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Survey: Stock Predictive Models Using Multilayer Perceptron

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Abstract— This paper comprehensively surveys the research work in the field of Stock Market Prediction Models that employ Multilayer Perceptron Feed-Forward Artificial Neural Networks. It examines the proposed and/or implemented predictive models by outlining the network configurations of the experimental setups as well as the methodologies utilized to train and improve their prediction accuracies.

Keywords— Artificial Neural Networks; Multilayer Perceptron; Back Propogation

I. INTRODUCTION

Artificial Neural Networks (ANNs) serve as significant prediction tools and are increasingly being used to develop Stock Market Prediction Models. Their popularity lies in the fact that their characteristic non-linearity can be trained to correlate the time series data's historical and upcoming values. This results in the extraction of previously unknown or hidden structures and interrelations between the data. Due to this, ANNs are extensively used in economic and financial forecasting. Deeply connected computational elements (neurons) act as the fundamental components of these Information Processing Systems. Message passing among these neurons occurs with the help of synaptic-like connections. Weights associated with the neurons govern the strengths of the interconnections and determine the meaningful relevance of a particular pattern. As soon as a particular neuron's summation of received inputs (stimuli) exceeds a pre-determined threshold value, the neuron transmits the stimuli to its adjacent neurons. This feature grants ANNs the essential ability to transform highly complex inter-relationships into binary decisions (yes or no). Multilayer Perceptron (MLP) is a Feed-Forward ANN formed by cascading a group of single layers. The layers are generally identified as input, hidden and output layers. The nodes at the input layer multiply the values of the input parameters layer by layer through the network. The hidden layer nodes play the role of pattern-detectors. Initially, the number of hidden layers, the number of neurons per hidden layer and the weights associated with the neurons are chosen randomly. Gradually, the weights are adjusted to lessen the error between the calculated output and the actual output. The process spans across large datasets, typically time series data, until the network gives outputs correct up to a given threshold of error. This paper investigates the topological dispositions of the Stock Market Fiscal Forecasters' architectural setups that facilitate data processing and trend analysis by utilizing MLP Feed-Forward ANNs.

II. LITERATURE SURVEY

S. Jabin has presented a Feed-Forward ANN model that predicts the Net Asset Value (NAV) of the State Bank of India (SBI) Magnum Tax Gain Scheme [1]. The model is fed with a two-year dataset that is stored in the Bank's website records. The duration of the accumulated dataset is from April 1, 2012 to April 4, 2014. The model's strategy involves utilizing the previous 4 days' index values to predict the index value on the 5th day. The ideal network topology for the predictive model is deduced using a trial-and-error methodology but the author suggests using a MLP having 2n+1 hidden nodes for every n input nodes. The author experiments with 3 different types of network training functions to update the weight and bias values in order to fine tune the network performance function. The 1st function utilizes Resilient Back Propagation Algorithm. The 2nd function utilizes Levenberg-Marquardt Optimization and Bayesian Regularization. The 3rd function makes use of the Scaled Conjugate Gradient method. From the results, the author has deduced that the flexibility of the network increases with increase in the number of hidden nodes but at the same time, an excessive number of hidden layers may cause the problem to be under-categorized.

M. B. Patel and S. R. Yalamalle have developed a MLP-based predictive model that targets the companies listed under the LIX15 Index of National Stock Exchange (NSE) [2]. The model has been implemented using MATLAB's Neural Network Toolbox. The following parameters are fed as input to the system – Learning Rate, Epochs, Total number of the input and the output neurons, Total number of hidden layers and the number of neurons per hidden layer. The system's input parameters are customizable and it creates networks based on the parameters fed to it at runtime. The dataset, sourced from authorized financial repositories, spans across 3 years of financial data from January 1, 2011 to January 1, 2014. The training of the model persists until either the input limit of the number of epochs is exhausted or the Mean Squared

Error (MSE) stops improving. The observed satisfactory outputs of the Median Normalized Error (MNE), the Median Correct Direction % and the Median Standard Deviation speak in favour of Feed-Forward MLP networks.

A. V. Devadoss and T. A. A. Ligori have attempted to predict the future 5 days' closing prices of 4 companies listed under the Bombay Stock Exchange (BSE) [4]. Dynamic Back Propagation is used to train their MLP ANN model and the performance is evaluated on the basis of Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD) and Root Mean Squared Error (RMSE). Based on the observed results, the authors have inferred that the number of input neurons and the continuity of the time-series data affect the Forecast Error %.

S. Simon and A. Raoot have surveyed the various enhancement techniques that have been researched and implemented, over the years, to improve the prediction accuracy of ANN models [5]. The techniques can broadly be categorized as follows – Using Statistical Techniques and Choosing ANN Relevancy. They have also outlined the following research strategies and the challenges faced in applying ANN to Stock Market Prediction – Hybrid Analysis, Choice of Inputs, Training ANN with Stock Data, Lagged Data Input, ANN Components Optimization, Problem-specific ANN Models, Target-specific ANN Models and Hybrid Models.

M. P. Naeini, H. Taremian and H. B. Hashemi have developed two neural networks [6]. The first is a MLP Feed-Forward network and the second one is an Elman Recurrent network. Both networks are fed lowest, highest and average stock values of a pre-decided number of previous days as input. The architectural configuration of the MLP comprises of a three-layer neural network. The input layer has 3 neurons to accept the previously-mentioned stock parameters whereas the output layer has one neuron for predicting the stock value for the next day. The dataset is sourced from Tehran Stock Exchange. It ranges from 2000 to 2005 and is spread across 1094 companies' traded shares. It takes macro-economic factors into consideration. Evaluation criteria are based on certain generic parameters such as MAD, MAPE, MSE and RMSE. It also takes into account specialized parameters, namely - Correct Forecast Trend (CFT), the ratio of CFT and the ratio of Incorrect Forecast Trend to the real trend of stock movements. The results of the MLP and the Elman Recurrent networks are compared with the Linear Regression method. It is observed that even though the MLP network is unable to forecast the direction of the changes, unlike the other two methods, it still has a considerably lower MSE and MAPE as compared to the other two methods. They have concluded by suggesting future research in the application of Support Vector Regression to financial predictive models.

M. Thenmozhi has outlined the basic methodologies of implementing ANNs for forecasting future financial states by reviewing implemented estimators [7]. The author has also implemented a predictive model that forecasts the movements of the daily returns of the BSE Index. The dataset comprises of daily index values of the BSE Sensex that are sourced from Capitaline 2000 stock data repository. It has a total of 3667 data points spread over a duration from January 16, 1980 to September 26, 1997. The model exploits the efficacy of a MLP driven network. The architectural setup consists of a three-layer network comprising of input, hidden and output layers with activation functions acting as intermediate mapping units. Error Back Propagation algorithm is utilized as a training scheme with the objective of tweaking the weights in such a manner so as to reduce the prediction error rate. The system is fed with the previous four days' consecutive daily returns and the output is the predicted daily return for the fifth day. From the results, it is observed that the significance of the immediate previous day's return in determining the next day's forecast is higher than the significance of the previous three days' returns combined. The author has concluded by stating that there is a scope for refining the prediction accuracy by taking weekly or monthly returns as well as micro and macro-economic factors into account.

Y. Shachmurove and D. Witkowska have studied the implementation of ANNs to the inter-dependencies among the Stock Markets around the world [8]. They have carried out a comparative study of ANN-based predictive models with statistical models such as Ordinary Least Squares (OLS) and General Linear Regression Model (GLRM) based on parameters like RMSE, Maximum Absolute Error (MAE) and the value of the objective function. They have extensively surveyed appropriate literature related to ANNs and have comprehensively summarized the intricate working of MLP. Their experimental setup is divided into two parts - Regression Analysis and the implementation of ANN. It is initiated by transforming the daily stock price indices into daily rates of returns. They have considered various models by utilizing varied combinations of the day-to-day stock returns. Their database consists of daily stock indices sourced from Morgan Stanley Capital International Perspective, Geneva. It encompasses 2,064 observations per stock market starting from January 3, 1987 to November 28, 1994. Significant variables are short-listed using Regression Analysis Models which are then served as input to two variants of the ANN models. Based on the results, the authors have observed and concluded that MLP-based models have better prediction rates as compared to their conventional OLS and GLRM model counterparts.

III. CONCLUSIONS

ANNs provide meaningful internal relationships among the nodes by detecting non-linear inter-dependencies in time series data, thereby, overcoming its volatile nature. This characteristic trait, not possible to emulate using traditional statistical approaches, makes them the preferred choice in implementing predictive models to forecast financial data.

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