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[ijirset@gmail.com](mailto:ijirset@gmail.com)

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# Applications of Machine Learning in Finance using LSTM Algorithm

K.V.Veeresh

PG Student, Department of Mathematics, Ramaiah University of Applied Sciences, Bangalore, India

**ABSTRACT:** The stock market is considered to be extremely complex and volatile, and people still seek to direct stock trading in reliable and efficient ways. Long short memory (LSTM) neural networks are generated by recurrent neural (RNN) networks and are of relevant significance in many areas. In addition, due to its special storage unit structure, LSTM prevents problems of long-term dependency and helps forecast financial times. A wavelet transformation is used to denote, based on LSTM and a focus mechanism, extract and train historical inventory data and to create an inventory price prediction model. Machine learning has recently been established in numerous sectors, including the financial sector, with commercial applications. This paper focuses on applications for the investment method, one of the main functions of finance. This includes return estimates, risk modeling and portfolio creation. A comprehensive overview of recent literatures assesses the present state of the art. Subjects, innovations, and the primary use cases are listed and categorized. Quantitative investment is the most common source of application in emerging literature, historically a leading domain in the adoption of new techniques.

**KEYWORDS:** Finance, LSTM, Deep Learning, Machine Learning.

## I.INTRODUCTION

Machine learning algorithms have covered various study subjects such as the use of machine learning in quantitative financial matters, the prediction of prices for management and restriction of the entire asset portfolio and the investment procedure. Machine learning in general is a term used to reveal patterns based on data only and does not use computers to schedule the whole algorithm. Several models have a wide range of approaches to be used for computer training in the prediction of potential value assets for quantitative finance and assets in particular. This model type provides a mechanism that combines poor information sources and makes them an odd tool that can be used efficiently. Recently, many machine learning algorithms have been polished by the mix of statistics and models. For example, neural networks, progressive regression trees, support for vectors and random projections. These algorithms can reveal both non-linear and some complex patterns relationships with linear algorithms which are difficult to detect. These algorithms are also more efficient than linear regressions, and multiple collinearity.

Many of the machine learning methods in the field of finances are involved at the moment, some studies use tree-based models to predict the returns from their portfolios[4]. Some writers have also looked at ADaBoost [10] for the prediction of returns. The Author's model employs the Support Vector Machine System (SVM) for portfolio choice and a Mid Variance (MV) approach[6] to forecast stock returns by using a special bond day trading decision model. Another paper discussed profound smart indexing learning models [3]. In addition, the literature review covered by the article includes retroactions to portfolio design, the wide range of machine training technologies and applications for quantitative finance[2] are ethics, fraud recognition, decision-making, language processing and feeling analysis. In this context, a class of algorithms for machine learning based on the Recurrent Neural Network is very helpful in predicting and forecasting the financial market; and are not based on a single long-term memory (passed data sequence).

A paper comparing the accuracy, as illustrative techniques when estimating time series data, of ARIMA and LSTM incorporated autoregressive average movements. The results show that the LSTM is much better than ARIMA[8]. The techniques are taken on the basis of a compilation of financial information. The key objective is for our LSTM RNN-based paper ML algorithm to predict future value of our portfolio, in the forecast of changing closing prices of an asset portfolio. The most advanced algorithm is used.

Traditionally, financial market forecasts were based on business and academia. [1] The variance is complex and non-linear for the stock market. [2] Clearly, analysis and decision making is not reliable and inefficient based solely on a trader's personal experience and perspective. In order to guide stock trading, people need an informed, scientific and successful process. As artificial intelligence evolves quickly, the application of profound education in stock price prediction has become the focal point for study. Because of its strong nonlinear approach capacity and adaptive self-learning, the neural network in deep learning became a common predictor. Long neural memory networks (LSTM) have been well-suited for speech acknowledgement[3, 4] and text processing. [5, 6] At the same time neural networks of LSTM have the characteristics of selectivity and memory cells and are suitable for a random sequence, for example stock price series.

## II. RECURRENT NEURAL NETWORK (RNN) AND LONG SHORT-TERM MEMORY (LSTM)

One of several forms of recurrent neural network RNN is a long-term memory (LSTM) which is also capable of collecting and using data for past phases in future predictions[7]. Generally, three layers consist of an Artificial Neural Network (ANN):

- 1) input layer,
- 2) Hidden layers,
- 3) output layer.

There is often a relationship called 'Synapsis,' in a NN[9] that has only one hidden layer, where the number of nodes in the entry layer depends on the data size. The decision factor for signals and the relation of each node is a coefficient called weight (the input of the hidden layer). The learning process is, of course, a continuous weight change and the Artificial NN is optimum for each synapsis after the learning process has been completed.

The hidden layer nodes are equipped with the sigmoid or tangent hyperbolic functions (tanh) in order to produce value, with the softmax function minimized error rate between the train and test results.

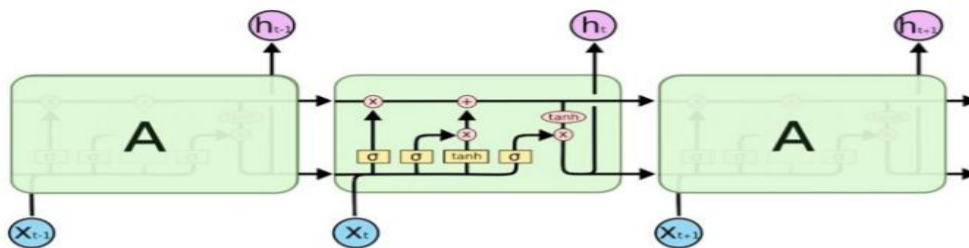


Figure 1. The internal structure of an LSTM

A back propagation protocol is implemented to target the best value of the mistake, the back propagation mechanism connects to the cached layer the output layer[10] and sends the signal that best suits the correct weight of the error for the specified number of times. This transformation results in the value of our NN output[5] layer. This method is repeated to refine our forecasts and to minimize the prediction error.

The model will be trained after completion of this phase. The groups of the NN, which predict the future value basis on past observer series, are referred to as the Recurrent Neural Network (RNN), such as this form of NN.

LSTM is a special kind of RNN since it can memorize the data series. The top line of each cell links models as transmission lines that pass data from the past into the present. The cell independence allows the model to dispose of a filter of add value from one cell to another. In the end, by disposing or passing data, The neural sigmoidal network gate layer results in optimum value[6]. The binary value (0 or 1) for each sigmoid layer is 0 "let nothing pass," and 1 "let anything pass through." The objective is to monitor each cell's condition and to regulate the gates:

- Forget Gate outputs a number from 0 to 1, where 1 "to hold it entirely," while 0 shows "to totally neglect it."
- the Memory Gate selects the cell's new info. First, the "input door layer" sigmoid layer determines which values are modified. Next, a layer of tanh produces an additional vector of new candidate values to the state.
- Output Gate can determine each cell's output. The output value and the filtered, freshest data will be dependent on the cell condition.

**III. RESEARCH FRAMEWORK AND METHODOLOGY**

Fig. 3 illustrates our research framework. In this analysis we integrate quality and quantitative analyzes of the papers. As shown in Fig. 4, seven primary F&B domains are classified and identified. Financial forecasts and Portfolio management to match the DL side with the F&B side. The tasks of prediction are critical, as Cavalcante et al stressed (2016). In this field we research three prediction-related aspects, namely currency, stock and oil. This application domain structure in F&B is illustrated.

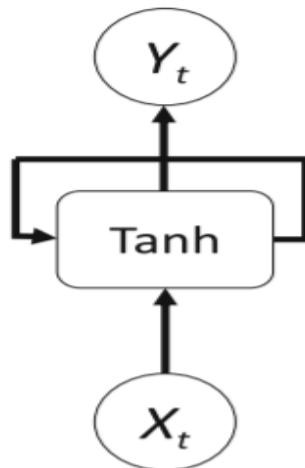


Fig. 2 The abstract RNN structure

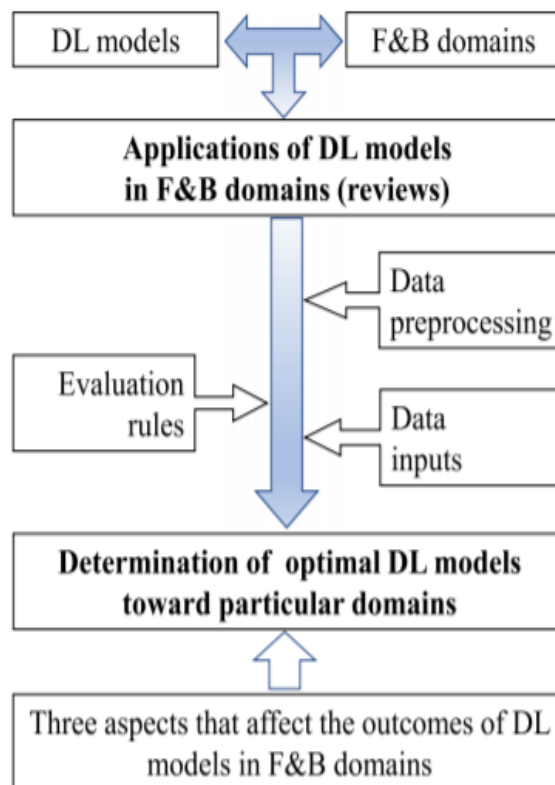


Fig. 3 This study's research methodology

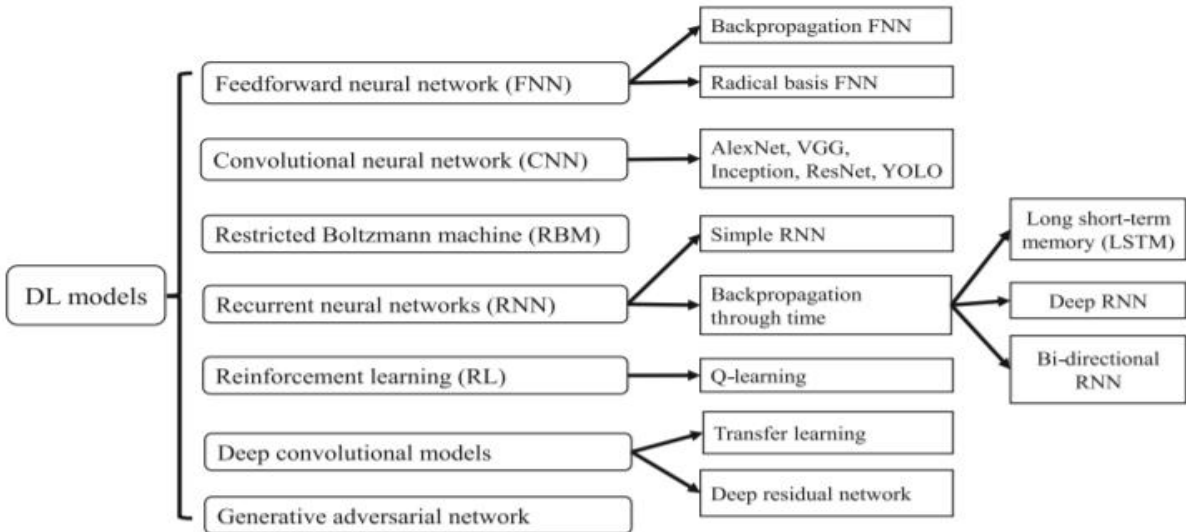


Fig. 4 F&B domains for DL applications are defined

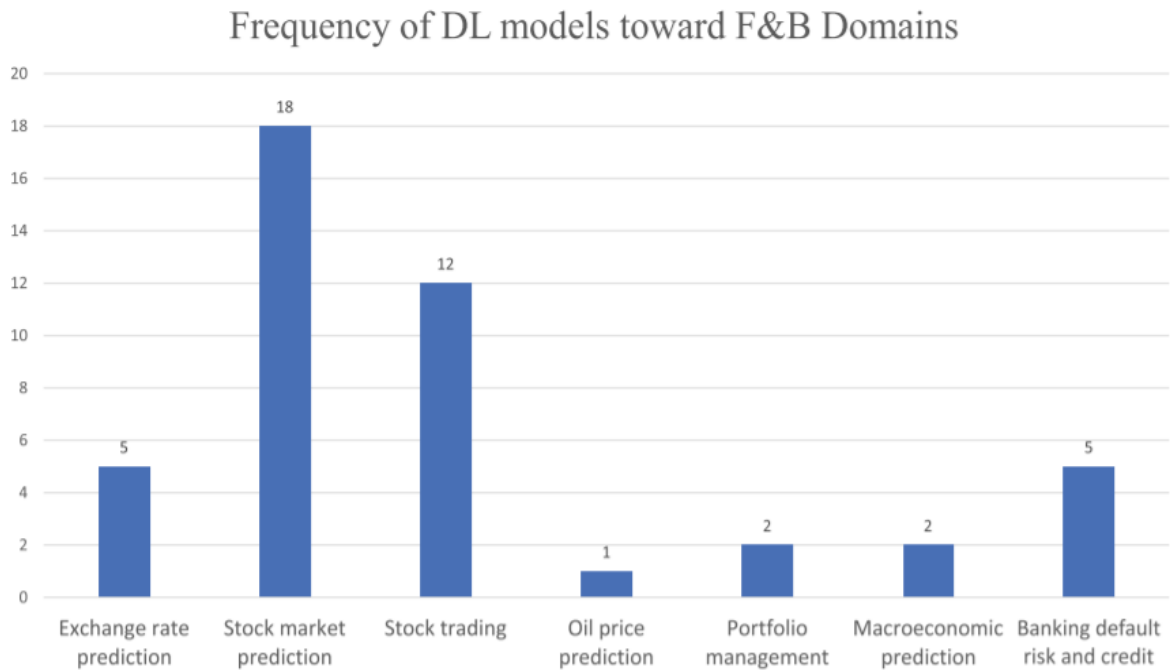


Fig. 4.1 A number of publications in seven F&B domains.



Fig 4.2. Opening price without denoising

The statistics in F&B domains are shown in Figure 4.1. The domains on the X axis for financial applications are illustrated and the number of items on the Y axis is counted. Notice that more than one domain can be covered by a reviewed article in this figure; thus, the number of the counts is greater than our review pool (45) (40 articles). The prediction and trade of stock marketing predictions and the prediction of exchange rates dominate the domains mentioned in Figure 4.1. In addition, we find two banking credit risk articles and two portfolio management articles. Price and macroeconomic forecasting are two potential topics which require further investigation. Figure 4.2 indicates the price curve of the wavelet before the denoise is used.

**3.1 Long short-term memory neural networks (LSTM)**

LSTM is used as one of the most common RNN forms. The recurrent neural network in this period is built to avoid long-term addiction issues and to treat and predict time series. The LSTM model[8], as proposed by Sepp Hochreiter& Jurgen Schmidhuber since 1997, has been a unique series of memory cells that replace the RNN neurons secret layers and their key is the state of memory cells. The LSTM model filters data through the gate structure for memory cell state maintaining and updating. Its arrangement of the door comprises gates for input, forgotten and output. There are three layers and one tanh layer in each memory cell. Figure 5 shows the LSTM memory cell structure.

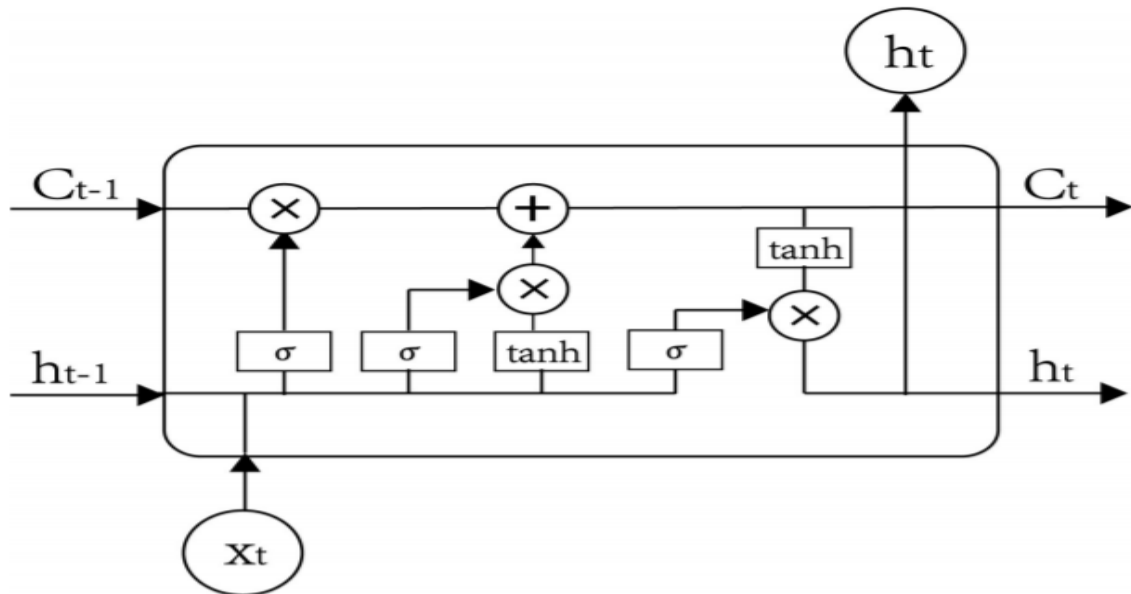


Fig 5. Structure of long short term memory(LSTM).

The data in the cell state is detected at the forgotten door of the LSTM unit. As Figure 5 shows, the memory cell accepts the  $h_{t-1}$  output and  $x_t$  of the current moment external information as an input and combines them into a long vector  $[h_{t-1}, x_t]$  by means of transformation.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

The weight and the weight of the forgotten door are  $W_f$  and  $b_f$  and the sigmoid function – respectively. The key function of the forgotten door is to record the previous cell state  $C_{t-1}$  for  $C_t$ . The door gives 0 to 1 based on  $h_{t-1}$  and  $x_t$ , with 1 indicating a reservation and 0 showing absolute distinction.

#### IV.CONCLUSION

This paper provides a predictive mechanism for the prediction of stock opening prices. We have used an LSTM neural network focused on attention to estimate stock opening price and outstanding results for processing stocks data through a wavelet transformation. Compared with the commonly used neural network LSTM, GRU, and LSTM models with wavelet transformation, The experimental results indicate that our proposed model is better adapted and better accurate to predictive results. The model thus has broad implementation prospects and is extremely competitive with existing models. This paper proposes LSTM RNN, based on GOOGL and NKE potential properties, with successful results. The results of the tests rely on our model to trace the developments in opening prices for both properties. In order to balance our assets in future and to maximize our prediction accuracy, we will attempt to find the most appropriate sets of training times and length.

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