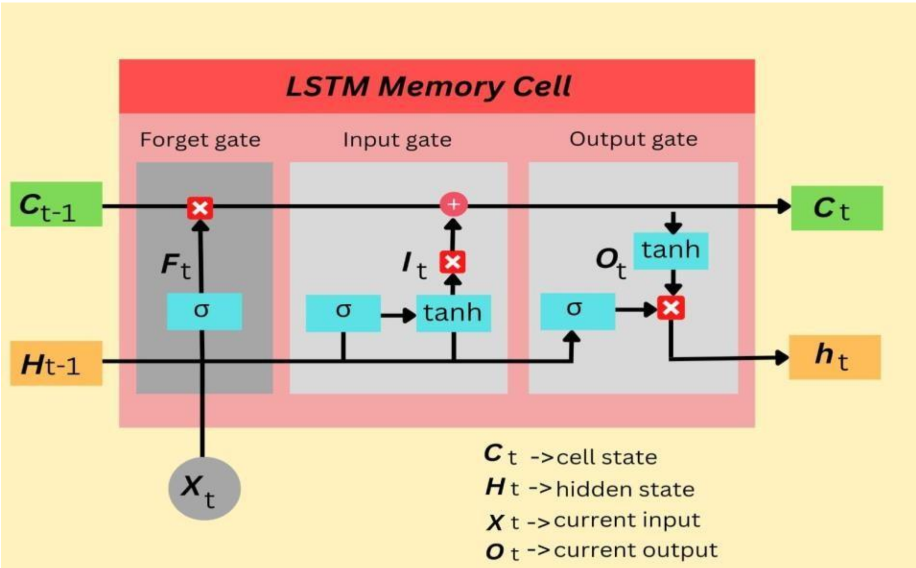

Figure 7 LSTM Physical Structure.

The three inputs (Ct-1, ht-1, and Xt) and the three outputs (Ct, ht, Ot) make up an LSTM. The inputs are the previous hidden state(ht-1), cell state (Ct-1), and current input (Xt). The outputs are hidden state(ht), cell state (Ct), and current output (Ot). Using a softmax layer, the hidden state branches out to the current output. The complete architecture will be split into three sections. These three major sections make the operation of the LSTM simple to learn.

First Part - The past hidden state (ht-1) and current input (Xt) are combined (ht-1 + Xt). The combined state is moved through a fully connected network, a sigmoid activation function, and the output vector is multiplied by the incoming cell state (Ct-1).

Second Part - The input gate refers to this second part. The past hidden state (ht-1) and current input (Xt) are combined (ht-1 + Xt). The combined state is moved through parallel branches. It has a fully connected network and sigmoid in the first branch. It has a fully connected network and a tanh function in the first branch. The two parallel branches' output vectors are multiplied elementwise. After the output has been multiplied and the cell state has been updated with the forget gate. The output is then added to the cell state. With the help of the input, it is learning to selectively update (add/subtract) the cell state vector using fully connected networks. The input gate branch and the cell state branch of these two branches will assure that the cell state is updated with the feature weights of the current input without overlooking the critical features in the cell state. It is significant to note that the forget gate (from the First part) and branch-1 (input gate) of the current block are identical; this should alert us to the fact that they have the same architectural characteristics and function in feature forgetting. Since the input features of the cell state in the second portion shouldn't be the same as how we choose to forget features of the cell state in the first state, so we can't re-use the forget gate. We must be careful not to confuse the LSTM's forgotten part with the input feature, which involves injecting a part of the LSTM into the cell state which has become common practice.

Third Part - The output gate refers to this third part. The past hidden state (ht-1) and current input (Xt) are combined (ht-1 + Xt). The combined state is moved through a fully connected network, a sigmoid activation function, and this output is sent through a tanh function and then multiplied element-wise with the cell state. The outcome of this multiplication is the current output or hidden state.

The input gate refers to the second part of the LSTM model which helps in deciding what information is relevant to be upgraded in the current state of the LSTM model. The forget gate helps in framing a vector value in the range between zero and one. The results of current input and the previous hidden state is the vector unit. The output gate helps in identifying the value of the next hidden state. This state is preloaded with previous inputs for further process.

Internal blocks and parameter calculations - The input (Xi) vector dimension is ‘m’. The hidden state(hi) vector dimension is ‘n’. The cell state (Ci) vector dimension is ‘n’. The hidden state (hi) and cell state (Ci) typically have the same dimension. In LSTM, there are four fully connected networks in various places. An input layer and an output layer are present in each fully connected layer network. The input is the number of neurons in each fully connected layer network and the output is influenced by the cell state vector (n) and the input vector's (m) dimension. The equations (1), (2) and (3) represents the formulae that is used to calculate the time series of LSTM algorithm based on the three gates.

$$FC = [(m+n)xn] + n \qquad (1)$$

$$4FC = 4[[(m+n)\,x\,n] + n] \qquad (2)$$

$$LSTM = 4m.n + 4n \wedge 2 + 4n \qquad (3)$$

5. Results and Discussion

In this paper, the closed price of three stock market data of the past 21 years were predicted with the LSTM model and training data were loaded to train the model and to show the predicted closing price of the individual stock data based on the past results.

Table 1 represents the average of different datasets used in this work. Based on the opening and closing stock, the market predictions were done and their deliverables were measured in percentage (%). The average percentage of deliverables of stock ranges from 0 to 1. The table 1 results predict the % of deliverables of each company based on the opening and closing stock.

Table 1 Comparison of different datasets of various top companies like Asian paints, ITC, Cipla with their opening and closing stock.

Stock Name	Open Stock	Close Stock	Low Stock	High Stock	% Deliverable
Asian Paint	1247.68	1247.41	1230.90	1264.63	0.63
ITC	420.63	420.27	414.24	426.63	0.59
CIPLA	541.46	540.42	532.14	549.59	0.51

Figure 8 represents the comparison graph between different datasets of top NIFTY companies like Asian paints, ITC and Cipla.This helps us to understand the opening and closing stock of top companies like Asian paints, ITC and Cipla. It also helps us to visualize the low stocks of the same companies for a period of 21 years.

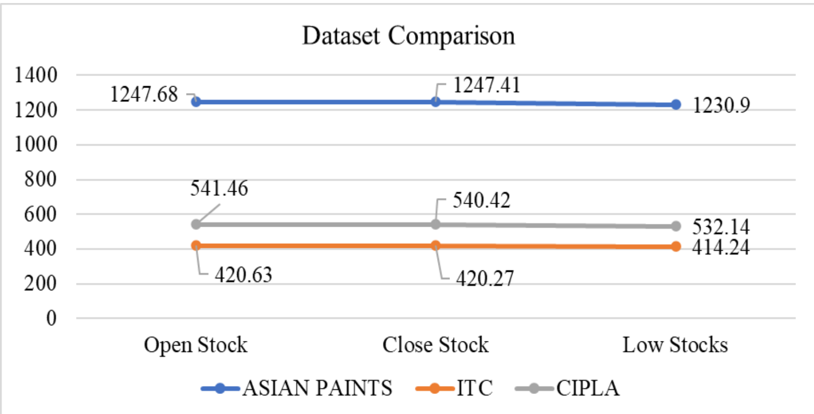

Figure 8 Dataset comparison of various top companies like Asian paints, ITC, Cipla.

Table 2 represents the deliverable percentage of Asian paints, ITC, and Cipla. With the use of these parameters such as stock price, Highest value, lowest value, and closing price. By using those parameters, we have obtained a certain deliverable percentage that is used to get higher accuracy results. On the comparison of these three stocks Asian Paints gives more accuracy than the other two making this algorithm work more efficiently.

Table 2 Comparison of deliverable percentage of companies like Asian paints, ITC, Cipla.

Stock Name	% Deliverable
Asian Paints	0.63
ITC	0.59
CIPLA	0.51

Figure 9 represents the deliverable percentage between different datasets of top NIFTY companies like Asian paints, ITC and Cipla.This helps us to understand the outcome of top companies like Asian paints, ITC and Cipla based on their stock exchange value. It also helps us to visualize the % of deliverables of the same companies.

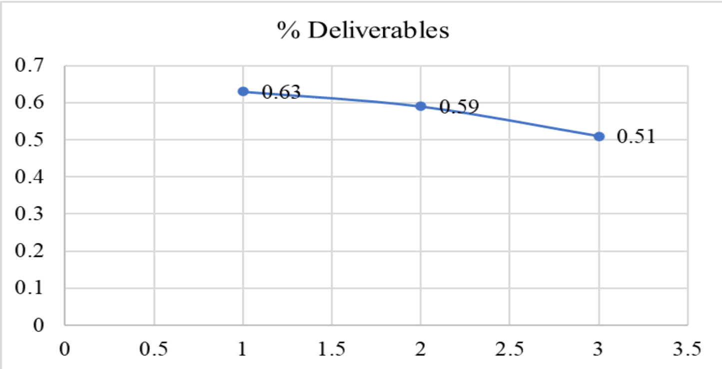

Figure 9 Deliverable percentage comparison of Asian paints, ITC, Cipla.

Table 3 represents the accuracy value of each and individual dataset for 2 different optimizers namely Adam and SGD respectively. The 3 companies' dataset were loaded into both the optimizer models for the same LSTM model and their accuracy values were calculated. Figure 10 represents the accuracy values (%) of individual companies for the corresponding optimizers. This clearly states the output of this proposed work and the suitable method to be implemented and tested in real time environment. This helps the customers to use this model to predict their stock values accurately.

Table 3 Comparison of accuracy (%) values of different companies under NIFTY-50 like Asian paints, ITC, Cipla.

	Optimizers (%)	
	Adam	SGD
Asian Paints	97.92	95.47
Cipla	96.27	95.97
ITC	98.14	96.17

Figure 10 represents the accuracy values between different datasets of top NIFTY companies like Asian paints, ITC and Cipla. This helps us to understand the outcome of top companies like Asian paints, ITC and Cipla based on their stock exchange value. It also helps us to visualize the % of accuracy of the same companies based on 2 different optimizers (Adam and SGD).

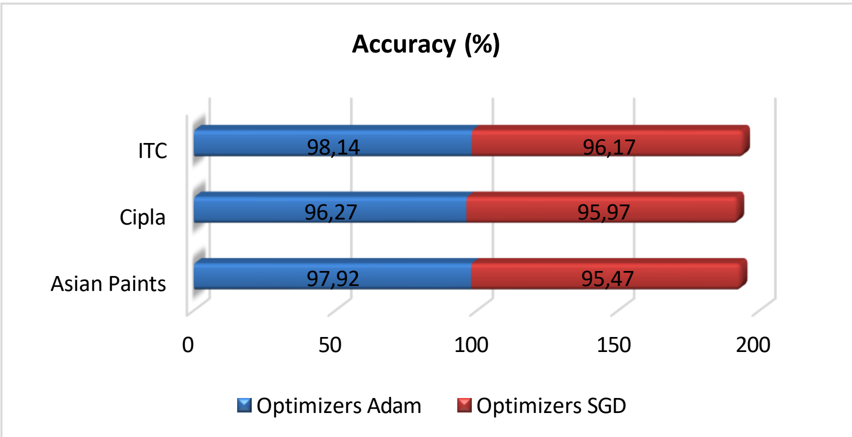

Figure 10 Accuracy (%) values for different company datasets like Asian paints, ITC, Cipla.

5. Conclusions

The most recent developments in market research and stock market prediction have started to incorporate these techniques in their analysis of stock market data since the arrival of machine learning and its powerful algorithms. For each date, the opening price of the stock, its highest and lowest prices on those days, as well as its closing price for the day, are all displayed. In the past, stock market forecasting was time-consuming and difficult to process. Machine learning is used to improve process performance as well as save time and resources. It is always preferred to use trained computer algorithms. It won't consider your emotions or preconceptions while giving you advice; instead, it will rely exclusively on statistics, facts, and data. The utilization of the LSTM application from machine learning makes stock market prediction simple and easy.

This proposed work helps customers to predict their stock values accurately using LSTM algorithm. From this results, it is clear that the percentage of accuracy value is more when using LSTM model with ADAM optimizer for all 3 different companies datasets. Hence it is clear that this model is suitable to be used in the market for predicting the stock values at the earliest.

The same proposed work can be enhanced with hyperparameter tuning with anyone of the optimizers [ADAM or SGD] for the same LSTM model and their results can be predicted to see which model gives better accuracy. Thus it is clear that LSTM model using ADAM optimizer is best suitable for predicted the stock market values for a longer period of time.

Ethical considerations

Not applicable.

Conflict of Interest

The authors declare that they have no conflict of interest.

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