Forecasting volatility trend of INR USD currency pair with deep learning LSTM techniques

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Abstract—**Volatility is an important and most discussed topic in finance. Many of financial trades and applications are based on the volatility. In the recent times currency pair conversion trades are new found interest among financial traders due to high instability in the financial market. The advancement in technologies, increased computing speed and capability to handle large data has given rise to deep learning techniques. In this paper, deep learning LSTM techniques have been used to solve volatility forecasting problem of INR USD currency pair. The research uses an innovative approach in arrangement of data to make use of recent 25 values for forecasting volatility trend. The algorithm forecasts uptrend or downtrend movement of volatility a day ahead. The experiments were conducted to forecast volatility using machine learning and deep learning techniques. The LSTM technique is experimented with several epochs and configurations to yield better accuracy. The results show that LSTM techniques produced better accuracy compared with neural networks, SVM, random forest, regression, decision trees and boosting techniques. One of the main application of this research paper is forecasting the rise and fall of INR versus USD. The approach can also be applied to forecasting problems in algorithmic trading, churn predictions, Lead optimization and Fraud detections.**

Keywords*—*Volatility, Forecasting, Deep learning, LSTM

I. INTRODUCTION

Volatility has been one of the most sought topic of research in finance, similarly deep learning techniques are one of the most used and researched topic in computer science. Here this paper propose to apply deep learning techniques to solve volatility forecasting problem. Deep learning and neural networks has as of late turned into a ground-breaking tools to solve complex issue because of upgrades in training calculations. Cases of fruitful application can be found in discourse acknowledgment and machine translation. There exist relative few finance publications were deep learning have been connected, yet existing articles demonstrate that deep learning can be effectively connected to issues in back. Forecast of volatility on financial market is a standout amongst the most much of the more often discussed topic. In real world it is relatively difficult to forecast the right direction and most investigate considers the instance of foreseeing whether the market will go up or down amid the following period. Besides, expectation of the market is of incredible enthusiasm for arrange both to guess about potential returns and to comprehend which factors that drive the market.

As indicated by the proficient market hypothesis, prices on financial resources mirror all accessible data and in this manner suggests that it is difficult to outperform market [1]. To attempt to show the future returns one must have a thought regarding which information and economic factors that impact the future prices. The examination about which information and economic factors that impact the future returns is an examination territory in itself and there does not exist any hypothesis indicating pertinent parameters [2] [3]. Besides, there exists confirm that future returns can be predicted by historical returns [4]. Most financial information can be considered as time arrangement, i.e. it has a period dependence. Consequently, strategies where the time arrangement structure is safeguarded is to lean toward. The relationship between the information is extremely unpredictable. In this way, machine learning calculations have been of enthusiasm since the information have complex connections and the measure of information has expanded. Resources crosswise over various markets can be thought to be associated [4]. In this way, particular markets have a tendency to take after each other and a multivariate model can be desirable over catch those sort of situations

II. LITERATURE SURVEY

There exists a broad writing with respect to expectation of value developments utilizing machine learning. The t forecasting volatility, is a challenging task within the presence of noise. Artificial neural network based LSTM techniques for time series forecasting are best in predicting financial trends [5]. The advances have together prepared for more compelling preparing novel models, for example, the Long Short Term Memory and now Memory (LSTM. In another paper he utilizes high-frequency data on four deep and liquidity future markets, to be specific unrefined petroleum, oil, flammable gas, and fuel, to recognize jumps and break down their effect on future volatility [6]. The HARQ models, of course, hold the guarantee of significantly more precise forecasts and better volatility risk premium evaluations, and thus new bits of knowledge a more profound comprehension of the financial mechanisms [7] [8].

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Techniques like help vector machines [9] [10], shrouded Markov models [11], and neural networks [12] [13] have been utilized. A fascinating overview that examines diverse works in deep learning is "Deep Learning in Finance" [14]. The article investigates how deep learning has been utilized for issues in financial expectation and order also, recommends distinctive approaches to enhance the techniques. Additionally, the creators give a prologue to Long Short-Term Memory, repetitive neural networks, and propose that the model can be utilized as an unpredictability display. The creators presume that deep learning can recognize designs in the financial information that is undetectable to the current financial economics hypothesis. Another intriguing article is "Utilizing machine learning for portfolio exchanging. They utilize distinctive machine learning techniques, linear regression, support vector machines, and feed forward neural networks, which is prepared on specialized markers. Their outcome demonstrates that it is conceivable to make productive exchanges. Also, Long Short-Term Memory neural network has been utilized in "Deep Learning Stock Volatility with Google Domestic Trends"[15]. They show the unpredictability of S&P 500, utilizing Google household inclines as markers of macroeconomic variables and the general population air. Their Long Short-Term memory display beat techniques like linear regression and GARCH benchmarks. As a result of their outcomes, there exist solid proof for expanded forecast precision for foreseeing securities exchange conduct utilizing deep learning and neural network models. Besides some researcher has connected deep learning in his lord postulation "Deep Learning for Multivariate Financial Time Series"[12]. Deep learning is utilized to develop an arrangement of some given stocks. His deep learning model comprises of a deep conviction network mapping into a feed forward neural network. Also, here it's presumed that deep learning strategies in back are solid and have great execution.

Two forecast models were built by Yakup in 2011 using ANN and SVM techniques to predict a day ahead stock price movement [16]. In another research paper examines the job of basic machine learning models to accomplish beneficial trading through a progression of trading reproductions in the FOREX market [17].

III. VOLATILITY

Volatility (fluctuation) is a fundamental measure for risks related with a financial market's instrument. It indicates an incidental constituent of an asset's price change and is accounted as a scope of the price modification inside exchanging session, exchanging day, month and so forth. Typically the more extensive scope of variances (higher volatility) implies higher exchanging risks included.

In this way volatility is regarded as an irregular esteem and its scientific displaying gives premise to all risk modeling strategies, utilized on foreign exchange showcase. For volatility estimation measurable standard deviation is computed. It additionally decides introduction of financial ventures. In intraday exchanging the most critical volatility pointer is normal every day value run; in longer positions assessment a normal week by week, month to month or yearly range might be utilized. Yearly volatility is most basic in long term financial venture's analysis.

A. Computing Historical Volatility

In theoretical option evaluating models, the articulation "volatility" has an indisputable and correct which implies, and academic and finance domain specialists quickly consider that elucidation when the volatility of security prices is discussed. Black and Scholes decided their option valuation condition under the assumption that stock returns, "log value derivatives" to be accurate, taken after a logarithmic dissemination process in persistent time with steady drift and volatility parameters, as showed up in condition (1) [2].

$$\frac{dS}{S} = \mu\, dt + \sigma\, dz \tag{1}$$

Starting from a fundamental quality S_0, the entry over the non-minute time span from 0 to T is given by

$$R = \ln \left(\frac{S_T}{S_0}\right)\ (3.9) \tag{2}$$

Moreover, R has a Normal distribution, with

$$\text{Mean} = \left(\mu - \frac{\sigma^2}{2}\right)T \tag{3}$$

$$\text{Standard deviation} = T \tag{4}$$

The justification of option assessing theory is that, under the suspicions of the model, in the event that one knows the genuine volatility close by the other, conspicuous, parameters, there exists a dynamic self-financing exchanging approach that can be taken after from the present until the point that the moment that the expiry date that will decisively reproduce the result on some random option. The volatility parameter anticipated that would execute that technique is the volatility that will be shown over the entire remarkable lifetime of the choice. Along these lines, what must be forecasted is the standard deviation of the log values derivatives for the basic resource from now until expiry day, which may be a period of years for a long development contract. Hypotheses of the basic Black-Scholes structure to consider volatility that vacillates (nonstochastically) after some time provoke same as result: the volatility parameter that goes into the model is the square base of the ordinary annualized return fluctuation over the option's lifetime, as showed up in condition (5) below [3].

$$\sigma_t^* = \left(\frac{1}{T-t}\int_t^T \sigma_s^2\ ds\right)^{\frac{1}{2}} \tag{5}$$

At some period of time when a asset's cost takes after the reliable volatility lognormal distribution model of condition (5), σ can be assessed viably from past data. The inconvenience develops in on the grounds that genuine price do not take after (1) absolutely, with the objective that value conduct may change after some time and differentiation over between times of different lengths. Also, the way by which condition (1) flops in practice certainly not developed and adequately broad for a specific model to have ended up being extensively recognized. It is typical, subsequently, to process volatility using chronicled value information as if condition (1) were correct yet to adjust the estimation strategy, or the volatility number it produces, in various ways to deal with equalization known or suspected issues. The consequent point gauge for σ at that point transforms into the volatility commitment to the Black-Scholes show or another settled volatility valuation condition. In spite of the way that genuine volatility may be acknowledged to move stochastically after some time, Black-Scholes is normal and less demanding to control than any valuation demonstrate that modifies for unpredictable volatility formally.

B. The Standard Historical Volatility Estimate

Consider an arrangement of recorded price data for some basic resource that takes after the technique portrayed in condition (5): { S_0 , S_1 , ... , S_T }. We begin by enlisting the log values derivates, i.e., the value change rate imparted as continually exasperated rates Rt = ln(St/St-1) , for t from 1 to T.

The estimate of the (predictable) mean μ of the R_t is the direct ordinary

$$\bar{R} = \frac{\sum R_t}{T} \tag{6}$$

The vacillation of the Rt is given by

$$v^2 = \frac{\sum(R_t \} \bar{R})^2}{(T-1)}$$

(7)

The denominator in condition (7) is (T – 1) because of the information contained in one observation is enough spent in computing the model mean. On the other hand, if the mean is known (or is constrained by the expert to be some particular esteem, for instance, zero), this information is not lost and the total of squared deviations should be apportioned by T.

Annualizing the fluctuation with result of N, the amount of significant worth recognitions in multi-year and taking the square root yields the volatility,

$$\sigma = \sqrt{N\, v^2}$$

(8)

In case the relentless parameter scattering model of (1) is correct, the above approach gives the best gauge of the volatility that can be gotten from the current information. This number by then transforms into the gauge for volatility proceeding, completed a period skyline of any length.

IV. DEEP LEARNING LSTM TECHNIQUES

Deep learning is advanced machine learning technique with advanced learning capability. The specialty of deep learning techniques that separates from other machine learning techniques is the ability to perform classification and regression tasks with an accuracy greater than state of art techniques. These techniques were visualized in early 1980's however became popular in recent times. The reasons are due to lack of computing power and handling of large data sets in those ages. Deep learning is prime algorithm behind driver less cars, language translations, image recognitions etc.

Long short term memory (LSTM) units are the extensions of recurrent neural network (RNN). A RNN composed of memory units can be referred as LSTM networks. A common LSTM unit consists of 3 gates namely input, output, forget and a cell. The cell is memory unit and it remembers values over certain duration of time interval and 3 gates control the flow of information inside and outside of the cell. The structure of LSTM network is shown in Fig. 1.

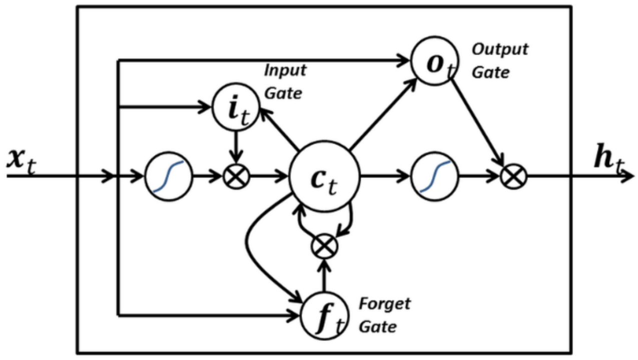

Fig. 1. *LSTM units with a cell, input, forget and output gates*

There are many structures of LSTM units. A LSTM cell takes an information and stores it for some timeframe. This is identical to applying the identity function f(x) =x to the input. Since the subsidiary of the identity function is consistent, when a LSTM is trained with back propagation through time, the slope does not vanish. The logistic function is generally used as activation function in LSTM. Naturally, the input gate controls the degree to which another value streams into the cell, the forget gate controls the degree to which a value stays in the cell and the output gate controls the degree to which the incentive in the cell is utilized to process the output activation of the LSTM unit. Many connections exists between in and out of LSTM gates, a couple of which are recurrent. The weights of these connections, which should be placed are learnt during the process of training. The LSTM network are applied in classifying, regression and forecasting problems.

V. DATA DESCRIPTION

In this paper, INR USD currency pair data is selected for forecasting volatility. Most of the researchers use either stock market data or stock index prices; here this paper is making use of forex data. The INR USD end of day data was downloaded from investing.com a trusted source. The data contained date, open, high, low, price and percentage change columns. For the experiment of forecasting volatility this paper uses data of 10 years containing 2680 days of data. In the Fig. 2. The sample graph indicating the INR USD conversion rate movement. Table I represents the sample data downloaded from the internet and Fig. 2.

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Shows the movement of INRUSD conversion rate for sample 100 periods.

TABLE I. A SAMPLE OF DOWNLOADED CURRENCY RATE

Date	Price	Open	High	Low	Change %
09-Mar-18	65.125	65.125	65.195	65.045	0.03%
12-Mar-18	64.985	64.965	65.07	64.957	-0.21%
13-Mar-18	64.855	64.985	65.01	64.845	-0.20%
14-Mar-18	64.84	64.89	65.062	64.82	-0.02%
15-Mar-18	64.99	64.925	64.993	64.81	0.23%

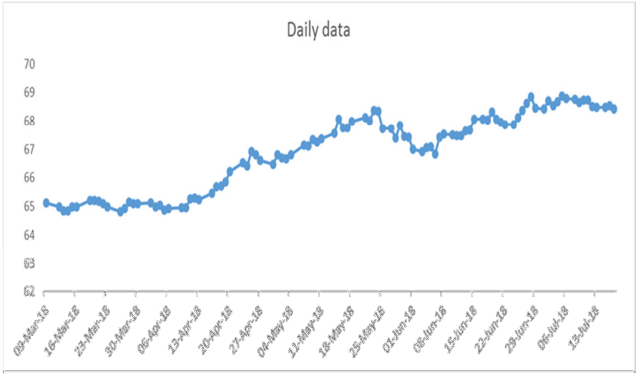

Fig. 2. A sample graph indicating INR USD conversion rate

VI. METHODOLOGY

In this section, discuss the application of data for forecasting with LSTM techniques. It also discuss the steps involved in building a forecasting model. The block diagram representation of forecasting model is shown in Fig. 3

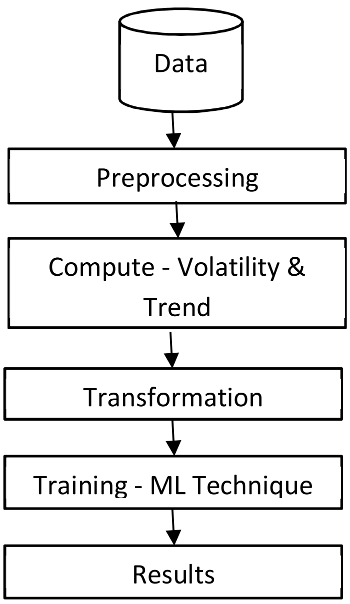

Fig. 3. Block diagram representation of INR USD volatility forecasting

A. Data

The INR USD conversion rate data downloaded from internet contains open, high, low and prices. However for the analysis needs volatility of the conversion rate. Hence methodology make use of standard volatility estimators to calculate volatility. The volatility is calculated using garman class estimator considered to be the best volatility estimation technique [12] among existing estimators. The computed volatility is represented in Fig. 4.

B. Preprocessing

The data is checked for missing values, outliers and noisy values. The missing values are eliminated from the analysis and outliers are fixed with 5th and 95th percentiles. The data is statically checked of value that lie above 95th percentile and below 5th percentile and they are replaced with 5th and 95th percentiles respectively. This takes care of outlier problems. The noisy data are identified through average and standard deviation and eliminated from the analysis.

C. Compute - Volatility & Trend

The Garman Klass method is accurate estimation method as it uses Brownian motion instead of standard deviation. Hence this method of estimation is better than close method. The advantage of using Brownian motion is the method has zero drift and no opening jumps. This method is 7.4 times accurate than close method estimation [18].

$$\text{Volatility}_{\text{Garman-klass}} = \sigma_{\text{GK}} \tag{9}$$

$$\sigma_{\text{GK}} = \frac{F}{N} \tag{10}$$

$$\frac{F}{N} = \sum_{i=1}^{N} \frac{1}{2} \ln\left(\frac{hi}{li}\right)^2 - (2\ln(2)-1) - \ln\left(\frac{ci}{oi}\right)^2 \tag{11}$$

Trend Calculation – the volatility trend is calculated from the differences of closing prices, when subtraction yesterday's volatility with today's volatility and if the difference value is positive then it is considered as uptrend, if the difference is negative then it is considered as downtrend. The uptrend are denoted as 1's and downtrend as 0's. The calculation of uptrend and downtrend are represented in the equations (1) and (2). The volatility estimated through garman class method is displayed in the Fig 3. The volatility sample trends are represented in Fig. 5.

Trend = 0 if price (i-1) – price (i) < 0 is downward trend (12)

Trend = 1 is price (i-1) – price (i) > 0 is upward trend (13)

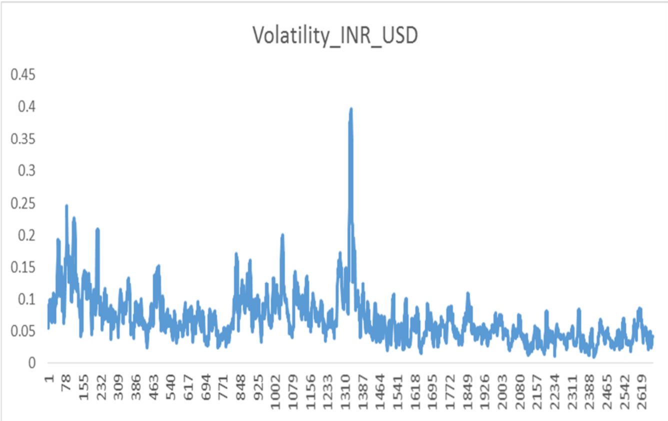

Fig. 4. Volatility of INR USD conversion rate

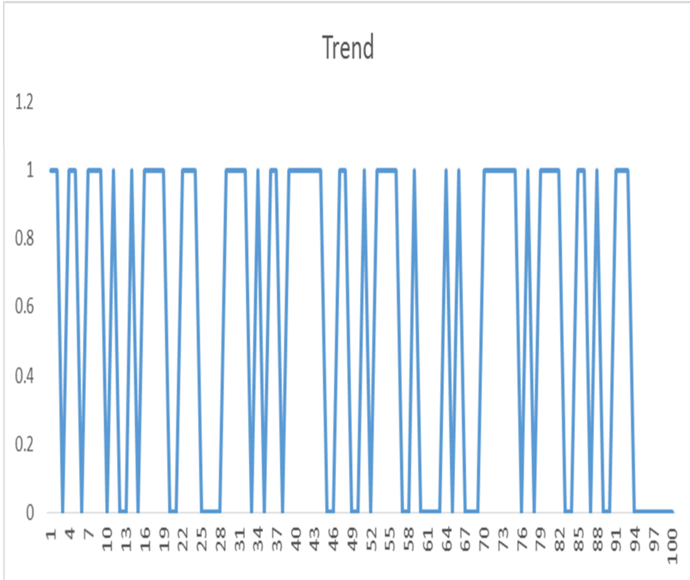

Fig. 5. A sample graph indicating uptrend and downtrends for first 100 values

D. Transformation

The data is arranged in matrix to have the volatility values in their increasing order of dates. The values are arranged to have 25 values in each row of the matrix. The second row starts with second another 25 values excluding the previous value. The target variable trend is calculated as discussed in the section A. In the table II a sample of data arrangement is tabulated.

TABLE II. TABLE REPRESENTATION OF DATA ARRANGEMENT

Day1	**Day2**	**…**	**….**	**Day24**	**Day25**	**Trend**
0.054448	0.074905			0.073909	0.076846	1
0.074905	0.076542			0.076846	0.100877	0
0.076542	0.073426			0.100877	0.092145	1
0.073426	0.090666			0.092145	0.089144	1

E. Technique

This experiment has considered Trend as target variable and all other columns the volatility values on 25 days are considered as independent values. A LSTM forecasting model is built with 25 input layers, 2 hidden layers and one output layer. The total dataset consists of 2680 number of data, out of these 70% data is considered as training dataset and other 30% data as testing dataset. The training and testing samples are chosen randomly to cover all the patterns in the dataset. The experiments are conducted for several epochs of LSTM model in several iterations and results are recorded.

F. Results Comparison

The results of forecasted values are compared with actual values of testing dataset; a confusion matrix of downtrend; uptrend and overall results are recorded in this section. The forecast accuracy with several attempts are tabulated in the table III. The experiments were conducted with LSTM with iterations of 250, 500, 750, 1000, 1250 and 1500. The LSTM with 1250 epochs have highest performance accuracy of 61.46% compared with other iterations. From table III there is variation of maximum of 3% with number of iterations in LSTM training. This paper also compares the results with other machine learning techniques such as neural networks, regression, decision trees, random forest, support vector machines and boosting techniques. The results of different machine learning techniques are tabulated in table IV. Out of all the techniques the overall accuracy of LSTM techniques are better.

TABLE III. VOLATILITY TREND FORECAST RESULTS WITH LSTM TECHNIQUES

LSTM Technique	Down Trend Accuracy	Up Trend Accuracy	Overall Accuracy
LSTM epochs = 250	39.35%	79.42%	60.85%
LSTM epochs = 500	38.71%	83.35%	61.29%
LSTM epochs = 750	32.86%	85.21%	58.73%
LSTM epochs = 1000	45.74%	75.73%	60.62%
LSTM epochs = 1250	39.93%	81.04%	61.46%
LSTM epochs = 1500	28.30%	89.35%	58.67%

VII. SUMMARY

In this paper, LSTM deep learning techniques for forecasting volatility trend of INR USD currency conversion rate. As its general fact that volatility is more dependent on recent dataset, this research uses as innovative approach to forecast volatility from previous 25 values. The data is arranged in matrix form containing volatility values in their increasing order and trend is calculated based on the increase or decrease of volatility. The algorithm randomly selects training and testing samples, the LSTM model is trained with training dataset where it learns the patterns of volatility and forecast for unseen dataset. The LSTM technique results outperform other machine learning techniques. In the Table IV the performance of LSTM technique is compared with other machine learning techniques and it’s evident that LSTM is better out of all the techniques.

TABLE IV. COMPARISON OF VOLATILITY TREND FORECAST WITH MACHINE LEARNING TECHNIQUES

Techniques	Down Trend Accuracy	Up Trend Accuracy	Overall Accuracy
Decision Trees	8.20%	95.09%	55.33%
Random Forest	31.48%	77.23%	56.30%
Boosting Techniques	44.44%	63.84%	54.96%
SVM	6.08%	96.65%	55.21%
Linear Regression	45.24%	75.89%	57.86%
Feed forward NN	47.88%	66.07%	57.75%
Long Short Term Memory NN	**39.93%**	**81.04%**	**61.46%**

VIII CONCLUSION & FUTURE SCOPE

The broad objective of this paper is to forecast volatility trend of INR USD conversion rate with LSTM technique. The smaller objective was to build a forecasting model that considers most recent data for forecasting volatility. This paper has achieved both the objectives, built a forecasting model using LSTM technique with an accuracy of 61.46% better than any other machine learning technique. The purpose of this paper is to predict the movement of volatility and with this paper forecasts uptrend or downtrend movement a day ahead. This paper also evaluates the performance of LSTM techniques with other machine learning techniques such as neural networks, regression, decision trees, random forest, SVM and boosting techniques and from results it’s observed that LSTM outperforms all other listed techniques.

The future work in this research is application of more feature extraction, selection and more advanced outlier technique to improve the accuracy. The accuracy is recorded after several iterations of forecasting is still less, the previous researchers with LSTM technique show there can be further improvement in accuracy with improvement in data quality. Although LSTM technique most advanced deep learning technique, the application of more complex techniques such as convolutional neural network or increase the complex of LSTM with few hybrid approaches to improve the accuracy.

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