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STOCK PREDICTION USING ENHANCED LSTM

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Abstract

Most analysts, researchers, and investors face trouble in predicting stock volume and stock price. People pay more attention to stock trends to earn money rigorously. LSTM (Long-Short-Term-Memory) is used because it is a time series notation. In this model, a stock system uses two user-defined or customized activation functions. This model avoids the drawbacks of Hyperbolic Tangent (Tanh), and Rectified Linear Activation (ReLU) activation functions are integrated with LSTM to achieve accuracy which became important in the current society because most people are attracted to stock market to enrich their economic status. Failure of this model leads to illegal activities by human beings. In this model, there is a comparison between two stocks. The prediction of stock is considered by taking the apple data set (AAPL), which consists of 10 years' data, and Microsoft (MFST) consists of recent years' data. By this model, we can predict the volumes of stock of a company.

Keywords: Stock Price, Stock Volume, Long- Short Term Memory (LSTM), Hyperbolic Tangent (Tanh), Rectified Linear Activation (ReLu), Apple Data Set (AAPL), and Microsoft Data Set (MFST).

I. INTRODUCTION

Today a very often word we here in our daily life is financial marketing, it keeps on changing continuously and has many sectors involves in it, and due to that, the system incorporated is a bit complex. Here, people generally trade on stocks, currencies, etc and each entity is bounded with some equities and derivatives. Since the system is international and tends to connect remote people, the whole process had been automated and is performed on virtual platforms. We also have brokers, who act as a mediator, to guide a fresher or one who can't make their own choice. Through the stock market, investors can buy and hold the share of local companies via 2 modes, one can be through exchange and the other through the counter market. Introducing this system benefited the investors irrespective of the amount they have invested in. This system had allowed low investors to trade their stock at a lower risk rate and helped in carving their life beautifully. Due to this facility, many fresher's had also jumped in and tasted its sweetness. Though they are profits on one hand it also has some loss on other hand. This is because of fluctuations in the market caused by many external factors. In general, humans with their ideologies can trade their owned goods in the market, but there is also an automated system known as ATS (automatic trading system) where operations are performed by a set of programs and with more effective trading. To ensure its efficiency few factors affecting human judgments are taken into consideration. For example, in the prediction of the stock value in the future ml algorithms are used and complex mathematical equations determine the state of a particular stock and many stock-related data can be analyzed.

The major challenge faced by the investors and analyzers is predicting the stock value and its state in the future. To predict the stock value we are using ml algorithms. To ensure a better decision in investing in the stock we find the stock value. The proposed system produces the prediction of stock value using all the techniques involved to achieve better stock prediction accuracy and issue profitable trades. We use LSTMs (long -short-term memory) which are good for solving sequence prediction problems because of their storing capacity of previous data. Due to this approach by keeping the previous predictions in mind we can accurately predict the stock value for various stocks even in a large amount of volumes.

II. RELATED WORK

In [1], Chun Yuan Lai Et.al. To predict stock price and volume, neural networks are being used regularly. CNN (Convolution Neural Network), and RNN (Recurrent Network) are two different ways that are used for prediction, and also LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit) are other models that are used in this existing model. However,

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according to this related work, RNN acts as a straightforward approach that helps to study information in stages. It predicts the best input, and the model was used to learn the historical data.

LSTM consists of three gates, the output gate: for controlling the unit's state, the input gate: for adding new information, and the forget gate: to check whether the input is from the previous or current state. In this proposed method, the neural network is fed with data and trained for prediction purposes. As old data that is stored in memory may increase the running time which is useless, hence RNN cannot connect to information. LSTM overcomes the problems of RNN and provides sufficient accuracy.

In [2], Guangyu Ding Et.al. Investors have now been paying close attention to the stock market. It has long been a hotspot for investors and financial firms looking to grasp the stock market's increasing regularity and predict its trend. For sequential data processing, a collection of neural networks called LSTM (Long Short-Term Memory network) is used which is also the type of RNN (Recurrent Neural Network). The addition or deletion of information for neurons is achieved by LSTM through a gating unit. There is a layer in the LSTM neural network that has a tanh activation function. This model enhances the system's expressive power by looping the body for every moment and performing it recursively. The dropout method was employed during the task model construction procedure.

LSTM-based on DRNN (Deep-Recurrent Neural Network) an associate net was proposed for predicting multiple stock prices parallelly. In this related work, the author presented the framework of the algorithm, the structure of the model, and the experiment design. By comparing the LSTM model with the DRNN model one can verify the accuracy and feasibility of the associated net, it can predict multiple values at the same moment. Finally, this work concludes by showing the average accuracy of every value that was predicted is greater than existing models.

In [3], KritiPawar Et.al. Today's world makes stock prediction a difficult task. RNN (Recurrent Neural Networks) and LSTM (Long Short-Term Memory) are adopted for predicting the stock market in this system. Traditional ML algorithms such as regression (for unit's connection), support vector machine, and random forest are

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compared with existing systems. The LSTM RNN system is evaluated and tested accordingly to the above terms.

For connecting units recurrently RNN which is a class of neural networks is adopted. The author makes use of Recurrent Neural Networks because to get stock data the necessity of long-term dependencies in given data is considered. RNN is not able to store memory for a long time, and vanishing problems may occur. These long- and short-term Memory cells are replaced instead of traditional neuron-like cells. LSTM with the RNN model is used to predict movements in stock data. The data is retrieved from an online source that uses financial data provider yahoo finance. After collecting data the model divides the data for training and testing. To build the LSTM RNN model, get trained using the training data that is divided in the above step which results in forecasting and predicting the sequence of stock data. Then, this model will be tested on several stock datasets like Apple Inc., Tesla Inc., and Google, and the forecasted versus the actual data is visualized through the plot in the results. The results are obtained from different configurations of the existing models with loss function and mean square error. Researchers conclude that to find the better model with the lowest loss value testing is vital. The loss observed for the Deep LSTM is much better than the other models.

In [4], GouravBathla. For predicting stock values since the trend begins, researchers have presented new ways day to day. Linear regression, ARIMA (Auto-Regressive Integrated Moving Average) and support vector machine, and standard ML approaches are adopted by researchers for price prediction of stock. The main drawback of these approaches is accuracy. Hence, through this early study, one can say that there is a need for a better model that achieves the maximum accuracy for predicting the significant price variations.

RNN (Recurrent Neural Network) is the modified version of LSTM (Long Short Term Memory). Because it can assess time-series patterns. RNN is ideally suited for price prediction. RNN has the drawback of being unable to save the state of result for a long-term dependency. In LSTM, there is a Forget gate that determines whether a prior state’s metadata is significant or insignificant. If the Forget gate’s output is binary one (1), the information is saved by the cell state. If the output is binary zero (0), the information is ignored by the cell state. Input gates and Output gates are also LSTM.

For predicting training values and target labels, SVR is applied in this related work.

For the Real-Value function, SVR is utilized. SVR is a regression technique that uses the best appropriate hyperplane to minimize error. This model employs an LSTM with seven hidden layers. The Adam optimizer is employed, as well as the sigmoid activation function. As it is clear that to improve accuracy deep learning is used in every model similarly in this existed model also deep learning is used for improving prediction accuracy. Support Vector Regression is compared to our LSTM- based neural network. This related study concludes that LSTM surpasses SVR when compared with prediction accuracy.

In [5], Md. ArifIstiake Sunny Et.al.LSTM is an enhanced RNN approach, works well in a wide range of situations, and is the most frequently utilized approach. Including gate units and memory cells made LSTM the best model for stock prediction, LSTM addresses the problem of figuring out how to remember input over time.The LSTM algorithm is used for solving problems of long-term dependency.

Different gates are employed in the LSTM model to transmit recently updated data from one cell to the next. Update gate, forget gate, and output gate are examples of the gates that are involved in implementing the model. These cells are responsible for LSTMmemory regulation. As a result, the cell produces two outputs: one is the activation, and the other is the candidate value. For situations involving sequence classification, BI-LSTM increases model execution.

Initially, LSTM uses one but Bi-LSTM uses two LSTMs in the training for processing sequential inputs. Regular RNN state neurons are divided into two types: forward states (used for positive time heading) and backward states (used for negative time heading). The processed dataset is then divided into two segments: the training dataset and the testing dataset. In splitting of data since the model needs to learn and get trained rigorously, training data consists of 88 percent of the dataset and the remaining 12 percent is utilized for testing.

Table 1: Existing System

SN O	Author Name	Algorithms	Advantages	Disadvantages
1	CHUN YUAN LAI	Recurrent Neural Networks(RNN) Long Short-Term Memory (LSTM)	LSTM is able to handle noise and Continuous values for long term dependencies.	LSTM takes longer to train and require more memory to train.
2	Guangyu Din g	Deep Recurrent Neural Networks(DRNN) Long Short-Term Memory (LSTM)	Deep Recurrent Neural network (DRNN) can process any length input.	Deep Recurrent Neural network computation is slow when compared with LSTM.
3	KritiPawar	Recurrent Neural Networks(RNN) Long Short-Term Memory (LSTM) Adam algorithm	The Recurrent Neural network is computationally powerful and used in many temporal processing models and applications.	Recurrent Neural network is not able to train with long-term dependencies.
4	Md. ArifIstiake Sunny	Recurrent Neural Networks(RNN) Long Short-Term Memory (LSTM) Bidirectional Long Short-Term Memory (BI-LSTM)	(BI-LSTM) In bi-directional The input will be flowing in both the directions to preserve the future and as well as the past information.	(BI-LSTM) has Two LSTM Cells so it is costly and it is slower model and takes more time for training.
5	GouravBathla	Long Short-Term Memory (LSTM) Support Vector Machine(SVM)	SVM works effectively on the unstructured and semi structured data.	SVM Requires long training time for large Databases.

III. Proposed System

The Proposed method is to predict stock price daily. Market forces influence stock prices every day. We're referring to the fact that stock prices fluctuate due to supply and demand. Many factors affect stock markets, resulting in high volatility and uncertainty. Neural networks can be used to predict stock prices. The primary goal of this System is to gather stock data from previous years and then predict the results in order to forecast what will happen next. Data mining can extract relevant information from a large data set, and it can also anticipate future trends and behaviours using a neural network.

LSTMs are commonly utilised for sequence prediction problems and have proven to be quite effective. They work because LSTM remembers important historical information while ignoring irrelevant data. The LSTM neural network is a modified recurrent neural network that is widely used and effective for a variety of problems. By combining gate units with memory cells in a neural network, the LSTM solves challenges related to data recollection over time.

To develop stock prediction using enhanced lstm, system will perform the below steps.

- Data pre-processing
- Feature selection
- Classification
- Performance evaluation

The process of modifying our data before feeding it to the algorithm is known as cleaning. Data cleaning is a technique for converting uncontrolled data into a format that may be used. To put it in another way, data is collected in raw format from various sources, the technique is efficient and impossible. The formatting in big data must be in the correct format to get acceptable results from the generated application. A specific classifying model requires data in a specified format.

A.Pre-Processing

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In Machine Learning Data pre-processing is applied to prepare the raw data suitable for building and training the Machine Learning models. Pre-processing is an important step in any of the data related information which helps to remove the unwanted data and make the data efficient for the particular model. Data pre-processing include some of the following techniques like Data Cleaning, Data Transformation, and Data Reduction.

B. Min – Max Scaler

The Minmaxscaler is a continuous variable scaling algorithm. The MinMaxscaler reduces the minimum and maximum values to 0 and 1, respectively. MinMaxScalermaintain the original distribution's shape. Has no effect on the information included in the original data.

The following equation is commonly used for Min-Max scaling:

$$Xsc=X-Xmin\ /\ Xmax-Xmin \qquad \textbf{(1)}$$

C. Scaling

Scaling in is a trading technique in which you acquire shares as the price falls. Setting a target price and then investing in volumes as the stock falls below that price is known as scaling in. This buying will continue until the price stabilizes or the trade size is achieved.
The process of moving the data's independent features into a particular range is known as scaling. It deals with rapidly shifting magnitudes, values, or units during data pre-processing. A machine learning model will be weighing greater values higher and smaller values lower if feature scaling is not performed, irrespective of the unit of values.

D. Normalization

In machine learning Normalization is applied for converting the numerical values of columns in data set to get a similar scale. It’s not required for every data set in a model.

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \textbf{(2)}$$

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IV. Feature Selection

This is where the data qualities that will be supplied to neural network are decided. Dates and Close Price of the stock are taken as selected features in this study. Feature Selection can help increase model accuracy by removing irrelevant or redundant features and decreasing the amount of features. It is also possible to achieve the goal of reducing the running time. Selecting relevant attributes, on the other hand, can help to simplify the model and make the researchers' data gathering process more understandable.

V. Classification

Classification is a predictive modelling technique that helps objects are identified and classified by the system data based on training data method is a common method that can be used to find patterns Performed on both structured and unstructured data. There are various classification algorithms in machine learning; here, the system uses binary classification, where this binary classification consists of two classes.

A. Long Short-Term Memory Network (LSTM)

LSTM is similar to RNN (Recurrent Neural Network) both learn to maintain long-term dependencies. Because of LSTM, RNN can remember long-term inputs, and similarly, to computers the inputs are stored in memory. Since it stores data in memory it has the authority to override or alter the data in it. It is just like a closed room, where the room itself decides whether the data should be kept or freed from it immediately after the description. The data in LSTM can be is passed through the input gate, forget gate, and exit gate. Using these gates we regulate the data. Each gate serves its purpose data input through the input gate, time allocation through the output gate and deletion through forget gate. In this gates rooms, data is stored by LSTM outside the RNN. Data is read from memory, and close and open gates determine when reading, writing, erasures, and storage are permitted. These gates, unlike virtual storage in systems, are analog, and also consist of the multiplication of elements in the range of 0 and 1. By using analog we can differentiate it from other models and it supports backpropagation over digital.

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Like the nodes in a neural network, gates react according to the received signal and they also perform actions like blocking, and passing information according to the strength the data pack has and the filter which they have imported from their weight sets. Here Weights sets are nothing but control input and state of input in RNN.

1. FORGET GATE: the forget gate controls when new info is inserted into certain room portions. And 1/4th of the room is selected and zeros are left behind.

2. INPUT GATE: This network category reads the scenario where the data needs to be stored and when it needs to be updated.

3. OUTPUT GATE: This gate selects the data which is to be transferred to the next block/room based on the input gate and room.

VI. ACTIVATION FUNCTION

The activation function is used in (ANN) artificial neural networks to output a small value for small inputs and a larger value if the inputs exceed a threshold. If the value is big, the activation is important; if the value is tiny, it has very little impact. To put it another way, the activation function will operate as a gate, ensuring that the incoming value is higher than the Critical number.

A. Hyperbolic Tangent (Tanh):

The Tanh is also referred to as the hyperbolic tangent activation function. It is similar to sigmoid activation function and also has the same S-shape. The Tanh is a zero Centred Function. Tanh suffers from a vanishing gradient problem. But, still it is better than the sigmoid activation function. It is a nonlinear activation function. The Tanh function takes a real value as input and outputs values in the range from -1 to1.

Tanh activation function can be calculated as:

(e^x – e^-x) / (e^x + e^-x) **(3)**

Where e is base of natural logarithm and is mathematical constant.

B. Rectified Linear Activation (ReLU)

ReLU means Rectified Linear Activation function, it is commonly used function for hidden layers. It is very easy and simple to implement and it also helps in overcoming the problems of other activation functions like Tanh and Sigmoid. It is mainly used to solve the issues related to vanishing gradients that frequently occur in Tanh.

ReLU Activation Function can be calculated as:

Max (0.0, x)

If input value (x) is negative, then the result is 0.0. Otherwise, the value is returned.

C. Enhanced LSTM

Enhanced lstm is the combination of two activation functions which used to overcome the drawbacks of tanh and ReLU. It uses two modified relu2 to get more accuracy when compared with normal lstm.

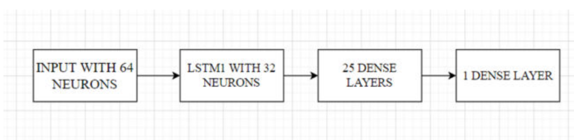

Figure 1: Enhanced LSTM

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D. System Architecture

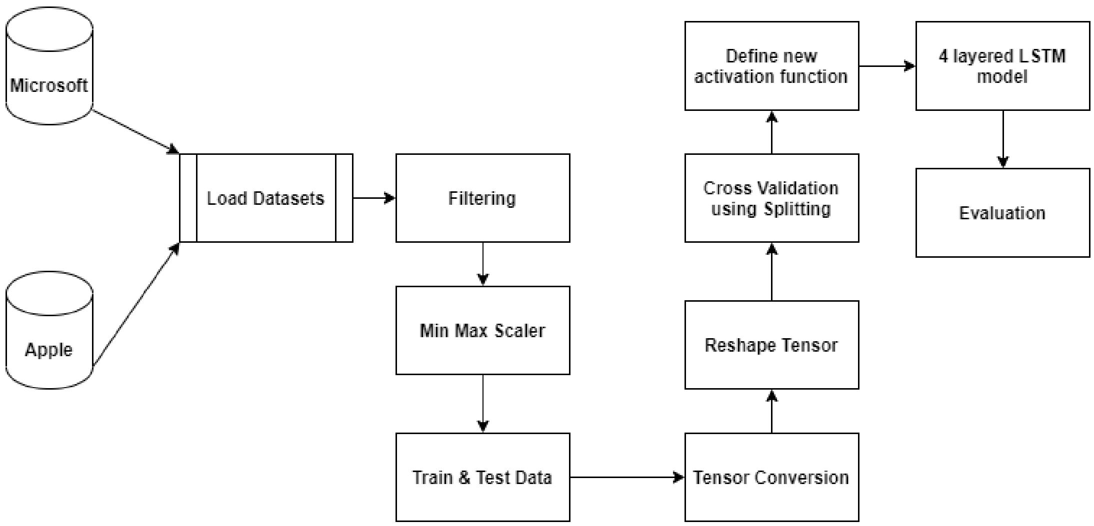

Figure 2: System Architecture

E. Dataset Design

The Apple Data Set includes stock data for Apple (AAPL) for the previous ten years (From 2010 to 2020). Dates, Open, High, Low, Close, Adj Close, and Volume are among the 7 attributes.

Date	Open	High	Low	Close	Adj Close	Volume
#########	100.59	100.69	98.04	99.62	93.51429	1.43E+08
#########	99.95	102.38	98.31	100.73	94.55624	2.8E+08
#########	101.33	101.78	95.18	97.67	91.68379	3.59E+08
#########	98.32	105.49	98.22	105.22	98.77104	3.59E+08
#########	104.85	108.04	104.7	108	101.3807	2.2E+08
#########	108.22	110.3	107.72	109.01	102.3288	2E+08
#########	109.02	114.19	108.4	114.18	107.6467	2.05E+08
#########	114.27	117.57	113.3	116.47	109.8056	2.33E+08
#########	116.85	119.75	116.62	118.93	112.1249	1.82E+08
#########	118.81	119.25	111.27	115	108.4197	2.67E+08
#########	114.1	114.85	109.35	109.73	103.4513	2.6E+08
#########	110.7	113.24	106.26	111.78	105.384	3.29E+08
#########	112.16	114.52	111.97	113.99	107.4675	1.19E+08
#########	113.79	114.77	107.35	109.33	103.0742	1.52E+08
#########	108.29	113.25	104.63	112.01	105.6008	2.83E+08
#########	112.6	112.8	105.2	105.99	99.92529	3.04E+08
#########	107.84	113.75	106.5	112.98	106.5153	1.99E+08
#########	113.74	120	109.03	117.16	110.4561	4.66E+08
#########	118.05	120.51	116.08	118.93	112.1249	2.71E+08
#########	118.55	127.48	118.43	127.08	120.2814	3.03E+08
#########	127.49	129.5	126.92	129.5	122.5719	1.94E+08
#########	130.02	133.6	126.61	128.46	121.5876	3.68E+08
#########	129.25	130.28	125.76	126.6	119.827	2.47E+08
#########	127.96	129.57	121.63	123.59	116.9781	3.27E+08
#########	123.88	129.25	122.87	125.9	119.1645	2.67E+08
#########	127.12	128.04	122.6	123.25	116.6563	2.09E+08
#########	124.05	126.49	123.1	125.32	118.6155	1.62E+08
#########	124.47	128.12	124.33	127.1	120.3003	1.82E+08

Figure 3: Apple Dataset

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F. MFST Data Set

The Microsoft Data Set includes stock market data from 1986 through 2019. Dates, Open, High, Low, Close, Adj Close, and Volume are among the 7 attributes.

Date	Open	High	Low	Close	Adj Close	Volume
#########	234.96	239.17	234.31	237.13	235.2141	29907600
#########	234.01	235.82	233.23	235.75	233.8452	22653700
#########	234.96	235.19	231.81	234.81	232.9128	26034900
#########	236.28	240.06	235.94	237.71	235.7894	28092200
#########	236.15	238.55	233.23	237.04	235.1248	29562100
#########	232.56	234.19	230.33	230.72	228.8559	34833000
#########	231.02	232.47	229.35	230.35	228.4889	46430700
#########	230.27	236.9	230.14	235.99	234.0833	30127000
#########	237.49	241.05	237.07	237.58	235.6604	31638400
#########	237.85	238	235.32	235.46	233.5576	25620100
#########	235.3	236.94	231.57	232.34	230.4628	34061900
#########	231.55	236.71	231.55	236.48	234.5693	25479900
#########	236.59	236.8	231.88	235.24	233.3394	25227500
#########	233.53	233.85	231.1	231.85	229.9767	24792000
#########	232.91	239.1	232.39	235.77	233.8651	43623500
#########	238.47	242.84	238.05	242.35	240.3919	30338000
#########	242.76	249.96	242.7	249.07	247.0576	36910600
#########	247.61	249.4	246.88	247.86	245.8574	22931900
#########	247.81	250.93	247.19	249.9	247.8809	22719800
#########	252.77	254.14	252	253.25	251.2038	23625200
#########	252.87	255.99	252.44	255.85	253.7828	24326800
#########	254.71	257.67	254.62	255.91	253.8423	27148700
#########	257.26	259.19	256.83	258.49	256.4015	23837500
#########	257.48	258.83	255.16	255.59	253.5249	23070900
#########	257.93	259.93	257.73	259.5	257.4034	25627500
#########	259.47	261	257.6	260.74	258.6333	24878600
#########	260.19	261.48	257.82	258.74	256.6495	23209300
#########	257.82	260.2	256.84	258.26	256.1734	19722900

Figure 4: Microsoft Dataset

VII. EXPERIMENTAL RESULTS

AAPL:

```
Average scores for all folds:
> Accuracy: 0.8771929889917374 (+- 1.2405382218507082)
> Loss: 0.008765941858291626
```

Figure 5: Accuracy and Loss of Apple Data Set

MFST:

```
Epoch 200/200
3/3 [==============================] - 0s 97ms/step - loss: 0.0265 - accuracy: 0.0070
Average scores for all folds:
> Accuracy: 0.6896547228097916(+- 1.3793094456195831)
> Loss: 0.002615844123065472
```

Figure 6: Accuracy and Loss of Microsoft Data Set

Table 2: Predefined versus Customized activation function

	Pre-defined Activations	Customized Activations
Microsoft	80.5	86.23
Apple	81.7	87.7

Here, x-axis represents the name of the datasets and y represents the measuring scale of the accuracy, which shows that customized activation function has improved the accuracy on both datasets with nearly 6% improvement.

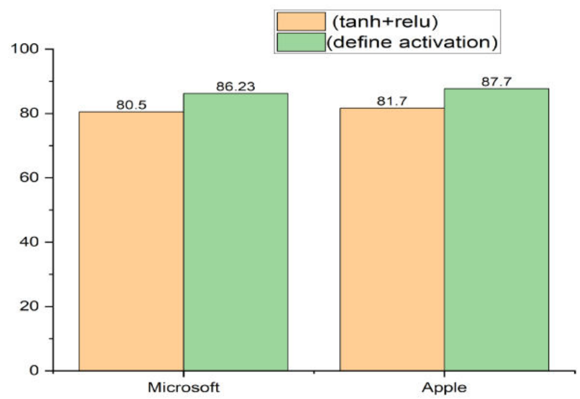

Figure 7: Efficiency of the customized activation function

Table 3: Comparison of cross validation results over two datasets

	Microsoft without cross validation	Apple without cross validation	Microsoft with cross validation	Apple with cross validation
Accuracy	78.1	80.5	86.5	87.1
Recall	76.3	79.8	84.2	82.09
Precision	75.4	79.8	83.9	83.14

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Here x-axis shows the comparison analysis of graph, which proves that both the datasets have acquired more accuracy in case of cross validation rather than without cross validation.

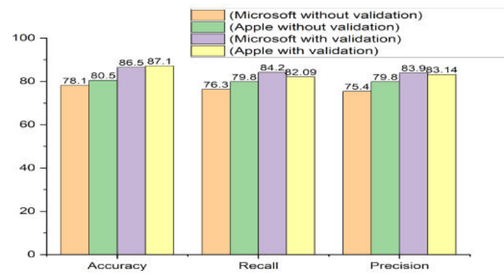

FIGURE 8: Comparison of cross validation results over two dataset.

Table 4: Accuracy Table

S .No	Author Name	Data Set	Accuracy	Recall	Precision	F-Measure
1	CHUN YUAN LAI	Taiwan stock exchange	1.841124	1.01234	1.06589	1.04567
2	Guangyu Ding	ZTE stock exchange	0.0132838	0.00512	0.01856	0.01523
3	KritiPawar	Tesla and google	0.0031980	0.00132	0.08917	0.07145
4	Md. ArifIstiake Sunny	Google	0.010156	0.12245	0.01123	0.12764

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4.1 Performance Evaluation

Results on Apple Data Set (AAPL.CSV)

```
Training for fold 1 ...
Epoch 1/20
4/4 [==============================] - 4s 63ms/step - loss: 0.1037 - accuracy: 0.0000e+00
Epoch 2/20
4/4 [==============================] - 0s 60ms/step - loss: 0.0984 - accuracy: 0.0000e+00
Epoch 3/20
4/4 [==============================] - 0s 62ms/step - loss: 0.0947 - accuracy: 0.0034
Epoch 4/20
4/4 [==============================] - 0s 57ms/step - loss: 0.0906 - accuracy: 0.0077
Epoch 5/20
4/4 [==============================] - 0s 60ms/step - loss: 0.0898 - accuracy: 0.0086
```

FIGURE 9: LSTMInitial Epoch on APPLE Data Set (AAPL.CSV)

From the above figure the model performs Epoch's based on lstm algorithm and produce output of loss and accuracy of Apple Data Set.

```
Epoch 15/20
4/4 [==============================] - 0s 57ms/step - loss: 0.0884 - accuracy: 0.0087
Epoch 16/20
4/4 [==============================] - 0s 61ms/step - loss: 0.0885 - accuracy: 0.0087
Epoch 17/20
4/4 [==============================] - 0s 60ms/step - loss: 0.0884 - accuracy: 0.0087
Epoch 18/20
4/4 [==============================] - 0s 60ms/step - loss: 0.0884 - accuracy: 0.0087
Epoch 19/20
4/4 [==============================] - 0s 59ms/step - loss: 0.0884 - accuracy: 0.0087
Epoch 20/20
4/4 [==============================] - 0s 61ms/step - loss: 0.0884 - accuracy: 0.0087
```

FIG
UR
E 10: LSTMFinal Epoch on APPLE Data Set (AAPL.CSV)

From the above figure the model performs Epoch's based on lstm algorithm and produce output of loss and accuracy of Apple Data Set.

```
Training for fold 1 ...
Epoch 1/20
4/4 [==============================] - 3s 55ms/step - loss: 0.1891 - accuracy: 0.0087
Epoch 2/20
4/4 [==============================] - 0s 62ms/step - loss: 0.1250 - accuracy: 0.0072
Epoch 3/20
4/4 [==============================] - 0s 60ms/step - loss: 0.1195 - accuracy: 0.0065
Epoch 4/20
4/4 [==============================] - 0s 57ms/step - loss: 0.1062 - accuracy: 0.0075
Epoch 5/20
4/4 [==============================] - 0s 57ms/step - loss: 0.1027 - accuracy: 0.0078
```

FIGURE 11: Enhanced LSTMInitial Epoch on APPLE Data Set (AAPL.CSV)

From the above figure the model performs Epoch's based on Enhanced lstm algorithm and produce output of loss and accuracy of Apple Data Set.

```
Epoch 15/20
4/4 [==============================] - 0s 64ms/step - loss: 0.0915 - accuracy: 0.0079
Epoch 16/20
4/4 [==============================] - 0s 61ms/step - loss: 0.0908 - accuracy: 0.0086
Epoch 17/20
4/4 [==============================] - 0s 60ms/step - loss: 0.0914 - accuracy: 0.0087
Epoch 18/20
4/4 [==============================] - 0s 57ms/step - loss: 0.0918 - accuracy: 0.0087
Epoch 19/20
4/4 [==============================] - 0s 59ms/step - loss: 0.0903 - accuracy: 0.0087
Epoch 20/20
4/4 [==============================] - 0s 58ms/step - loss: 0.0902 - accuracy: 0.0087
```

FIGURE 12: Enhanced LSTMFinal Epoch on APPLE Data Set (AAPL.CSV)

From the above figure the model performs Epoch's based on Enhanced lstm algorithm and produce output of loss and accuracy of Apple Data Set.

Results on Microsoft Data Set (MFST.CSV)

```
Training for fold 1 ...
Epoch 1/20
5/5 [==============================] - 4s 90ms/step - loss: 0.1585 - accuracy: 0.0000e+00
Epoch 2/20
5/5 [==============================] - 0s 86ms/step - loss: 0.1359 - accuracy: 0.0000e+00
Epoch 3/20
5/5 [==============================] - 0s 88ms/step - loss: 0.0980 - accuracy: 7.1963e-04
Epoch 4/20
5/5 [==============================] - 0s 84ms/step - loss: 0.0445 - accuracy: 0.0061
Epoch 5/20
5/5 [==============================] - 0s 86ms/step - loss: 0.0372 - accuracy: 0.0063
```

FIGURE 13: LSTMInitial Epoch on Microsoft Data Set (MFST.CSV)

From the above figure the model performs Epoch's based on lstm algorithm and produce output of loss and accuracy of Microsoft Data Set.

```
Epoch 15/20
5/5 [==============================] - 0s 93ms/step - loss: 0.0271 - accuracy: 0.0070
Epoch 16/20
5/5 [==============================] - 0s 86ms/step - loss: 0.0270 - accuracy: 0.0070
Epoch 17/20
5/5 [==============================] - 0s 90ms/step - loss: 0.0270 - accuracy: 0.0070
Epoch 18/20
5/5 [==============================] - 0s 85ms/step - loss: 0.0271 - accuracy: 0.0070
Epoch 19/20
5/5 [==============================] - 0s 88ms/step - loss: 0.0270 - accuracy: 0.0070
Epoch 20/20
5/5 [==============================] - 0s 86ms/step - loss: 0.0268 - accuracy: 0.0070
```

FIGURE 14: LSTMFinal Epoch Microsoft Data Set (MFST.CSV)

From the above figure the model performs Epoch's based on lstm algorithm and produce output of loss and accuracy of Microsoft Data Set.

```
Training for fold 1 ...
Epoch 1/200
3/3 [==============================] - 4s 259ms/step - loss: 0.5183 - accuracy: 0.0000e+00
Epoch 2/200
3/3 [==============================] - 0s 92ms/step - loss: 0.2429 - accuracy: 0.0011
Epoch 3/200
3/3 [==============================] - 0s 96ms/step - loss: 0.1139 - accuracy: 0.0046
Epoch 4/200
3/3 [==============================] - 0s 94ms/step - loss: 0.1299 - accuracy: 0.0051
Epoch 5/200
3/3 [==============================] - 0s 91ms/step - loss: 0.0903 - accuracy: 0.0052
```

FIGURE 15: Enhanced LSTMInitial Epoch Microsoft Data Set (MFST.CSV)

From the above figure the model performs Epoch's based on Enhanced lstm algorithm and produce output of loss and accuracy of Microsoft Data Set.

```
Epoch 195/200
3/3 [==============================] - 0s 97ms/step - loss: 0.0265 - accuracy: 0.0070
Epoch 196/200
3/3 [==============================] - 0s 108ms/step - loss: 0.0264 - accuracy: 0.0070
Epoch 197/200
3/3 [==============================] - 0s 104ms/step - loss: 0.0267 - accuracy: 0.0070
Epoch 198/200
3/3 [==============================] - 0s 99ms/step - loss: 0.0264 - accuracy: 0.0070
Epoch 199/200
3/3 [==============================] - 0s 104ms/step - loss: 0.0262 - accuracy: 0.0070
Epoch 200/200
3/3 [==============================] - 0s 97ms/step - loss: 0.0265 - accuracy: 0.0070
```

FIGURE 16: Enhanced LSTMFinal Epoch Microsoft Data Set (MFST.CSV)

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From the above figure the model performs Epoch's based on Enhanced lstm algorithm and produce output of loss and accuracy of Microsoft Data Set.

V. CONCLUSION

The stock market is extremely unpredictable and it changes accordingly. The machine learning approaches which are used before are unable to predict stock prices and stock volumes accurately. Predicting the volumes of the Stock is a challenging task with this implemented model one can predict an organization's closing stock volume and stock price, the developed model has an interface for predicting the price of closing stock and the volume of stock using Enhanced LSTM. Apple (AAPL) and Microsoft (MFST) are the two datasets used in this model to achieve accuracy. While Performing LSTM and Enhanced LSTM on Both Data Sets i.e. AAPL has 10 years of data and MFST has recent years data Predicted Accuracy is high for Apple data Than the Microsoft Data Set Because LSTM is mostly used for Long Term Dependencies. By using LSTM and enhanced LSTM we can predict that Apple Stock has higher volumes of stock than Microsoft Stock.

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