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Efficient Machine Learning Techniques for Stock Market Prediction

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Abstract
Stock market prediction is forever important issue for investor. Computer science plays vital role to solve this problem. From the evolution of machine learning, people from this area are busy to solve this problem effectively. Many different techniques are used to build predicting system. This research describes different state of the art techniques used for stock forecasting and compare them w.r.t. their pros and cons. We have classified different techniques categorically; Time Series, Neural Network and its different variation (RNN, ESN, MLP, LRNN etc.) and different hybrid techniques (combination of neural network with different machine learning techniques) (ANFIS, GA/ATNN, GA/TDNN, ICA-BPN). By extensive study of different techniques, it was analyzed that Neural Network is the best technique till time to predict stock prices especially when some de-noising schemes are applied with neural network. We, also, have implemented and compared different neural network techniques like Layered Recurrent Neural Network (LRNN), Wsmpca-NN and Feed forward Neural Network (NN). By comparing said techniques, it was observed that LRNN performs better than feed forward NN and Wsmpca-NN performs better than LRNN and NN. We have applied said techniques on PSO (Pakistan State Oil), S&P500 data sets.
***Index Terms*—** Feed Forward Neural Network, Recurrent Neural Network, Stock Market, Machine Learning

I. INTRODUCTION

Stock market prediction is one of challenging issue, catches attention of many researchers and investors. Investors all across the globe showed their great interest in stock predicting systems. Investors start relying on predictions systems to make their important business decisions. A lot of research is made in this domain but still no complete solution is found. Is stock market prediction fully possible is still debate of the hour. This is due to difficulty in predicting stock market with full accuracy because there is a great influence of external entities (social, political, psychological, and economic) [1] [20]. Secondly, it requires huge amount of historical data. Various machine learning techniques are being used to predict market states. This research covers many state of the art techniques to find out some optimal solution to the problem.

Several machine learning techniques are being in use for stock market prediction. There is no specification made by which we can choose the optimal solution for stock market prediction. This research will study different machine learning techniques being in use for stock market prediction. This research will follow a comparative approach to find out optimal technique for stock market prediction. Comparison will be made on the basis of their performance. Every technique has some advantages and disadvantages. This research will analyze advantages and limitations of these techniques. And find that which technique is comparatively better for stock market prediction.

Fundamental and Technical analysis are two famous methods being in use for risk analysis from very old age. When there was no computational method to analyze risk these methods were used.

To predict stock prices (by analyzing past data) there are many conventional methods. Generally used two methods are [1][20][10][18].

i. Fundamental and
ii. Technical

In Fundamental analysis, accurate and reliable information of company's financial report, competitive strength and economic conditions are required to find out the accurate value of product in which they have interest. This value is used for making decision for investment. It is based on this idea *"If the intrinsic is higher than the value it holds in the market, invest, else it will be considered a bad investment and avoid it"*.

Fundamental analysts believe that 90 percent logical factors and 10 percent physiological factors define a market. Fundamental analysis is useful in long-term predictions. The advantages of fundamental analysis are its systematic approach and its ability to predict changes before they show up on the charts. [1]

Technical analysis requires history of market. *"The idea behind technical analysis is that constantly changing attributes of investors in response to different forces/factors make trends/move of stock prices"*. Different technical factors like volume and maximum and minimum prices per trading period are used for analysis. Rules are extracted from data. On the basis of these rules investor take decisions for future. According to some chartists, market trend is 90 percent psychological and only 10 percent logical. The major disadvantage of technical analysis is that trading rule extraction from charts study is very subjective so different analysts might derive different rules from same charts [1]. Technical analysis is used for both long and short term analysis.

The basic purpose of this research is to find the optimal among many state of the art techniques. What is the optimal technique for stock prediction? By combining multiple techniques can we get a better system or we have already optimal solution? On which basis one prediction system is preferred on other? For this purpose we compare and analyze some current an efficient techniques on the basis of their produced results.

II. TECHNIQUES USED FOR STOCK MARKET PREDICTION AND COMPARISON

Prediction is making decision on the basis of past known data (knowledge). Predicting stock market trends is challenging task. It is because of non-linear behavior of stock data. Many other factors are also present here, which create hurdles in the way to predict stock (economic conditions, trader's behavior, investor psychology, politics etc.). To some extent, artificial intelligence makes it possible to predict stock trends. The main purpose of any model built for prediction of stock is to reduce risk (minimize error). Models built for prediction by using these (Neural Networks, Genetic algorithms etc.) techniques showed successful For many past years different techniques are being used for predicting systems. Few of techniques will be defined here are Time series, Neural Networks, Hybrid techniques.

2.1 Time Series

Ordered lists of values of one parameter or variable, which are provided in equal time intervals called time series. The prediction is the continuous of pattern over time like growth in sale, stock market analysis or gross national product (Gosasang et al. 2010). The common time series methods are

i. ARMA (Auto Regression Moving Average)
ii. ARIMA.(Auto Regression Integrated Moving Average)

ARMA is combination of AR (auto regression) and MA (moving average) models. Used to predict future values. ARIMA is variation of ARMA. Any Time series is stationary if mean and variance is constant. Otherwise, it's non-stationary. Non stationary time series are difficult to predict these are full of noise. Stock prices are characterized as non-stationary and for that purpose de-noising techniques are used for removing noise from data. [4]

2.2 Artificial Neural Networks (ANN)

In 1943, W.S.Mcculoch and W. Pitts established Neural Network (NN) and its mathematical model. The established model was named MP model. Than MP model was used to put forward the network construction method and neuron's formalization mathematical description and proved that each single neuron performs logic function, so a new time of Neural Network research began. Neural network are used in pattern recognition, prediction etc.

Network is a set of interconnected nodes. A node is a computational unit which receives inputs and after processing produces output. The flow of information between nodes can be determined by the connections between the nodes. [2] The detailed introduction to ANNs is given by [12]. The basic structure of ANN with one hidden layer is given in fig . 1.

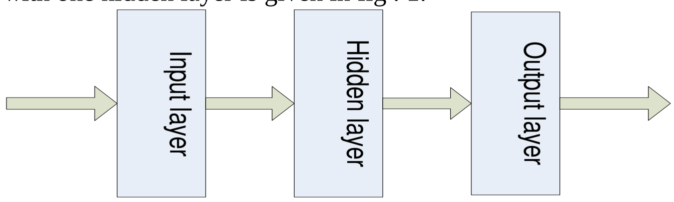

Fig . 1 Artificial Neural Network

The basic architecture of ANN is Multi- layer feed forward used by [2]. In this architecture, information flows in one direction only (from input to output). It consists of one input , one or more hidden and one output layer. Inputs are sent into units in input layer than weighted output from these units is taken as input in next hidden layer, weighted output of this layer is sent as input in next hidden layer and so on. Until output of last hidden layer is send to output layer. Output layer gives the predicted output. Back propagation algorithm is used for learning process in NN. In this algorithm, network is trained by repeatedly comparing the output and target output. And minimizing error. log-sigmoid is used as an activation function. To check the error, mean square error is used. A very simple approach is given in [2]. The author used very general and simple architecture of ANN. Author performed pre-processing on data. Author used Relevance Attribute Analysis method to remove unwanted attributes and then applied min-max normalization for normalizing data. That decrease risk of error or producing in sufficient answer.

2.2.1 Multi-Layer perceptron with back propagation learning algorithm

Artificial Neural networks are applied in many different ways for stock prediction. Multi-layer perceptron (MLP) is used with supervised learning algorithm (back-propagation). It has ability to solve non-linear problems; stock prices usually used are non-linear. MLP works as it first initialize weights of all network and train the training pattern then get output then error is propagated by using back-propagation. Basic model of MLP with back propagation is used in [10] to analyze the importance of Neural Networks for stock prediction. They used five attributes as input previous close price, close price, open price, low price, and high price. Correlation (R), Average Absolute Error (avg abs), Max Absolute Error (max Abs), Root Mean Square Error (RMS), Accuracy, Confidence internal are the performance measures used to measure error. The model was applied on Indian stock Market. TCS company data was taken to test this model. This Model gives 20% of Accuracy between target output and calculated output. This model is made to predict in short-term. This model can be used further for error percentage reduction. [10].

In ANN, a large number of historical data required. Accuracy and result network becomes complex. Results statical relevance is required. Best topology of network is unknown. NN requires a careful data design and systematically analyzed. There are many different models of Neural Networks made to remove/cover these flaws. To overcome these flaws advance/new approaches of NN are become in use.

2.2.2 Recurrent Neural Network with wavelet transforms

Recurrent neural network (RNN) is type of Neural Networks with back-loop in it. Recurrent neural network has advantage over ANN that it saves patterns with time.

RNN are applied for stock market prediction by [4] with Wavelet transform as pre-processing technique to remove noise from data. Recurrent neural networks are available in two categories, Elman and Hopfield [4].Hopfield networks are less used in practice. There can be spurious stable points in Hopfield network that may lead to incorrect results.

The Elman network commonly is a two-layer network with feedback from the first-layer output to the first layer input. This recurrent connection allows the Elman network to both detect and generate time-varying patterns. The Elman network has 'tansig' neurons in its hidden (recurrent) layer, and 'purelin' neurons in its output layer. Algorithms used for training data .Least Mean Squared (LMS) algorithm which involves Gradient descent with momentum and batch learning rate back-propagation. Least Mean Squared (LMS) algorithm which involves Gradient descent without momentum and batch learning rate back-propagation. It is also observed that Least Mean Squared (LMS) algorithm which involves Gradient descent with momentum and batch learning rate back-propagation performs better. *It is observed that RNN gave different results when applied on different data. From this one can say that performance of network relay on data being used for it.*

2.2.3 Layered Recurrent Neural Network

LRNN consist of two parts

i. Recurrent layers (for temporal patterns)
ii. Feed-forward part

In LRNN, input passes through the net more than once so it helps to learn temporal patterns. It is due to recurrent layers and new input and previous temporal patterns are given to feed-forward part as input. Basic structure of LRNN is given in fig. 2

Different variations of ANN are tested by [16] for stock price prediction. Models compared by author are Back-Propagation Neural Network (BPN), Radial Basis Function Neural Network (RBFNN), Generalized Regression Neural Networks (GRNN), and Layered Recurrent Neural Networks (LRNN). It is observed from results that LRNN outer-perform than other three. And BPN performs better than other two. LRNN is type of RNN. They have dynamic behavior. *Due to the dynamic behavior of stock market, RNN has been found an attractive tool for performing nonlinear time series prediction*

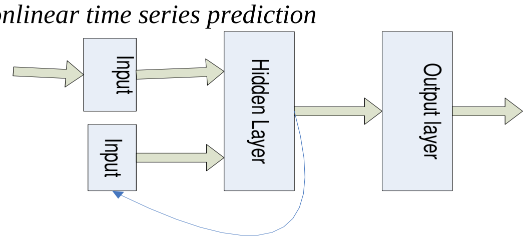

Fig. 2 Layered Recurrent Neural Network

2.2.3 Echo State Network

Echo state networks, Subset of RNN. It can be trained comfortably. *This network is developed in the emerging field known as reservoir computing. In reservoir computing, the recurrent connections of the network are viewed as a fixed reservoir used to map inputs into a high dimensional, dynamical space–a similar idea to the support vector machine*. For RNN, architecture and supervised learning is provided by ESN. Finding random large, fixed RNN is the main task of ESN.in ESN, input travels through the network more than once. This improves the output results. Only output weights are trained in echo state network. With a sufficiently high dimensional space, a simple linear decode can be used to approximate any function varying with time. ESN are used for financial time series forecasting by [13]. Author applied ESN for forecasting and compared its performance with Kalman filter (also used in forecasting process).

It is observed from [13] that ESN outer perform than Kalman filter. The Kalman filter uses linear dynamical model. That model estimates the process state recursively by reducing error (Mean square error). Quick changes in the stock price can be captured by ESN. Whereas, Kalman filter is unable to capture. Powerful black box method is used by ESN for modeling time dependent phenomena. Black box methods are appealing because they require no prior assumptions or knowledge of the underlying dynamics of the time series data. The Kalman filter does not have enough features to predict prices and capture rapid movement in the stock price.

This model is checked on S&P500 indexes. Input features used in this model are current price, trading volume, and the S&P500 price.

Different models of ANNs are evaluated to test the effectiveness of neural networks for stock price prediction. MLP, Dynamic Artificial Neural Networks (DAN2), and hybrid neural networks using generalized auto regression conditional heteroscedastticity(GARCH) were analyzed by[15]. It is observed that MLP performs better than other two techniques.

Gradient descent for stock prediction is applied by [7] and compared with Recurrent Neural Network for stock market prediction. Gradient descent back-propagation learning algorithm is used for supervised training of Neural Network. Learning rate is required for gradient descent algorithm. To check whether algorithm is working properly convergence test is taken. If learning rate is too small then convergence is slow, if learning rate is too large than may not convergence. To make his model work appropriately, [7] performed pre-processing using R/S analysis method. As quality of input data effects output. In output, model gives newer open price. Sigmoid transfer function is used in it. Mean square error is calculated to check the model. This Model is applied on NASQAD stock. Two models (Multi-Layer feed forward and Recurrent Neural Network (RNN)) are built by using Gradient descent back-propagation Algorithm [7]. It is observed that RNN outer performs than ANN.

2.3 Hybrid Techniques

From last few year researchers move their attention to merge different techniques to get more optimal results. Our next section covers some of hybrid techniques used for stock prediction. Here we analyze few hybrid techniques used for stock prediction. Fuzzy logic and genetic programming are widely used with integration of other techniques for stock price prediction. Fuzzy logics are used to build rules for prediction on the basis of past knowledge available.

2.3.1 Using GA with different ANN techniques

Genetic Programming (GP) first introduced by Koza (Koza 1992) by developing symbolic regression. It is a computational optimization tool. This tool is used to derive optimal model from time series data. Reproduction, crossover, and mutation are main operation of GP. Fitness Function is the main factor on which final population based. The process of switching nodes in a population is known as cross over. For making new generation based on fitness function GP reproduces. The task of mutation is to get and substitute the information of one node with those individuals. To evaluate new generation fitness function used (Langdon & Poli 2002).

Genetic Algorithms (GA) are used with two different types of NN to improve performance of network. GA's are used here to identify input variables and weights for these variables [28][31]. Time delay Neural Networks (TDNN) and Adaptive time delay neural network (ATNN) are used here for their ability for saving temporal patterns. GA-TDNN and GA-ATNN are proposed by [28] for forecasting stock. It is observed from result given by author that GA-TDNN and GA-ATNN outer performs than individual TDNN, ATNN and RNN.

2.3.2 Integration of genetic fuzzy systems and artificial neural networks

Integration of genetic fuzzy systems and artificial neural networks for stock price forecasting is an example of such hybrid technique developed by combining Neural Network, fuzzy logic and genetic programing. In this model three techniques are used to build better prediction system. There are three main stages of this model. Variable selection is first phase of this model. Stepwise regression analysis (SRA) is applied for key variable selection. Second phase is to divide data, self-organization map (SOM) neural network is used for this purpose. SOM reduce complexity of data by dividing it into useful sub part. Last phase is to build GFS for stock price prediction, data clusters are sent to GFS for forecasting purpose [24].

Stepwise regression analysis (SRA) finds out the set of independent factors. SRA is recursive function. On every step, a variable enters or remove from model. SOM clustering is being used to combine related data. From previous literature made on clustering methods it is observed that SOM clustering performs better than other techniques of clustering (hierarchical). Next phase of this model is to build, a genetic-fuzzy system. Mamdani-type fuzzy rule based system to deal with stock price forecasting problems.
There are two general steps of this evolutionary process used to make knowledge based (KB) of fuzzy rule based system. First step is to evolve rules (through genetic algorithms). And second step is to tune database of fuzzy system.
Fig. 3 illustrates main steps of this model.

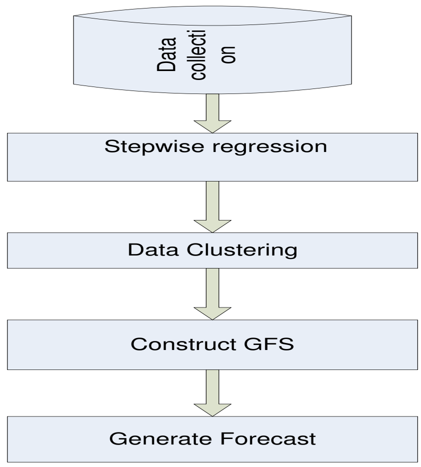

Fig. 3. Integration of GF systems and ANN

2.3.3 Rough Set-Neural Network

Another technique used for making stock market decisions is a hybrid Artificial Neural Network and Rough Set model. Used to find best sell and buy in Dhaka Exchange. In this model, Neural Networks are used for its ability to predict (learn from knowledge) and Rough set is used for its ability of Powerful Rule Extraction.

In Rough Set (RS), Decision Table is used to organize data. This table contains attributes and data elements. Where attributes are placed in columns and data elements are placed in rows. Analysis of limit Discernibility is Main theme of Rough set Model. Three regions are defined by RST. These regions base on equalent classes induces by attribute values. These regions are lower approximation, upper approximation, and boundary. Rough set is here to reduct data and extract rules from data for prediction. Johnson's reducer algorithm is used by [20] to find all reducts and Levenberg-Marquardt Back-Propagation algorithm is selected to train ANN. Confusion matrix is used to analyze performance of this model.
This technique is applied on Dhaka Stock Exchange. And its Performance is compared with individual RS and ANN. It is observed that Hybrid RS-ANN is better than alone ANN and RS.

2.3.4 Independent component analysis (ICA) with Back Propagation Neural Network (BPN)

As noticed in above mentioned techniques that data is full of noise. Noise in data could lead over-fitting and under-fitting problems. Another method to remove noise from data with combination of Neural Networks is Independent component analysis with Neural network (ICA-BPN). There are two basic steps of this technique. One is to get independent components from data and second is to input these data elements to neural network architecture as input.
Author compared this technique with wavelet-BPN and single –BPN and observed that ICA-BPN outer performs than other two. From all above mentioned methods it is concluded that using ANNs alone have flaws in it.

2.3.5 Adaptive Neuro-Fuzzy Inference system (ANFIS) for Stock Prediction

Another technique being in use is ANFIS. A neuro-fuzzy system is created by using this method. These systems are built by using Adaptive neuro-fuzzy based system controller. This controller is further used to control the stock market process. In Basic architecture of the model, Input is mapped to input membership function. Then that Input membership functions are mapped to rules. These rules are then further used to set output. And then like input, this output is mapped to output membership functions.

ANFIS are applied for stock market short trends by [24]. Gaussian-2 shaped membership functions are chosen over bell shaped Gaussian and triangular ones to fuzzily the system inputs due to the lowest RMSE [24]

The ANFIS model is a Sugeno first order model with two inputs and one output. Five Gaussian-2 membership functions correspond to each input, very small, small, medium, big and very big. The combination of two inputs and five membership functions creates twenty five rules (5)2

The PR-ANFIS model is a Sugeno first order model with three inputs and one output. Three Gaussian-2 membership functions small, medium, and big correspond to each input, for a total of twenty seven (3)3 rules [24].

2.3.6 ANFIS with indirect Approach TKS-fuzzy based

ANFIS is used for stock prediction, by applying all this method on a rule based. To analyze stock market a complex system is built. *Neuro-Fuzzy Inference System followed by a Takagi–Sugeno–Kang (TSK) type Fuzzy Rule Based System is developed for stock price prediction*. Technical indexes are used as input and output of this model is linear combination of these indexes. To identify number of rules Fuzzy C-Mean (FCM) Clustering is used. Gaussian function is used in premise section. FCM algorithm is used to define number of rules. Membership degree is assigned to the output of last step. At last step, neuro-fuzzy inference system is used to tune parameters of system. The forecasting capability of the system is greatly improved by applying this technique [25]. This model is applied on Tehran stock exchange indexes.

After all above literature it is observed that (Feed-Forward Neural Network) NN are used mostly for prediction. Different models are built using Neural Networks. NN are preferred for stock prediction because they can learn from past data. And they map the input to output. From a survey in 2012 it is concluded that Neural Networks are used 80% for prediction system. *It is analyzed from above literature that every hybrid technique used Neural Network*. It is concluded from previous study that for prediction recurrent type of Neural Networks are preferred. Comparisons and results of different models shows that Recurrent Neural Network (RNN) is comparatively better then (Feed-Forward Neural Network) NN. But RNN are less used because it has complex structure and it takes more memory. *Major point analyzed from the study is importance of data pre-processing. Different models used different data preprocessing methods to normalize their data*. After above literature, we took three models (Feed-Forward Neural Network (NN), Layered Recurrent Neural Network (LRNN), wmspca-feed forward neural networks and apply them. Firstly, we apply simple feed-forward neural network and then we apply a de-noising method (wmspca) on simple feed-forward neural network and compare their performance.

III. METHODOLOGY

This research compares different models of Neural Networks being in use for stock price prediction. Here we will apply few methods and compare their results. Neural Networks are chosen for this purpose. *Neural Networks are selected to implement on the basis of previous literature. From year 2000-2012 Neural Networks are used 80% for stock prediction* In above literature it is also observed that performance of Recurrent Neural Network (RNN) in better for prediction when compared with Feed-Forward Neural Network. From above literature, it is observed that data pre-processing (de-noising) has better impact on output. So, we will use de-noising technique with feed-forward neural network. All this working is performed by using tool MATLAB, Neural Network toolbox is used for simulation. Predefined methods/functions are used for this purpose.

1. Data collection
2. Built different models (Feed-Forward Neural Network (NN) , wmspca- feed-forward neural network , Layered Recurrent Neural Network (LRNN))
3. Check on different data sets
4. Compare their output performance on the basis of their *performance measure and time consumed*.

Fig. 4 shows flow chart of main steps of this methodology.

At first, data sets are collected for experiment. Data is collected from yahoo.finance.com and google.finance.com, **PSO (Pakistan State Oil)** and **S&P500** data is collected for these experiments. After collecting data, we applied three models using MATLAB**.** For checking performance of these techniques, we took one month data of PSO as input to check models. After that we increase the amount of data with 6 month data and again test models.

After getting results, techniques will be compared on the basis of performance measure used and time taken by a technique to give output.

3.1 Implementation

As, basic aim of applying these models is to compare their performance. So some features will remain same for all models. These elements and their values are defined in tab.1

From research, it is observed that levenberg-Marquad. It is better training function when compared with other training function (gradient, resilient back-propagation). Whenever we use any model for prediction, our aim is to minimize error.

Performance measure used for checking output is normalized mean squared error with regularization performance function.

Applied models are feed-forward neural network, layered recurrent neural network and wmspca- feed-forward neural network.

TABLE 1
RESULTS OF DIFFERENT TECHNIQUES ON S&P500 DATASET

Factors	Values
Input data	PSO/S&P500
Training Function	*Levenberg-Marquardlt*
Performance measure	*Msereg*
Training data	*60%*
Validating data	*20%*
Testing data	*20%*

Table 1 holds factors and their values that are same for all applied techniques. Input data is sub divided into 3 categories. same data sets in

3.1.1 Feed-Forward Neural Network

Firstly, feed-forward net is created**.** This function built a feed forward net. Then we set input and target data. and train network. Training method takes input data and network used. Here data is divided into three parts (train, test, validate). We use 60% data to train the network, 20 % for testing and 20% for validation. Fig. 5 shows flow chart of feed-forward neural network.

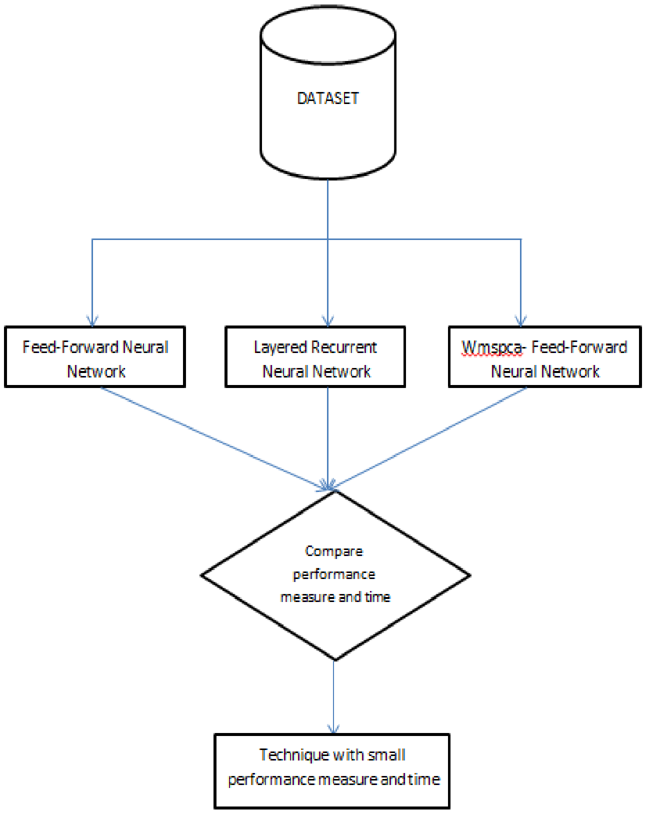

Fig. 4 Methodology

3.1.2 Layered Recurrent Neural Network

After applying feed-forward Neural Network, Layered Recurrent Neural Network (LRNN) is implemented. LRNN function creates a layered recurrent net by taking input data, target data, no. of neurons to create the net. (NOTE: we can also set other values of the network at the time of creating this net). After creating network we use same methodology used in feed-forward neural network to train network. Fig. 6 shows flow chart of layered recurrent neural network.

3.1.3 Wmspca-Feed-Forward Neural Network

We used a wsmpca (multiscale principal component analysis) to pre -process data. This method is use for pre-processing data. Now input this pre-processed data into Feed-Forward Neural Network. Fig7 shows flow chart of feed-forward neural network.

This method takes input matrix, levels of wavelet decomposition name of wavelet and principle components. And returns a simplified version of ***input*** matrix ***X*** obtained from the wavelet-based multi-scale Principal Component Analysis (PCA). This wavelet decomposition is performed using the decomposition level *'LEVEL'* and the wavelet *'WNAME'*. Now input this simplified data into Feed-Forward Neural Networks.

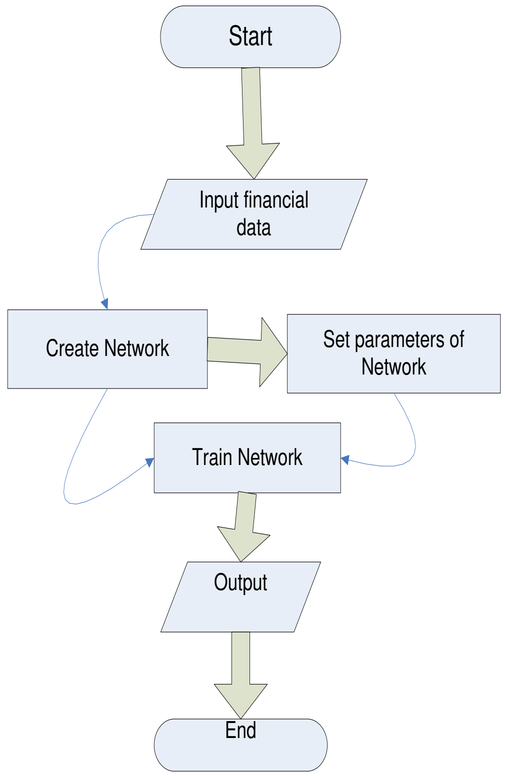

Fig. 5 Feed-Forward Neural Network

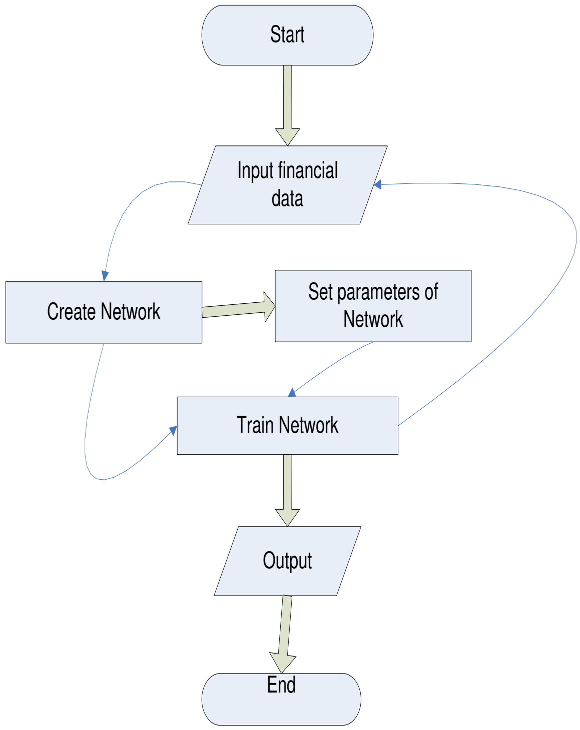

Fig. 6 Layered Recurrent Neural Network

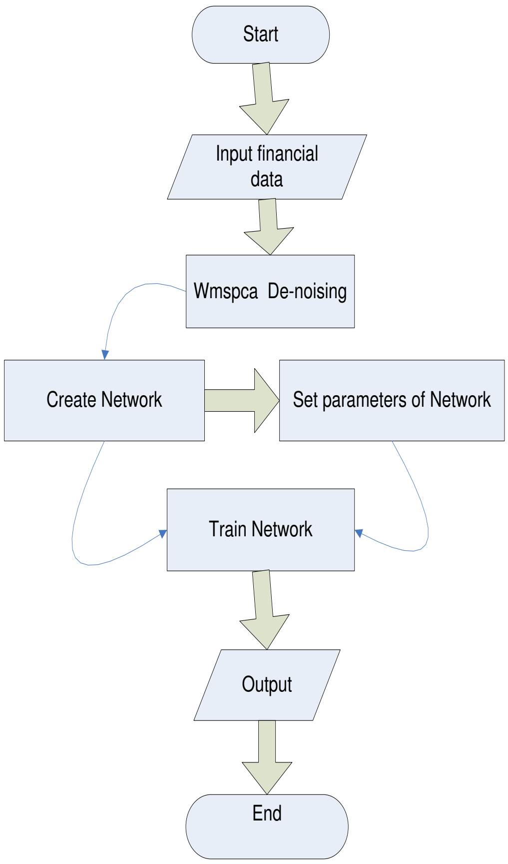

Fig. 7 wmspca-Feed-Forward Neural Network

IV. EXPERIMENTS AND RESULTS:

After creating models, we get their results in form of graphs and values. Results are sub-divided according to the data sets used to check above mentioned models.

Our result holds different parameters while training. Here is short introduction of these parameters. Parameters used are epoch, time, gradient, performance.

Epoch: is number of iterations taken by a network to train data. Training method perform training, testing and validation of data in single method

Time: shows time interval taken by a network while training data.

Performance: shows performance measure. Performance measure shows the error value given by any network. If the value of this performance is small it shows that network works properly. If value of this performance measure is large then more training is required.

Gradient: is learning rate. It is speed of learning. If learning rate is small than training will be slow. If learning rate is large than learning will be fast but may not give better results.

4.1 Results on PSO (PAKISTAN STATE OIL) dataset:

Fig. 8 and 10 holds results of Feed-Forward Neural Network,

Fig. 11 holds results of Layered Recurrent Neural Network,

Fig. 14 and 15 holds results of wmspca-Feed-Forward Neural Network when applied on PSO data.

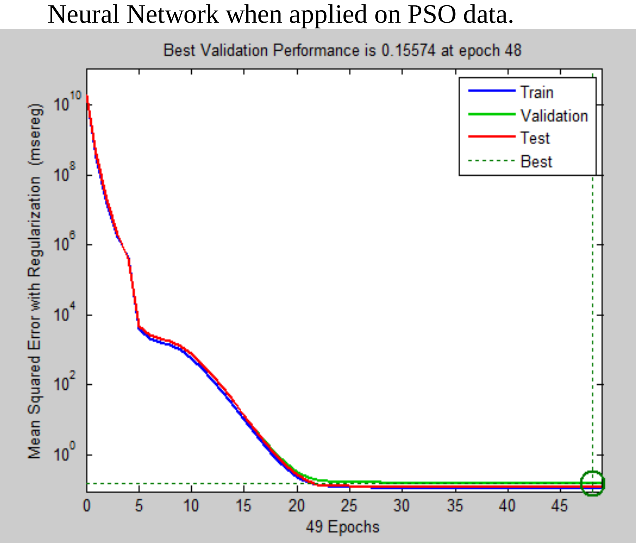

Fig. 8. Show performance measure at y- axis and number of epochs on x-axis. This figure shows that 49 epochs are required to train network without over training.

Fig.9 plots the data fitting, on 4 different stages of data,

i. When data is training
ii. When testing data
iii. When validating data
iv. When catching target
v.

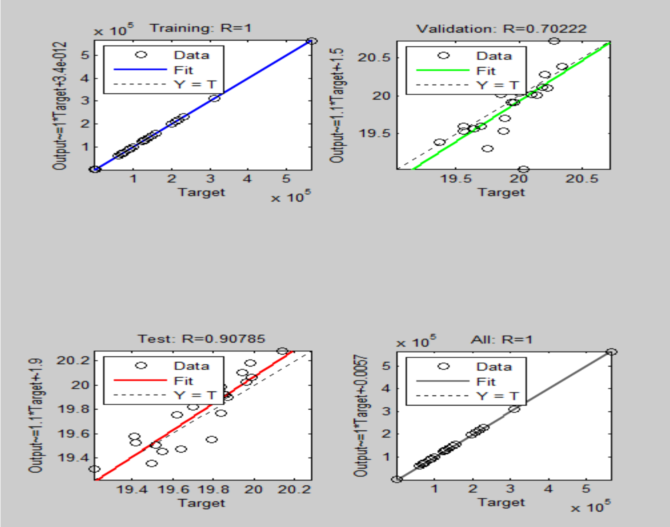

Fig. 9 This plot show values of 'R' (regression). Basically, regression shows relation between target and selected input data. From provides most probable target value. This shows the state of data fitting while training, testing and validating. Value of 'R' near to '1' shows that data fitting is better performed

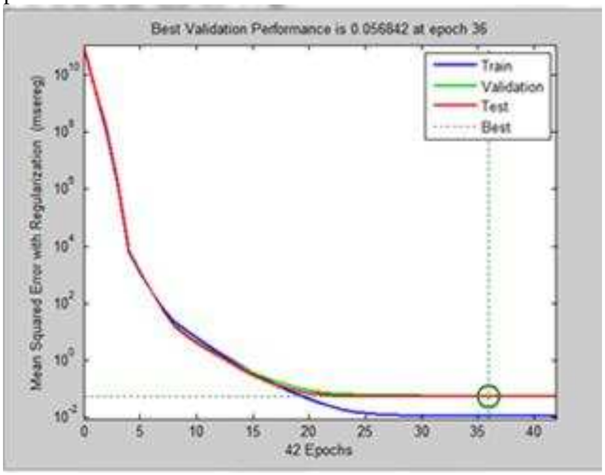

Fig. 10. Performance measure at y- axis and number of epochs on x-axis. This figure shows that how many epochs are required to train network without over training

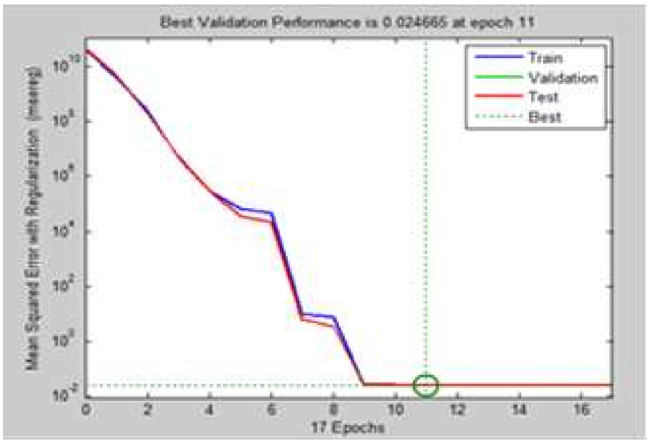

Fig. 11. Show performance measure at y- axis and number of epochs on x-axis. This figure shows that how many epochs are required to train network without over training

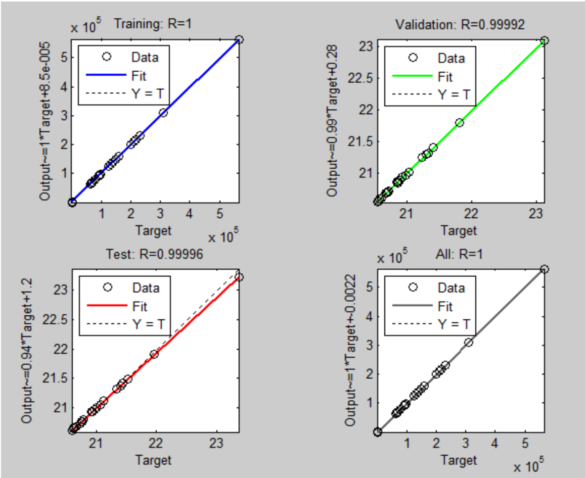

Fig. 12. This plot show values of 'R' (regression). Basically, regression shows relation between target and selected input data. From provides most probable target value. This shows the state of data fitting while training, testing and validating. Value of 'R' near to '1' shows that data fitting is better performed

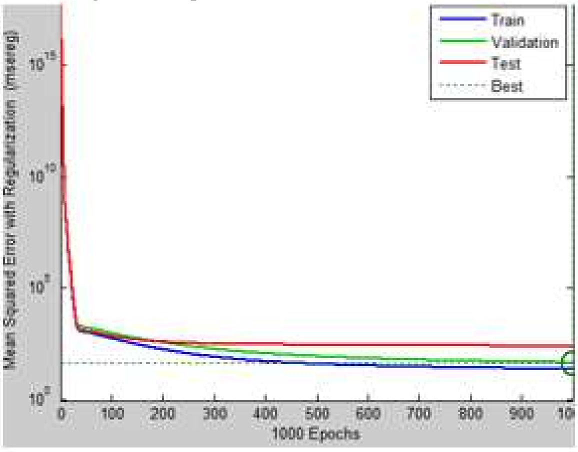

Fig. 13 Show performance measure at y- axis and number of epochs on x-axis. This figure shows that how many epochs are required to train network without over training

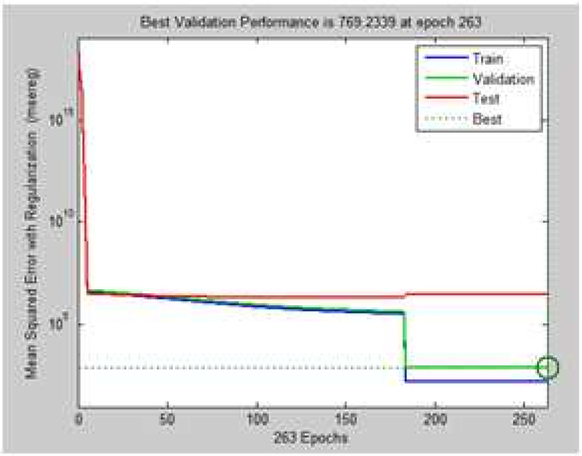

Fig. 14. Show performance measure at y- axis and number of epochs on x-axis. This figure shows that how many epochs are required to train network without over training

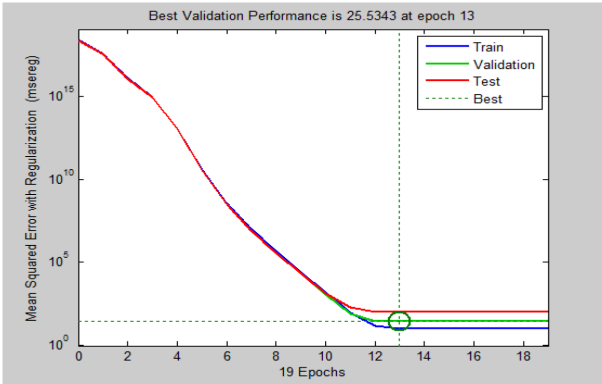

Fig. 15 Show performance measure at y- axis and number of epochs on x-axis. This figure shows that how many epochs are required to train network without over training

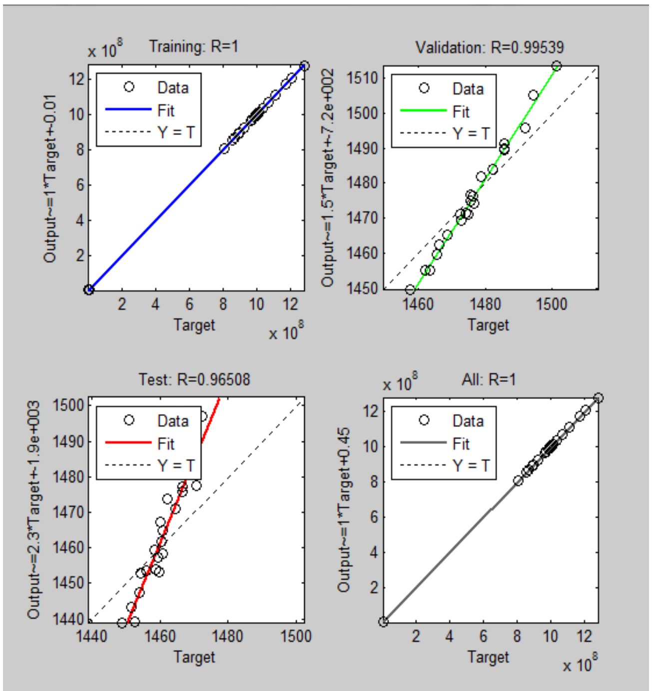

Fig. 16 This plot show values of 'R' (regression). Basically, regression shows relation between target and selected input data. From provides most probable target value. This shows the state of data fitting while training, testing and validating. Value of 'R' near to '1' shows that data fitting is better performed.

4.2 Comparison

TABLE 2
FEED-FORWARD NEURAL NETWORK (NN)

Dataset	Epochs	Time	MSEREG (performance Measure)
PSO	48	00:00:19	0.15
S&P500	1000	00:31:51	21.9

TABLE2 contain results of Feed-Forward Neural Network. In this experiment we took one month data of PSO and 6 month data of S&P500, we observed that when amount of data increased , number of iteration and time of execution also increases.

TABLE 3
LAYERED RECURRENT NEURAL NETWORK (LRNN)

Dataset	Epochs	Time	MSEREG (performance Measure)
PSO	36	00:06:22	0.05
S&P500	263	01:09:57	151

TABLE 3 holds results of LRNN own both data sets. It is observed that LRNN takes more time but less number of iterations.

TABLE 4
WMSPCA-FEED-FORWARD NEURAL NETWORK

Dataset	Epochs	Time	MSEREG (performance Measure)
PSO	11	00:00:07	0.02
S&P500	19	00:00:35	9.64

TABLE 4 holds results of wmspca-NN results. Visible changes can be observed in time, epochs and error in comparison with TABLE 2 and 3.

TABLE 5
RESULTS OF DIFFERENT TECHNIQUES ON S&P500 DATASET

Techniques	Epochs	Time	MSEREG (performance Measure)
Feed-Forward Neural Network	1000	00:31:53	21.9
Layered Recurrent Neural Network	263	01:09:57	151
Wmspca- feed forward Neural Network	19	00:00:35	19

TABLE5 holds different techniques results on S&P500 data. It shows time, performance and epochs used by different techniques on same data set. It is observed from results that data pre-processing methods enhance performance of NN and give better results.

TABLE 6
RESULTS OF DIFFERENT TECHNIQUES ON PSO DATASET

Techniques	Epochs	Time	MSEREG (performance Measure)
Feed-Forward Neural Network	48	00:00:19	0.15
Layered Recurrent Neural Network	36	00:06:22	0.05
Wmspca- feed forward Meural Network	11	00:00:07	0.02

TABLE6 holds results on PSO data set. This table holds values of time , msereg and epochs to make the comparison easy. From this table one can easly conclude that wmspca outer performs than other two methods.

TABLE 7
COMPARISON OF PERFORMANCE MEASURE (MSEREG)

Dataset	Msereg in feed-forward NN	Msereg in LRNN	*Msereg in Wmspca-feed-forward neural network*
PSO	0.15	0.05	*0.02*
S&P500	21.9	151	*9.64*

TABLE7 holds performance measure values on both data sets when applied on above mentioned models. It is clear that wmspca-feed-forward give small value of performance measure.

TABLE 8
COMPARISON OF TIME CONSUMED

Dataset	Time in feed-forward NN	Time in LRNN	*Time in Wmspca-feed-forward neural network*
PSO	00:00:19	00:06:22	*00:00:07*
S&P500	00:31:53	01:09:57	*00:00:35*

TABLE8 shows time consumption on both data sets in three applied techniques.

TABLE 9
COMPARISON OF NO. OF EPOCHS

Dataset	epochs in feed-forword NN	epochs in LRNN	*epochs in Wmspca-feed-forward neural network*
PSO	48	36	*11*
S&P500	1000	263	*19*

TABLE9 holds number of epochs required for training data sets in three applied techniques.

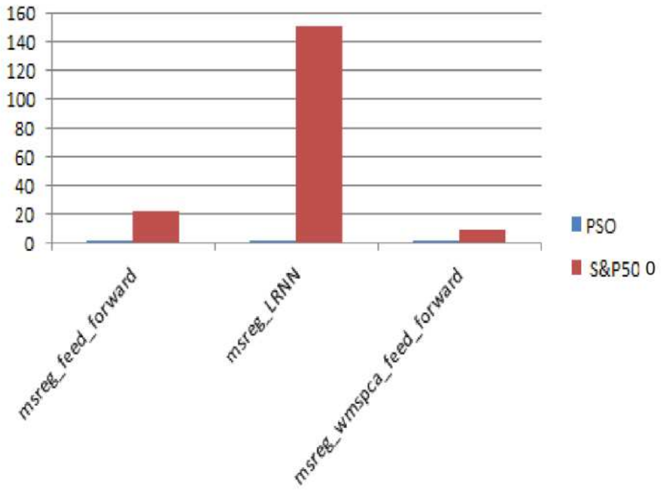

Fig. 17. Error measure by three mentioned techniques on both data sets. It is observed that wmspca-feed-forward neural network provides smallest error for both data sets.

It is observed that wmspca-feed-forward neural network use Fewer epochs for both data sets. From all above results, it is observed that wmspca-feed-forward neural networks outer perform than other two techniques. Wmspca-feed-forward neural network used less iteration, less time and small error measure. It is analyzed from results that using appropriate de-noising scheme gives better results.

V. CONCLUSION

Different machine learning techniques are available and being used for stock market prediction. It was observed from the comprehensive literature survey and results of applied techniques that, although, many state of the art techniques are available but data pre-processing and post-processing have great effect on results. It is also observed that Recurrent Neural Network (RNN) performs better than Artificial Neural Network (ANN) for prediction and Layered Recurrent Neural Network (LRNN) performs better than Feed-Forward Neural Network (NN). Layered Recurrent Neural Network (LRNN) takes less iteration, but more time. Time consumption factor of LRNN makes it odd to use. Wsmpca was applied as pre-processing on Feed-Forward NN and it was observed that pre-processing methods enhance results of Feed-Forward Neural Network (NN).

Applying Independent Component Analysis or Rough Set on Recurrent Neural Network (RNN) may improve the performance of RNN.
Similarly, Kalman filter may also be used with Echo State Network (ESN) to improve its performance.

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