Analysis of Stock Market Volatility using Neural Network for Apple Stock Index

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Abstract

Stock market is global business, every day thousands of stocks are purchased and sold. In this business it is important to identify the market risk. An asset is volatility, which describes the market risk of the stocks. Neural networks are implemented successfully in vast financial applications. Implementation of neural networks provides considerable success for forecasting future assets and features of stock market which helps us pick the best stock. In this project, we focus on the volatility forecasting in the financial markets. It begins with a general description of volatility and its properties, and discusses its performance in financial risk management. This project then examines the accuracy of neural networks. The forecasting accuracy of the models is tested using the Apple stock index. This work is designed to be of concern to both theoretical researchers and practitioners in the finance industry.

Keywords: Volatility, Forecasting, Neural Network, Stock Market, Finance

I. INTRODUCTION

Neural Networks (NNs) are implemented in vast fields like finance, pattern recognition, parallel computing, image processing, biomedical applications[l]and optimization [3], in addition to a large number of financial applications, of which Financial Forecasting is most relevant to this work. NN's are identified by a nonlinear, brain-like structure and the ability to learn complex and hidden patterns amongst several related and non-related elements. Following characteristics of NN's provides the ability to forecast time series data of stock market, prediction of the movement of financial instruments and optimization of trading strategies.

The main characteristic of any financial asset is its return. Return is typically considered to be a random variable. An asset's volatility, which describes the spread of outcomes of this variable, plays an important role in numerous financial applications. Its primary usage is to estimate the value of market risk. Volatility is also a key parameter for pricing financial derivatives. All modern option-pricing techniques rely on a volatility parameter for price evaluation. Volatility is also used for risk management applications and in general portfolio management.

Majority of related works focus here on forecasting time series elements, for this we used Feed-Forward Neural Network. Most Feed-Forward Neural Networks methodology is to train and predict and/or forecast, our neural networks is not entirely far from train and forecast methodology, as our network model is trained on a set of historical inputs consisting of prices and volatility. Based on this data model is trained. After training, the trained neural network model is simulated to forecast the future results, these results are then compared the actual and live trading target results. Then the forecasted results are compared with the different models along with the different error rates to find out the percentage error in this model.

II. LITERATURE SURVEY

A. Neural Networks

1) Overview

A Neural Network is "A collection of parallel processors connected together in the form of a directed graph, organized such that the network structure lends itself to the problem being considered"[3]. The basic unit in every neural network is a Neuron. A unit modelled after human brain cells, and is essentially an elementary information processor[4]. A certain number ofneurons form a layer, and a neural network consists of anumber of those layers, of which the first layer is called the input layer, followed by one or a number of layers called the hidden layers, then a final layer called the output layer, out of which we obtain the output. A neuron is connected to others through weigh labelled links, and the data-value in the neuron is typically altered by a transfer

function such as the linear, log-sigmoid, tan-sigmoid functions that along with the weight of the connection combine to pass an output in the range of [-I, I] to the next neuron. Those values are altered through training in every training cycle. This structure is analogous to the physical brain in such case our neurons need enough stimuli to respond and pass it along. The learning process takes place when the output that is obtained from the last layer is compared to the expected data during the training period, and the measured error (the difference between the output and real data) is used to adjust the weights connecting the neurons.

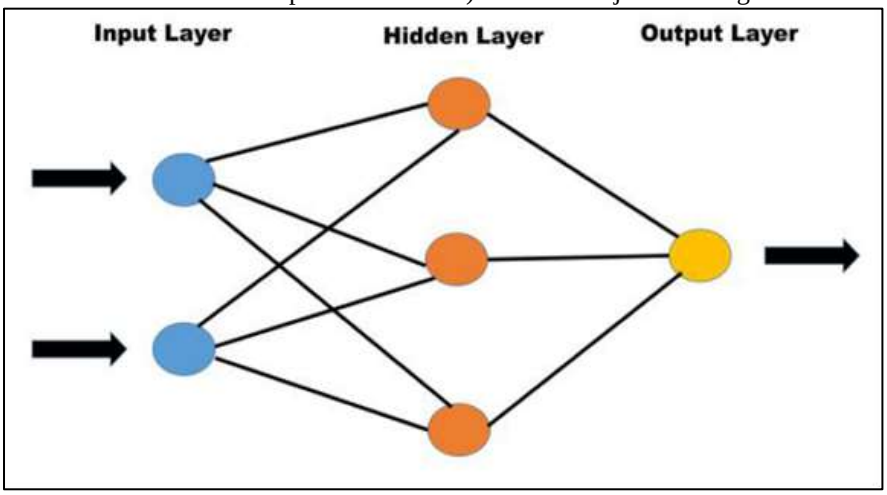

Fig. 1: Neural Network

With every cycle (also called epoch) the network measures the error through an error or performance function, a function that compares output data to target data and adjusts the weights connecting the neurons accordingly. This process is repeated until the error is minimized to a satisfactory degree, or another halting condition is triggered. Most suitable for time-series prediction are feed-forward neural networks with multiple hidden layers, which may also include a time delay input vector for one-step-ahead prediction [2]. In our case, we have chosen a feed forward neural network model, using both the Levenberg-Marquardt learning algorithm (LM) and scaled conjugated gradient (SCG) as training functions, finally settling on LM for memory and efficiency purposes.

B. Feed-Forward Neural Networks

Feed Forward Neural Networks (FFNNs) consist of several layers of neurons, where a neuron in a certain layer is connected to every neuron that belongs to the layer x+ I, and so on. Cycles cannot form, and FFNNs can be described as directed acyclic graphs (DAGs). FFNNs are typically first thought of when problems of approximation, fitting, forecasting and filtering come across. They are considered the standard type of NNs for a problem such as the one in this work.

III. ANALYSIS

A. Technical Analysis

Technical analysis is a branch of finance that uses past, price-related, mostly mathematically derived values (called technical indicators) to assist in the decision making process when trading in the stockmarket, though it can be applied in almost any type of market. Two of them found in principles behind technical analysis are (a) all information are contained in price movement, and (b) markets tend to move in trends.

Ever since technical analysis started becoming popular in the 70's, several attempts have been made to challenge the ability of technical analysis in predicting the market, most notably Burton Malkiel's "A random walk down wall street", a study that attempts to prove that technical analysis is no better than random systems, citing that historical market data cannot be used to predict the future [6]. Renowned stockmarket trader Warren Buffet criticized technical analysisharshly as well. However, a recent study was conducted on 75% of the most popular technical indicators andmethodologies used by technical traders, testing their predicting abilities of future values. The results were surprisingly good, providing irrefutable evidence that technical analysis is a valid form of prediction. The complete study can be found in [7]. It should also be noted thattechnical analysis draws some of its power through its continuous wide use around the world, as the more traders use an interpretation of a certain indicator (or a popular combination of indicators) to place their orders, the more likely that interpretation will manifest in the market due to the sheer volume of orders placed based on that interpretation alone.

B. Expert Advisors in a Neural Network

The technical indicators that make up the rules of an expert adviser can act as a part of the neural network inputs. With the weights and connections amongst the hidden layers adjusting as the network runs through the time-series data learning the

relevancy of indicators to the target output. A large number of research works used technical analysis as the neural networks' basis for prediction, and we present some of the most relevant results in the next section. One will have to note here that the effect of combining Neural Networks and Technical Indicators in one system is not necessarily synergistic, but technical indicators provide rich material though which a neural network can learn and subsequently form decisions. In the model presented in this work, technical indicators construct a type of "environment" that represents happenings around the signal at the time of execution.

C. *Volatility*

Volatility refers to the spread of all outcomes of an uncertain variable. In finance, we are interested in the outcomes of assets returns. Volatility is associated with the sample standard deviation of returns over some period of time. It is computed using the following formula:

$$\hat{\sigma} = \sqrt{\frac{1}{r-1}\sum_{t=1}^{T}(r_t - \mu)^2}$$

Where it is the return of an asset over period t and μ is an average return over T periods. The variance, σ^2, could also be used as a measure of volatility. But this is less common, because variance and standard deviation are connected by simple relationship.

Volatility is a quantified measure of market risk. Volatility is associated to risk, but it is not accurately the same. Risk is the improbability of a negative outcome of some event (e.g. stock returns); volatility measures a spread of outcomes. This includes positive as well as negative outcomes.

Volatility is a key parameter for derivatives pricing models. The market of financial derivatives is one of the biggest financial markets. Derivatives are financial contracts for which values are derived from the prices of the fundamental assets. Major classes of derivatives are: futures/forwards, options and swaps. There is a great variety of derivative contracts within these classes. The Black-Scholes formula and the binomial tree models are the most widely used approaches for derivative assessment. All approaches, however, have the volatility of the fundamental asset as a key parameter. Moreover, an accurate forecast of the prospect volatility results in a more accurate derivative pricing.

Volatility is used in many financial ratios. For example, the Sharp-ratio is a measure of excess return per unit of risk. It is one of the most commonly used measures for comparison of the investment performance.

$$S = \frac{E[R] - R_f}{\sigma}$$

Where E[R] is the expected return of the portfolio, Rf the risk free rate and σ the volatility of the portfolio.

IV. RELATED WORK

The study and the experimentation of this project were conducted to forecast the value of APPLE stock index. The results of the study shows the superiority of the Artificial Neural Networks over the other traditional time series forecasting models such as STL, Holt Winter, ARIMA, TBATS. This experimentation has proven that the Artificial Neural Networks are greatly potential technique to forecasting stock market prices and volatilities. The value of Apple index have been studied and nearly two and half hears of data has been used for training. Here the neural network we used is a single hidden layer Feed-Forward Neural Network.

A Comparative study conducted in this work demonstrates limitations of forecasting prices and volatility by all the models except the Artificial Neural Networks. Results validated for the correctness of the model shows ANN's outperformed traditional statistical model.

V. MODEL

A. *Neural Network Model*

The Neural Network Model has been developed with three layer among this, one input layer, one hidden layer and one output layer. The input layer is trained with the training data set of around two and half years, where each month is considered as a cycle.

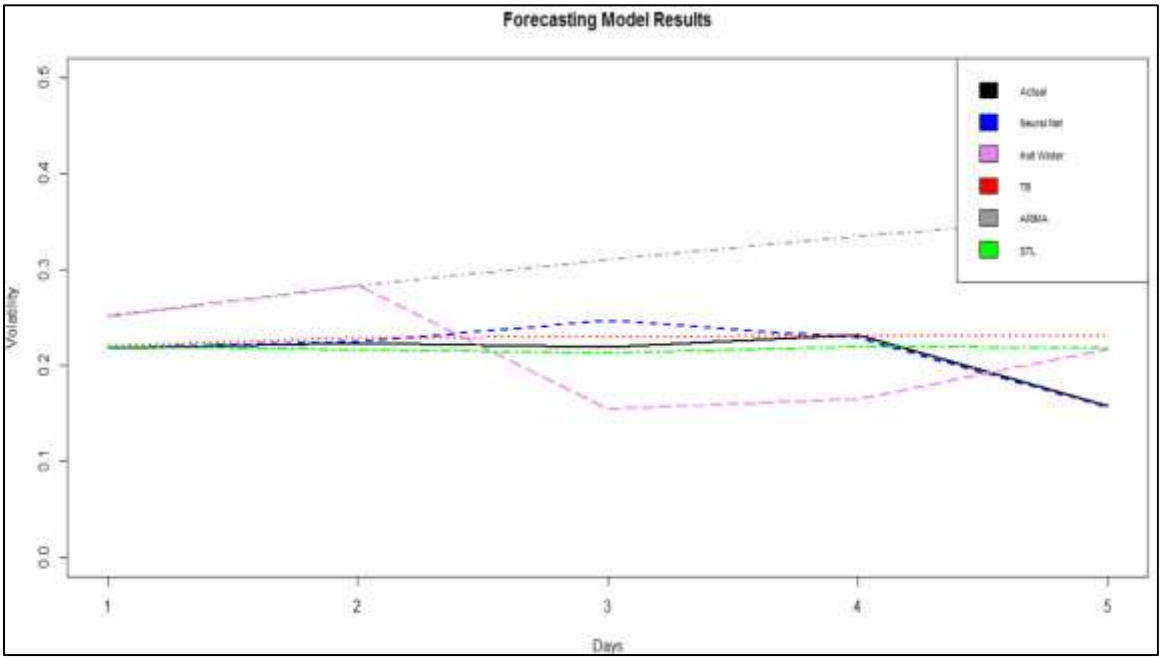

Fig. 2: Forecast Results of Various Models

Accordingly we have picked the neurons of the hidden layers, these results in the number of neurons equal to the number of cycles in the training data set. After selecting the number of neurons in the hidden layer the model is repeated for hundred steps and finally the output layer neurons are selected based onthe output forecast parameters.

This model is used to forecast the prices or the volatilities of stock market indexes. The forecasting could be done for a day or a week or month or so. These forecasted values could be validated and could be measured for various error rates.

The model validation is done on the validation data set. This could be done by comparing actual values by the forecasted values and the results are plotted in the figure 2. The accuracy measures of the model are tested by considering various error parameters.

This error parameters shows how well the model has trained and what is the error percentage in the model and how well can anyone rely on the developed model.

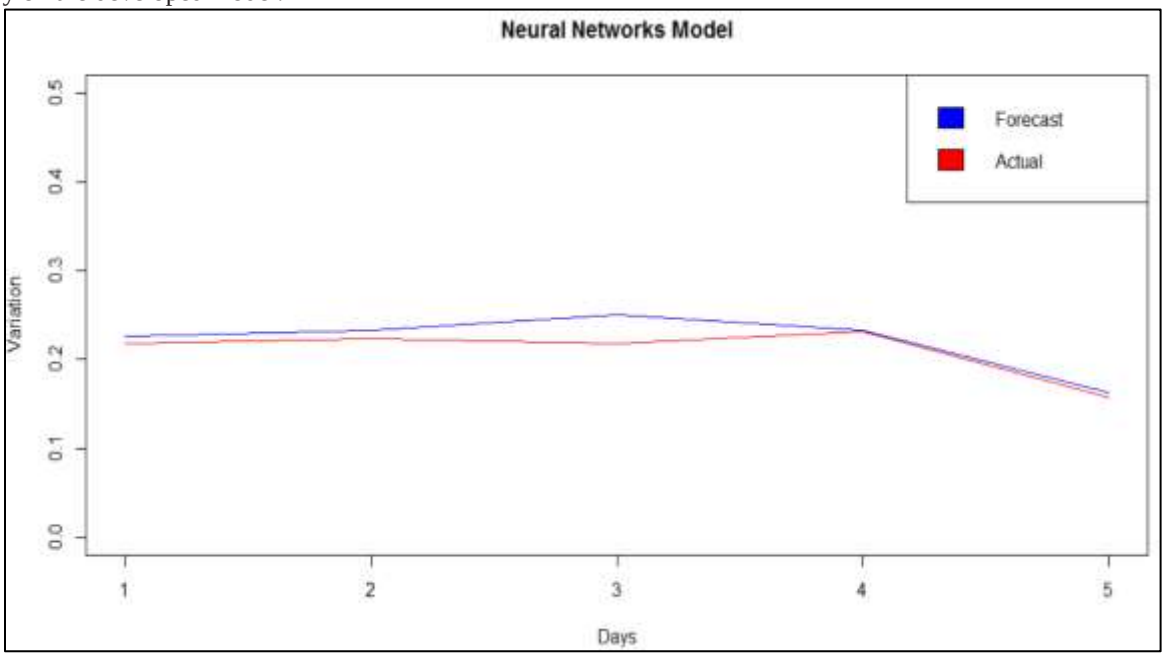

Fig. 3: Forecast results of Neural Network Model

VI. RESULTS

In the case of Neural Networks model, the error rates are shown in the table

Model	*Mean Error*	*Root Mean Square Error*	*Mean Absolute Error*	*Mean Absolute Percent Error*
Formula	$\frac{1}{N}\sum_{i=1}^{N}(\hat{\sigma}_t - \sigma_t)$	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{\sigma}_t - \sigma_t)^2}$	$\frac{1}{N}\sum_{i=1}^{N}\lvert\hat{\sigma}_t - \sigma_t\rvert$	$\frac{1}{N}\sum_{i=1}^{N}\frac{\lvert\hat{\sigma}_t - \sigma_t\rvert}{\sigma_t}$
Neural Network	*0.001124344*	*0.351985*	*0.07120943*	*35.43955*
Holt Winters	*0.03898101*	*0.6002668*	*0.1269911*	*61.47594*
TBATS Model	*0.05124884*	*0.6326325*	*0.09732958*	*19.0723*
ARIMA Model	*9.563148e-05*	*0.5657951*	*0.09055183*	*37.28478*
STL Model	*2.200219e-05*	*0.5889363*	*0.05645273*	*20.97023*

VII. CONCLUSIONS

This project is dedicated to addressing the problem of forecasting volatility in financial markets. We have selected several methods that are heavily used in practice and tested their accuracy using real data (i.e., Apple stock index). Each family of methods has its advantages and disadvantages, some methods are simple but yield poor results. Other methods provide improved results but are difficult to implement. In short, there is no single perfect approach. Nevertheless, we found that the Artificial Neural Network methods is efficient and are relatively easy to implement. We suggest that Artificial Neural Network can be used for a quick approximation of the volatility forecast. Although it can give a good initial benchmark of a forecast, the final estimations should always rely on several models. This is a relatively new class of models, and we confirmed that this class of models can be successfully used for volatility forecasting. A logical continuation of this work would be to combine several volatility forecasting models into a single predictor. Application of such a predictor can potentially overcome the disadvantages of individual models and provide the best forecast.

VIII. FUTURE WORK

The neural networks are advanced technologies for forecasting when compared to other statistical models, this neural networks could be used to forecast almost all the pricing parameters in the stocks by developing individual neural network for each parameter. But the stock market is highly risk so patterns can vary miserably by not letting normal neural networks forecast the results accurately. These issues could be tackled by the implementation of the deep belief network and/or the deep neural networks. The deep neural networks are the extended version of the present neural networks which are implemented for the recognition of complex patterns and forecasting them. The implantation of deep neural networks in the filed like stock market which has complex patterns provide better and accurate results on which users can rely. A basic deep neural networks has minimum of three hidden layer, this helps in training deep neural networks with complex patterns, and hence the resulting complex patterns are forecasted accurately with this kind of networks.

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