

General Regression Neural Networks Based On Stock Prediction

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ABSTRACT

In an unclear financial market, it's hard to guess what the price of a stock will be. Financial professionals and academics equally utilise statistical, economic, and neural network theories to make investments and gain market insights. In this study, we evaluate the performance of five prominent neural network models—back propagation (BP), radial basis function (RBF), general regression neural network (GRNN), and support vector machine regression (SVMR)—by assessing their ability to make accurate predictions. ARIMA and LSTM have been utilised to forecast the stock market, but more precise models may be possible. In this study, stock price forecasts are generated utilising neural networks and other methods.

Keywords: SVM Regression, General RNN, back propagation, radial basis function.

INTRODUCTION

Stock price forecasting attracts substantial theoretical and applied attention. On the one hand, investors stand to gain the most when predictions are within a reasonable range. Many market players, particularly institutional ones, expend substantial time and resources in gathering and analysing data before making investment decisions. However, academics often consider the ability to predict prices as a measure of market efficiency. Furthermore, they innovate new models, implement existing ones, or make minor adjustments to existing ones in order to increase the accuracy of predictions. For the foreseeable future, academics and the financial industry will seek a "good" approach to more accurately estimating stock prices. The equity market's inherent dynamism, nonlinearity, complexity, nonparametricity, and pandemonium make valuation forecasting problematic in the money time series prognosis process. BPNN has applications in economics as well [1]. A hybrid forecasting model (Wavelet Denoising-based Back Propagation) was proposed to predict the Shanghai Composite Index (SCI) closing price. The original data was first

decomposed into multiple layers by wavelet transform. A single hidden layer makes up the RBFNN's straightforward architecture, making it a feedforward neural network. Specht proposes a generic regression neural network (GRNN) that excels in predicting stock prices, groundwater levels, and other patterns. shown that GRNN can accurately anticipate the stock price at the end of the day. The absence of a comparison to other data mining techniques is a shortcoming of their work and the other sources presented in this article [2,3]. Vapnik and his coworkers developed the first support vector machine (SVM) using statistical learning theory principles. It has been the focus of much study because of its potential in a number of classification and regression tasks, including time series prediction and financial-related applications. The support vector machine improves generation performance and identifies a single, globally optimal solution by transforming the problem-solving method into a conical linear programming challenge using the structural risk reduction concept.

METHODOLOGY

BP neurons

A neural network typically consists of one input layer, numerous concealed layers, and one output layer [4,5]. Assuming there are L layers in total, we will refer

to a single layer as l. Two buried layers and one output layer are present. Figure 1 depicts a simple, open network with one concealed layer (L = 3). Figure 1 shows the network with three neurons located in an input layer, four neurons situated in the buried layer, and one cell in the output layer.

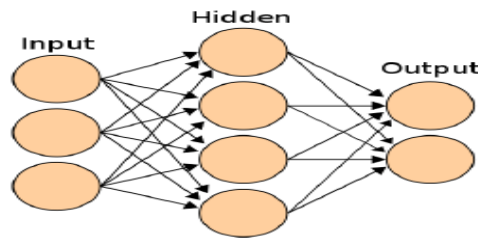


Fig 1. Locations of Neurons

Assuming the asset's price at time t is represented by the symbol P_t , a straightforward gross return over a single period is obtained by holding the asset between periods t-1 as well as t while disregarding dividends and dividend returns. This is the only method for producing a straightforward gross return in a single time period.

$$P_t = P_{t-1}(1+R_t)$$

The following must be used to calculate the same kind of simple return throughout the course of a single period:

$$R_t = (P_t/P_{t-1})-1$$

Financial time series display several statistical characteristics that are distinguishable from those of other forms of time series that are more conventional [6]. These characteristics include:

Outliers:

After being subjected to the influence of macroscale factors, such as those affecting individuals and government policies, a financial time series may produce outcomes with substantial variation [7,8,9]. This is because large-scale effects may have an outsized effect on the outcomes.

$$\sum_i w_i \rho(\|x - c_i\|^2)$$

$$\phi(x) = \frac{\sum_{i=1}^l \rho(\|x - c_i\|^2)}{\sum_{i=1}^l \rho(\|x - c_i\|^2)}$$

Trend:

Every financial time series, regardless of magnitude, will exhibit a distinct upward or downward trend over the medium to long term [10]. Even when contemplating lesser time periods, this holds true.

Mean reversion:

Mean reversion is the tendency of financial time series to revert to their initial values. Financial time series are susceptible to this effect [11,12].

Fluctuation focus:

Typically, larger scale variations are followed by even larger scale variations, whereas smaller scale differences are nearly always followed by smaller scale variations.

RBF networks

A radial basis function (RBF) network typically contains input, concealed (with a nonlinear RBF activation function) [13,14], and output layers. Assume there are l neurons concealed within, with each ith neuron's value at location c_i being w_i . $x \in R^n$ represents the input as a vector of real integers, while $y \in R^n$ is a scalar function of x.

where $x_i^2 = \exp(-\beta_i)$. Note that x is the weighted average of w_i with weight c_i^2 . The cost function is quadratic.

$$C = \frac{1}{2n} \sum_x \|y(x) - \phi(x)\|^2 \stackrel{\text{def}}{=} \frac{1}{2n} \sum_x C_x$$

Reducing C determines the values of w_i , c_i , and i .

Neural systems for extended regression

A subset of RBNNs is the generalised radial basis neural network (GRNN). D.F. Specht suggested GRNN in 1991 [15]. The number of hidden-layer neurons at the start of training is indicated by n in

$$\sum_i y_i \rho(\|x - x_i\|^2)$$

$$\phi(x) = \frac{\sum_{i=1}^{n-1} y_i \rho(\|x - x_i\|^2)}{\sum_{i=1}^{n-1} \rho(\|x - x_i\|^2)}$$

$\exp(-x_i^2) = x_i^2$, and c_i^2 is a constant. The output y is simply the weighted average of y_i for each input x , with weight equal to $(x - x_i)^2$. We emphasise that GRNN does not require any form of instruction in order to predict outcomes. Implementing GRNN requires only the selection of an acceptable normalising value.

Support vector regression

Vladimir N. Vapnik and his friends created the support

n

$$\sum_i |f(x_i) - y_i| \leq \epsilon$$

i

Problem solve:

$$\min \frac{1}{2} \|w\|^2, \quad \text{s.t. } \|Xw + b\| \leq \epsilon$$

the RBF network architecture. In addition, x_i represents the i th sample, which functions as the neuron's "seed," and w_i represents the expected output, $y_i = y(x_i)$. If x is a new parameter, then the answer is

vector machine (SVM) for regression (SVR) in 1996 [2,16]. To determine a linear relationship between x and y , the model employs the formula

$$y = mx + b, f(x) = w \cdot x + b.$$

Let's call it "tolerance" for mistakes. The subsequent step is to determine the ideal values for w and b such that

RESULTS AND DISCUSSIONS

Problem domain	NN architecture	
	Algorithm	NN structure
Predicting stock performance (classification)	Backpropagation [8] Backpropagation [9] Boltzman machine [4]	2,3, and 4 layers (9-3-3-2) [8] 6 feedforward networks [9] 2 layers (88-1) [4]
Stock price predictions	Backpropagation [3] Backpropagation [7] Perceptron [7] ADALINE / MADALINE [7]	3 layers (24-24-1) [3] 4 layers (10-10-10-1) [7] 2 layers (40-1) [7] 2 layers (40-1) [7]
Modeling the stock performance (ANN combined forecasts)	Backpropagation [6] Hybrid approach (Backpropagation NN + expert system) [12]	4 layers (3-32-16-1) [6] 3 layers (4-7-2) [12]

The BP neural network has the lowest MSE and highest MAPE among all three securities when compared to the other four models. Figure 2 in the following section illustrates the predictive accuracy of the BP method for the Bank of China. SVMR consistently ranks second among the three stocks. SVMR's MSE and MAPE results are at least 10 percent superior than BP's. In addition, both Bank of China and Vanke A anticipate BP to outperform

SVMR by at least 20%. After a specific number of repetitions (epochs) that can be calculated using performance metrics, the mean squared error becomes minimal or stable. On the tick dataset (15-min dataset), time is not proportional to the number of iterations, as evidenced by the fact that Scaled Conjugate Gradient provides the optimal validation after 103 (54) iterations, while Levenberg-Marquardt does so after 10 (13) iterations.

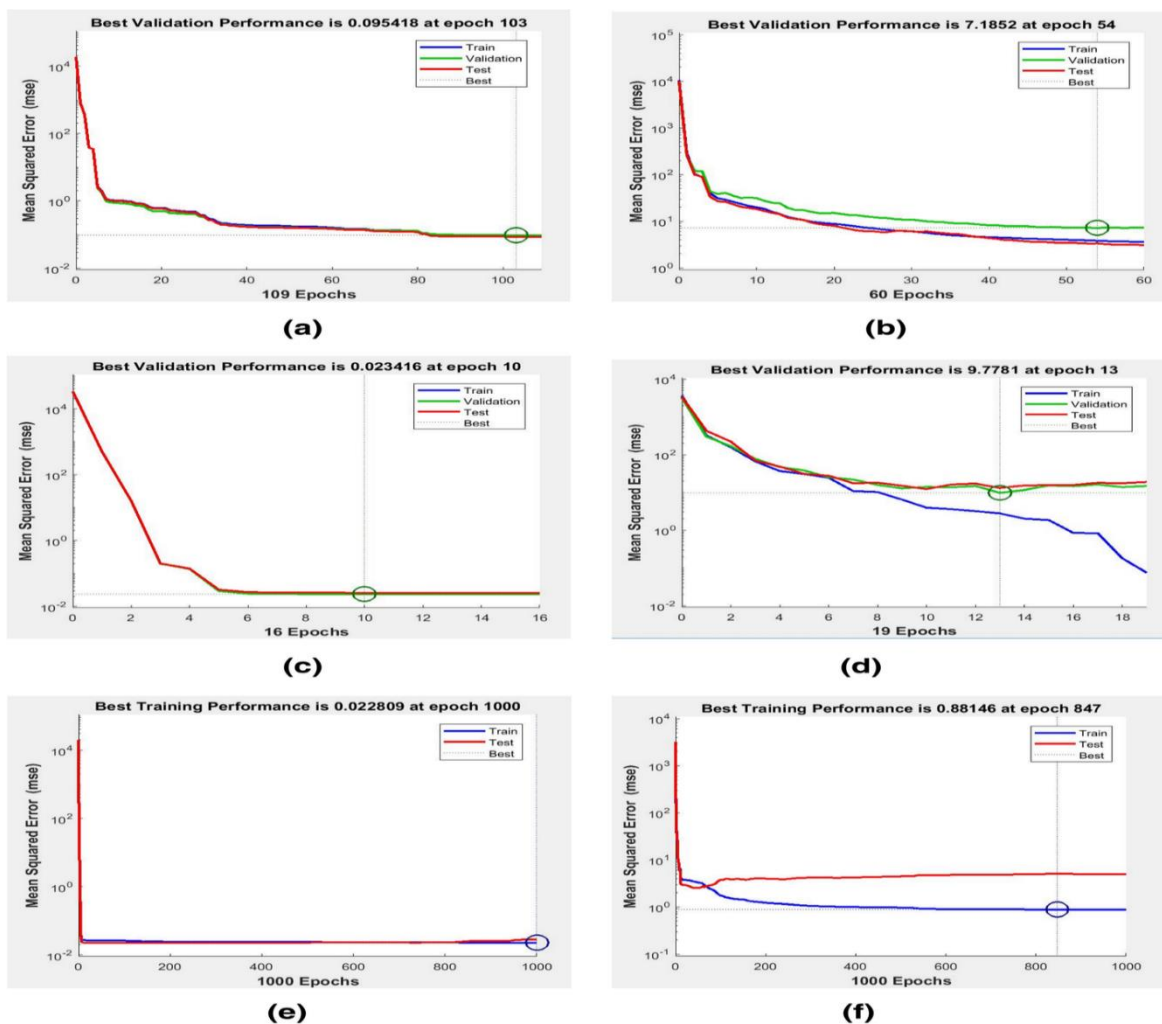


Fig 1: validation performance plot

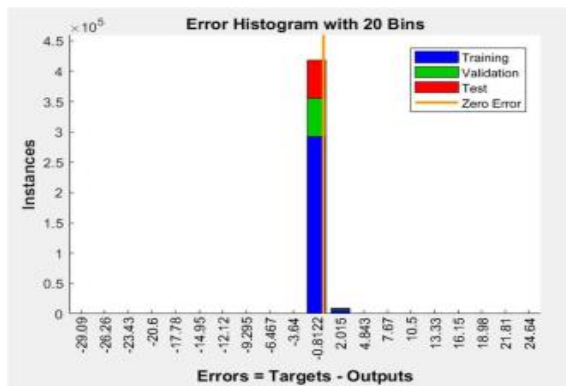
Error histograms

Blue bars reflect the training set, green bars the validation set, and red bars the testing set. Using a 20-bin error range (from the greatest negative error to

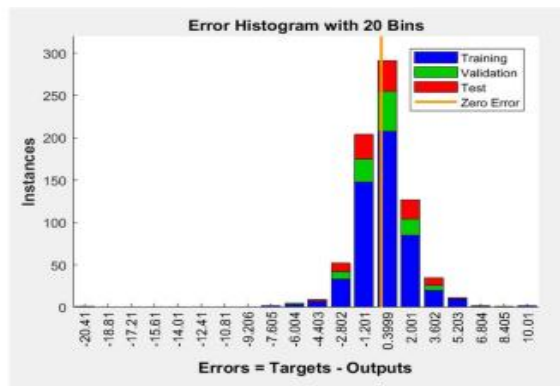
the greatest positive error), the charts are created. Histograms facilitate the identification of extreme values. Outliers are, therefore, data elements whose

fit is significantly worse than the remainder of the data. In this instance, we can see that tick data

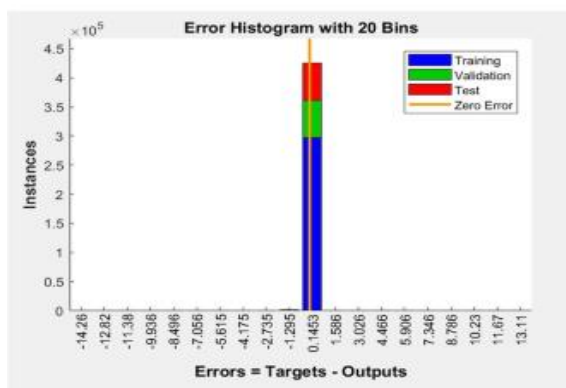
outperforms 15-minute data based to all three methods.



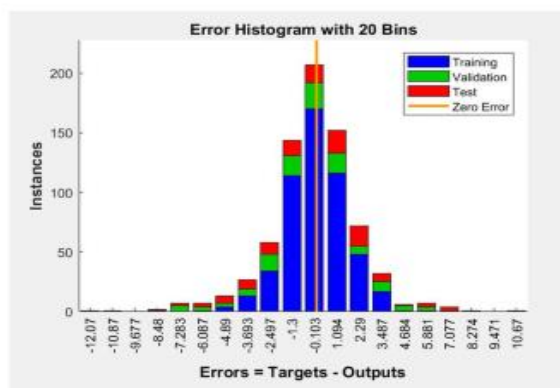
(a)



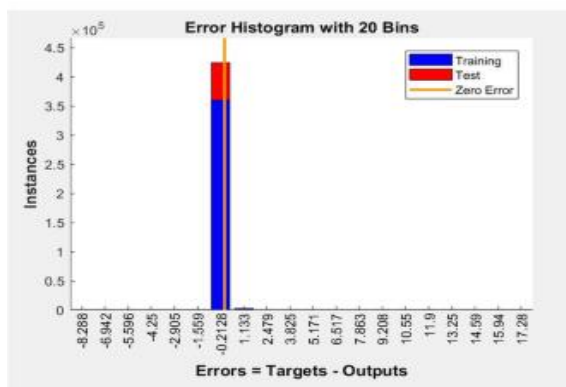
(b)



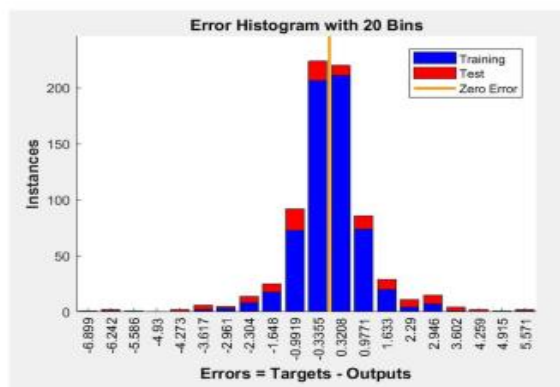
(c)



(d)



(e)



(f)

Fig 2: Errors Histogram Plots

CONCLUSION

We demonstrated that all five neural network models effectively extracted actionable lessons from different

price histories. When compared to the other four brands, BP outperforms them on practically every statistic. To ensure the reliability of BP, numerous

iterations of the procedure and observations of the standard deviation are employed. Our investigation into various kernels led us to conclude that consumers of this publication should not take the default kernel for granted. We can integrate annual and seasonal factors that affect volatility in stock markets with a larger data set. We can use historical data over an extended period of time and still obtain comparable results if we estimate the data on a minute-by-minute basis. This may minimise the data set size by 70%. The results of this research's computational models, such as LSTM (Long Short-Term Memory), may not provide the most accurate predictions. Since the words and opinions of notable individuals have an impact on the market, sentiment analysis may provide an advantage when attempting to predict stock prices.

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