International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

RNN LSTM Architecture to Improve the Accuracy of Forecasting Stock Price Moment

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Submitted: 28/12/2023 **Revised**: 04/02/2024 **Accepted**: 12/02/2024

Abstract: Earning a good share market profit is difficult to achieve because of its non-linear nature and volatile moment. Nowadays, programmed algorithms with deep learning are used to predict the direction of moment and they are more accurate and efficient to provide the prediction of stock. In this work, RNN LSTM architecture and artificial neural network have been utilized to predict the stock moment and exact entry point in particular stocks. The financial data of five different companies of different sectors are used as inputs for our model. The model processes the variables like volume, Opening price, and closing price along with Bollinger Band and RSI indicators. In this work, the RNN LSTM architecture and deep learning have improved the efficiency by 80-98 percent compared to past methods.

Keywords: *RNN LSTM architecture, stock prediction, RSI Indicators, accuracy*

1. Introduction:

People have always been attracted by the stock market as it has created enormous wealth over some time. Many have made fortunes; on the dark side, they have lost the capital. Why is there volatility in the stock market? The primary cause is the difference in stock supply and demand. The stock market rides heavily on sentiments, political conditions, performance reports of companies, and global economic conditions. Because of this dynamic and non-linear nature, analysis and prediction of stock is a challenging task. Over the past few years, a variety of strategies and algorithms have been employed to identify the stock's trend and anticipate future prices to safeguard our profit and reduce our losses [1]. There are two traditional ways to predict the moment of stock. Fundamental analysis is qualitative analysis in which the profile of a company, its quarterly performance sheet, and its order books are analyzed. Second is the technical analysis that uses the price of stock in historical days, volume, along some indicators like the Relative strength index [2]. Nowadays, advanced price prediction techniques, either based on fundamentals or technical, are used in an organization. On the stock market, a variety of stocks are listed on exchanges which are non-linear and dynamic. To deal with the prediction model, it should be efficient to handle large data with hidden patterns and complex relations of data with other unknown parameters.

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2. Related work:

Previous research in this field used traditional algorithms to predict the stock price moment. In 2012 Anshul Mittal [3] used machine learning and sentimental analysis to find the correlation between market sentiments and public sentiments. He cross-validated the method on financial data and achieved 75.56% accuracy, such as linear regression [5], and most linear models, such as Autoregressive Integrated Moving Average (ARIMA) [8] and Autoregressive Moving Average (ARMA), to forecast future stock prices. Recent research demonstrates that deep learning and artificial neural networks can improve stock market prediction. Nelson D M [4] used deep neural networks like Long Short Term Memory (LSTM) and recurrent neural networks (RNN) have demonstrated promising results in stock prediction [6][13]. Selvin et al.[7] used deep learning techniques to conduct a comparative examination of different equities listed on the NSE and projected the stock price of NSE-listed companies. Hamzac ebi et al.'s [9] ANN experimental study include the stock market's forecasting on multiperiod time series utilizing iterative and directive approaches. Rout et al.[11] tested and predicted it using the Bombay Stock Exchange and S&P 500 index dataset using a low complex RNN model. Roman et al. used the networks to forecast the trend in stock returns on stock market data from five different countries: Canada, the United Kingdom, the United States, Hong Kong, and Japan, after training the networks with RNN models. [12].

The issue of RNN long-term dependency is solved by using LSTM. Though it cannot hold a word in long-term dependence, the RNN makes more accurate predictions.

As a result, the gap length grows and RNN performs less well than ideal. LSTM solves this issue by retaining the information for an extended length of time, which reduces data loss. This LSTM feature is applied to stock prediction and time-series data classification.

3. Methodology:

In this section, discussed some of the methods used in this work.

3.1 Description of Data:

The website investing.com has provided historical data for five different sectors. The data set includes data from 1/1/2017 to 1/1/23 of top leader companies like SBI from the sectors of banking and finance, TCS from the information technology sector, Sun Pharma from the Pharma sector, Tata Motors from the automobile sector, Tata Steel from the metal sector. The historical data contains the day-wise information of each stock including open, low, close, and volume, along with two indicator lines: Bollinger band and Relative strength index (RSI).

Parameter	Time Interval	Training Data set	Testing Data Set
Low	1/1/2017	1/1/2017-1/12023	1/1/19-1/1/2023
High			
Close			
Open			
Volume			

Table 1 Description of Data with parameters

3.2 Variables:

The following new variables have been applied to price and moment prediction. These variables were used in the model's training. The following are the new variables:

1. High and Low prices of stocks (H & L)
2. Open price and close price (O & C)
3. The fourteen-day moving average (14DMA) of the stock price
4. The Bollinger Band Indicator
5. Relative strength Index (RSI)
6. Stock volume

3.3 LSTM network:

Long short-term memory banks (LSTM) are an intelligent data mining technique that identifies a fundamental trend in data and draws conclusions from it. When it comes to simulating and interpreting complex patterns in unstructured data, ANN performs better than most conventional methods. The model makes use of the basic architecture of a neural network, which is made up of neurons with different layers.

The weights of each input load are summed, multiplied, and delivered to the neurons. The hidden layer, sometimes referred to as the activation layer, is composed of these neurons. The whole weight is moved to the third layer, the output layer, following computation. The output layer has a single neuron, and it is this neuron that will forecast the stock's price.

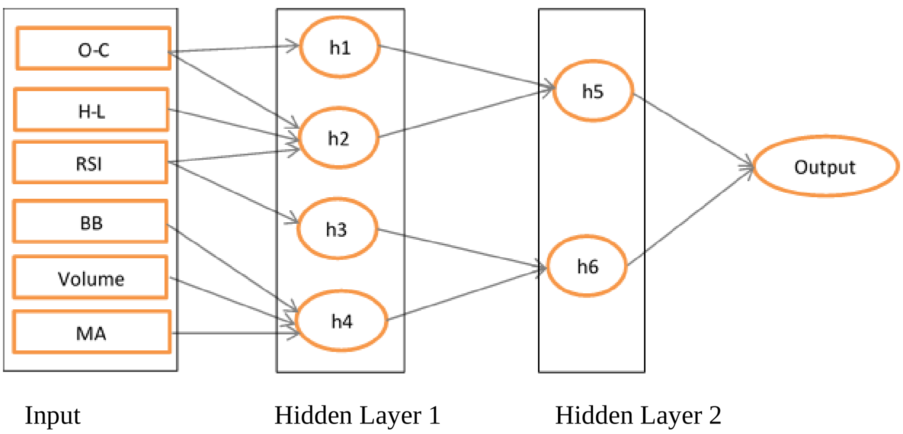

Fig.1 Detailed Architecture of RNN LSTM

3.4 RNN Architecture:

Recurrent Neural Networks, or RNNs for short, are capable of processing both sequence and time series data. The RNN that we are modeling is called LSTM. A modified RNN called an LSTM (Long Short-Term Memory) is very good at learning long-term dependencies, which helps make the next estimate more reasonable. In order to forecast the layer's output, RNNs operate on the basis of storing the output of a certain layer and feeding it back into the input. One of RNN's advantages is that it can handle time series data, takes the context of the data into account while training, and is excellent for stock prediction. Because stock prices are non-linear and volatile nature, there is frequently some correlation between them and prior trends at a given time.

Recurrent Neural Networks, or RNNs for short, are capable of processing both sequence and time series data. The model we are using is called LSTM, and it is an RNN. A modified RNN called an LSTM (Long Short-Term Memory) is very good at learning long-term dependencies, which helps to make the next estimate more reasonable. RNNs function is primarily by storing the output of a given layer and feeding it back into the input to forecast the layer's output. RNN has the advantage of processing time series data, taking into account the context of the data during training, and being highly appropriate for stock prediction. Because of the volatile nature of stock price, at a certain moment, RNN often has some connection with previous trends.

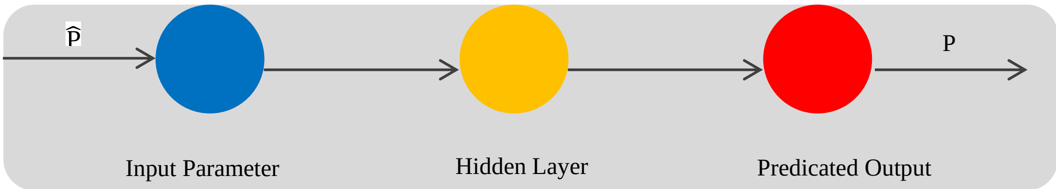

Fig 2 Simple architecture of RNN

4. Simulation and Result:

Simulation of proposed model and its result on real time data is discussed.

4.1 Steps for creating and training deep learning models

1. Check the input data: collect relevant information on stocks and parameters that act as input to the model.
2. Clean data: Collected data is in CVS format. Clean the data as per the requirement of the model.
3. Build a model: Choose the right model architecture based on accuracy in prediction.
4. Train the model: Show it lots of data and let it learn how to make predictions
5. Parameter tuning: Architecture includes a hidden layer that tunes the parameters
6. Evaluate the model: Test the model on new data and evaluate the performance of the model. Also, check the accuracy.
7. Making predictions: Use the trained model to predict data.

4.2 Experimental model training

Model Training

Epoch 1/5

1875/1875 [=========================] – 112s 59ms/step – loss : 0.7750 – accuracy : 0.7387

Epoch 2/5

1875/1875 [=========================] – 112s 60ms/step – loss : 0.1909 – accuracy : 0.9477

Epoch 3/5

1875/1875 [=========================] – 114s 61ms/step – loss : 0.1258 – accuracy : 0.9664

Epoch 4/5

1875/1875 [=========================] – 114s 61ms/step – loss : 0.0937 – accuracy : 0.9748

Epoch 5/5

[=========================] – 111s 59ms/step – loss : 0.0780 – accuracy : 0.9792

1875/1875

Model Evaluation

313/313 [==========================] – 7s 20ms/step – loss : 0.0664 – accuracy : 0.9814

313/313 [==========================] – 6s 19ms/step – loss : 0.0664 – accuracy : 0.9814

RNN (LSTM) Model Test accuracy : 0.9814000129699707

Fig 3 Experimental model accuracy

4.3 Output of the proposed model :

In the experiment, we compared the performance of LSTM RNN models - on five different sector companies: SBI, TCS, Sun Pharma, Tata Motors, and Tata Steel. We evaluated the predicted prices using three metrics: Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Bias Error (MBE).

RMSE is computed by taking square root of MSE.

RSME = $\sqrt{MSE}$

MSE is calculated by

MSE= 1/n $\sum_{i=1}^{n}(Oi - Fi)$

Where Oi = observed price

Fi = Predicted Price

n = Number of data point

MAPE is calculated by

MAPE= MAE *100

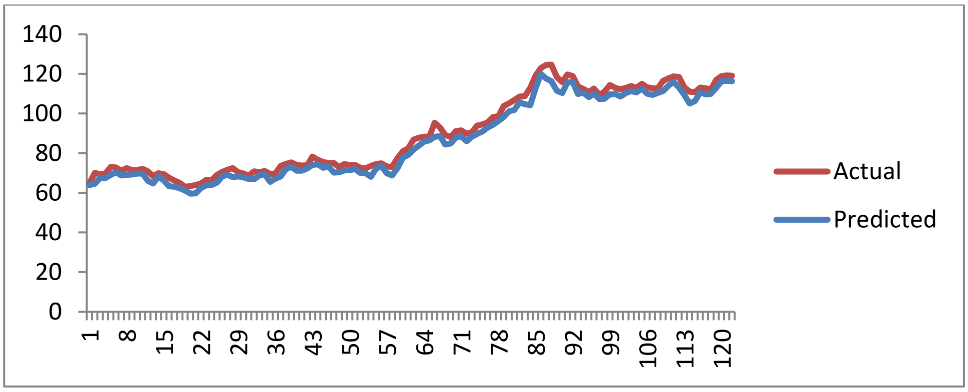

Fig 4 Comparision of Actual price and Predicted price of Tata Motor

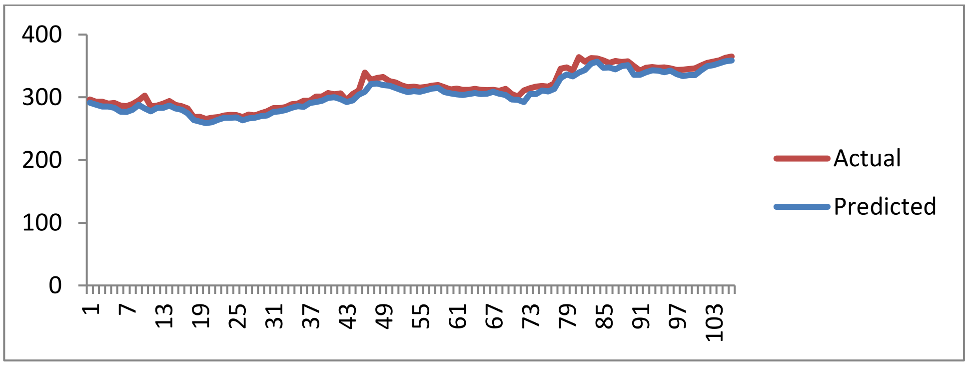

Fig 5 Comparision of Actual price and Predicted price of Tata Steel

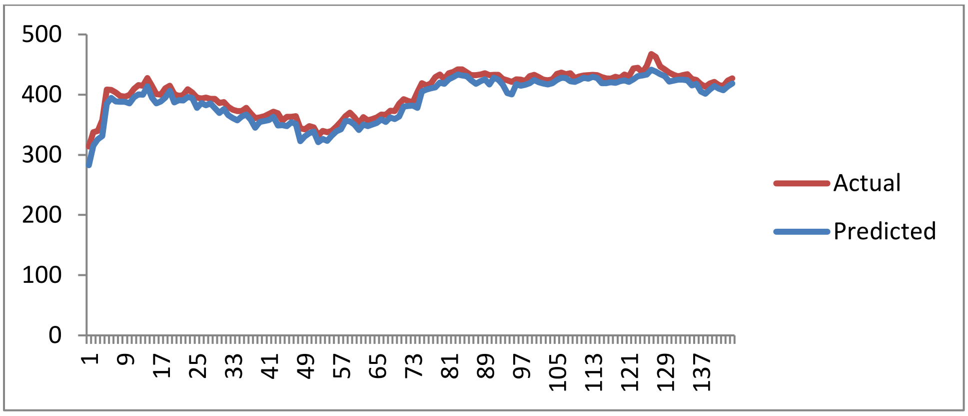

Fig 6 Comparision of Actual price and Predicted price of SBI

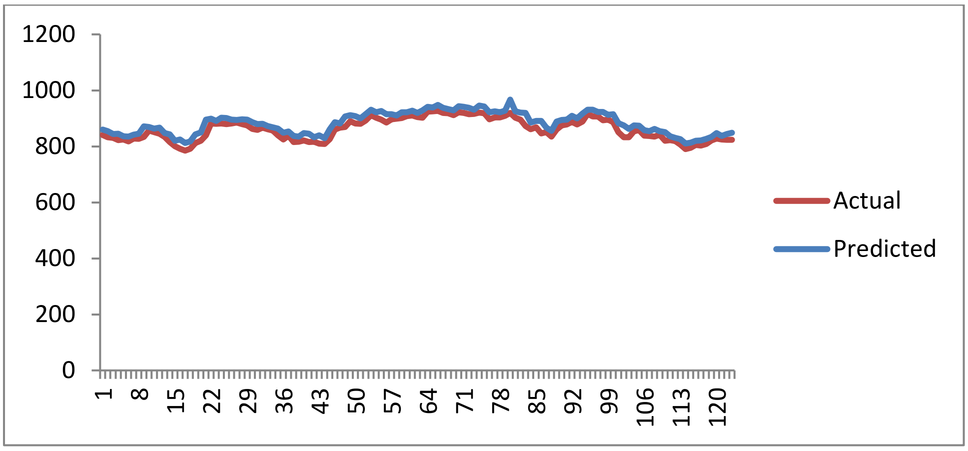

Fig 7 Comparision of Actual price and Predicted price of Sun pharma

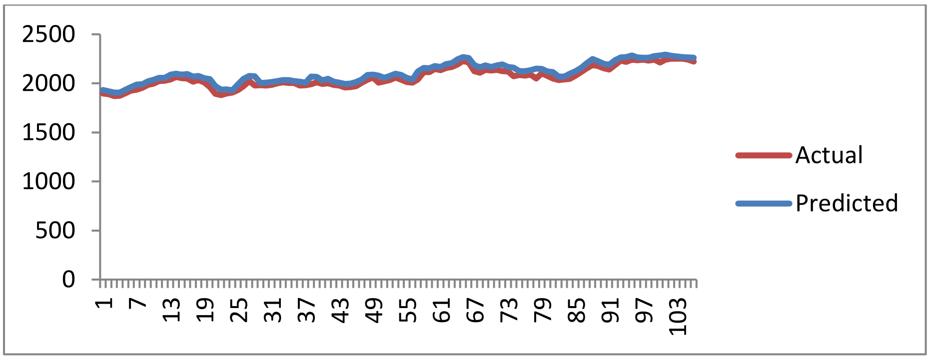

Fig 8 Comparision of Actual price and Predicted price of TCS

4.4 Results:

The accuracy of the proposed model, as observed from the experimental output, is

Accuracy Score of Model	
RNN(LSTM)	98.14%
CNN	97.86%
DNN	97.64%

5. Conclusions:

Based on research, it has been found that the RNN LSTM architecture in deep learning is more accurate compared to the CNN and DNN architectures. The LSTM RNN model is specifically designed to learn patterns in time series data and use them to predict future events. The model is capable of capturing and remembering important context, even when there are significant gaps in time between relevant events in the sequence. This makes the LSTM RNN model a more reliable and effective approach for time series prediction.

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