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THE PREDICTIVE POWER OF MACROECONOMIC VARIABLES ON THE INDIAN STOCK MARKET UTILIZING AN ANN MODEL APPROACH: AN EMPIRICAL INVESTIGATION BASED ON BSE SENSEX

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Abstract

Research background: The paper focuses on the use of Artificial Neural Networks (ANNs) for forecasting time series data of the stock market since ANNs are dynamic and are more capable of handling complex data sets in comparison to conventional forecasting techniques such as regression, Logistic regression, and have massive potential for the prediction of stock market prices.
Purpose: Artificial neural networks are an effective method for forecasting time series. Therefore, this study aims to forecast the closing price of the BSE Sensex using artificial neural networks (ANNs).

Research methodology: The study uses nine input variables, including macroeconomic and global stock market factors, to estimate the BSE Sensex using scaled conjugate gradient algorithm artificial neural networks (SCGANNs) and Bayesian regularized artificial neural networks (BRANN).
Results: As per the empirical results of the study, the ANN model can forecast the closing values of the BSE Sensex with a Bayesian Regularization (BR) method with an accuracy of over 99 percent, thus leading to significant implications for domestic institutional investors (DIIs), foreign institutional investors (FIIs), investment houses, and so on. This study adds more value to the existing literature by proving that the BRANN models outperform SCGANN in stock market forecasting.
Novelty: This is the first study to employ macroeconomic variables as input variables for predicting the Indian stock market using ANN. The study highlights the ANN model's forecasting potential, giving investors robust and accurate stock value prediction capabilities.

Keywords: foreign exchange, index of industrial production, BSE Sensex, macroeconomic variables, prediction

JEL classification: G170

Introduction

Stock market prediction has long been of great interest to several investors, professionals, and researchers. Due to an inherently noisy and highly volatile environment, an accurate prediction of stocks is a difficult procedure (Ticknor, 2013). Various factors, including market news, political developments, and crises like COVID-19, influence the stock market's movement. Several factors that affect the stock market have been discussed in previous literature, including the foreign exchange rate, the "index of industrial production," the "consumer price index," the "long-term interest rates," the price of gold, Crude oil prices, the Indian Volatility Index, Morgan Stanley Capital International (MSCI) World Index, and the MSCI Emerging Market Index is added as a new variable to add novelty to the research.

According to a review of earlier studies, many researchers have used various models and approaches when projecting stock market time series (Gao, Zhang, Yang, 2020; Selvamuthu, Kumar, Mishra, 2019; Ticknor, 2013; Zhong, Enke, 2019). Generally, the review yields two kinds of models: statistical models and models based on machine learning. Regression techniques and ARIMA are the most widely used models in the field of statistical models. Machine learning algorithms and Artificial Neural Networks (ANNs) have rarely been used to predict the Indian stock market. Therefore, the current study has used artificial

intelligence approaches such as the Scaled conjugate gradient (SCG), and a Bayesian regularized (BR) algorithm of artificial intelligence to forecast the stock market.

Contrary to other conjugate algorithms, SCG is a class of conjugate gradient algorithms that do not line search iteratively. In the line search, each search requires computing each network's responses to all training inputs, which is computationally expensive (Selvamuthu *et al*., 2019). The Bayesian regularised algorithm, on the other hand, considers the probabilistic character of network weights concerning the data set. Also, as the network's number grows, i.e., a greater number of neurons are added in the hidden layer, the problem of overfitting increases significantly; therefore, a validation data set is required to determine the stopping point. However, a significant disadvantage of BR over SCG is that it requires more time for training (Ticknor, 2013).

Most studies have used technical indicators for predicting the stock market (Ajoku, Nwokonkwo, John-Otumu, Oleji, 2021; Chandrika, Srinivasan, 2021; Zhong, Enke, 2019). Moreover, a few studies have employed the ANN model to predict the Indian stock market (Ajoku *et al*., 2021; Chandrika, Srinivasan, 2021; Zhong, Enke, 2019). But this study employs macroeconomic variables for predicting the Indian stock market as none of the studies in the literature have used macroeconomic variables as input variables for predicting the stock market using ANN. To close this research gap, the study uses ANN to forecast the Indian stock market while using macroeconomic factors as input variables. Therefore, this study aims to forecast the closing price of the Bombay Stock Exchange (BSE) Sensex using artificial neural networks (ANNs). Our study contributes to the existing literature regarding the factors considered to predict the Indian stock market. Second, our study compares the stock market forecast accuracy of the SCG and BR algorithms. This study employs two machine learning algorithms, the SCG and BR algorithms, to forecast the closing price of the BSE Sensex.

1. Review of the literature

Gao *et al.* (2020) predicted the development and developed stock markets using four different models, i.e., CNN, LSTM, MLP, and attention-based neural network model. The study's empirical results show that the attention-based neural network outperformed every other model. Moreover, the findings reveal that the ANN models gave higher accuracy in developed markets than in developing markets. Similarly, Kamalov (2020) also employed CNN, LSTM, and MLP to predict the stock market. The authors postulate that the LSTM model accurately predicted the US company's stock prices. Anand (2021) employed CNN,

LSTM, SVM, RNN, and MLP to predict the companies selected randomly from the National Stock Exchange (NSE). The findings of the study report that the CNN model outperformed all other models used for forecasting. Moreover, the authors report that the trained model can predict other stock markets with common inner dynamics.

On the contrary, Ajoku *et al.* (2021) used an ensemble neural network to predict the stock market. The authors report that the proposed model outperformed conventional MLP algorithms. The authors also state that the proposed method was adopted for better predictions. Chandrika and Srinivasan (2021) applied the deep learning technique of the ANN model to predict the direction of various indices such as "The Nifty 50", "S&P 500", the "New York Stock Exchange (NYSE) Composite Index," the "Dow Jones Industrial Average (DJIA)," the "Shanghai Stock Exchange (SSE) Composite Index" and the "Korea Stock Exchange Index (KOSPI)." The study's empirical results reveal that the ANN model handles uncertainty better than conventional linear and nonlinear models. However, the proposed ANN model is only effective for short-term predictions. Nova, Mim, Rowshan, Islam, Nurullah, and Biswas (2021) employed feed-forward and backpropagation algorithms using different data sets. The findings show that the high-frequency data achieved the highest accuracy compared to other datasets. The following year, Al-Najjar (2022) examined the linkages between emerging and developed markets using regression and the ANN model. The study's findings show that the ANN model is more effective than the conventional regression model in finding the linkages between emerging markets and international stock exchanges. Fuchs, Wahl, Zagst, and Zheng (2022) investigated the potential of the ANN model in forecasting financial crises using micro, macro, and economic factors. Moreover, the authors developed a factor reduction model to avoid over-parameterization. The empirical findings report that the proposed model is better than choosing the variables from the literature. Sharma, Hota, Browna, and Handa (2021) introduced a hybrid model by combining the ANN and Genetic algorithm to forecast the DOW30 and NASDAQ100. The study results reveal that the proposed hybrid model is better than the traditional BPANN model in the short and long run.

Similarly, Zhong and Enke (2019) used a hybrid model to predict the stock market time series data. The authors used 60 financial and economic parameters as input variables to forecast the S&P 500 exchange-traded funds (ETF). The empirical results show that the deep learning neural network is better than the hybrid models used in the study.

It is evident from the literature that most studies have used technical indicators for predicting the stock market. Moreover, a few studies have employed the ANN model to predict the Indian stock market. However, this study employs macroeconomic variables for predicting

the Indian stock market as none of the studies in the literature has used macroeconomic variables as input variables for predicting the stock market using ANN. To close this research gap, the study uses ANN to forecast the Indian stock market while using macroeconomic factors as input variables.

2. Method

The researcher has taken into account the 90 data points from monthly data spanning the last eight years, from 2012 to 2019; Sensex data from the official BSE website; and information on inflation and the rupee exchange rate from the Reserve Bank of India website. The official websites of the "Organization for Economic Co-operation and Development (OECD)" and "Morgan Stanley Capital International (MSCI)" were used to retrieve information on industrial production, interest rates, and the MSCI world index and MSCI emerging market index, respectively. Gold and crude oil data were obtained from Multi Commodity Exchange's official website. The period from 2012 to 2019 provides a relatively recent historical perspective, which can be valuable for understanding developments, trends, and changes in various domains, including economics, politics, technology, and society. However, the years from 2012 to 2019 encompass both periods of relative stability and significant transitional phases in various regions and industries. Researchers interested in stability or change can find relevant data.

Table 1. Macroeconomic variables found in the literature

Variable	Authors
Foreign Exchange rate (FX)	Akter, Rana and Anik (2020)
Index of Industrial Production (IIP)	Srivastava (2010)
Consumer Price Index (CPI)	Areli Bermudez Delgado, Bermudez Delgado and Saucedo (2018)
Long-Term Interest Rates (LTINT)	Mohammed and Abu Rumman (2018)
Morgan Stanley Capital International World Index (MSCI-WI)	Mensi, Hammoudeh, Yoon and Balcilar (2016)
Crude Oil	Basher, Haug and Sadorsky (2011), Ghosh and Kanjilal (2016)
Gold	Shahani and Bansal (2020), Singh and Sharma (2018a), Singh and Sharma (2018b)
India Volatility Index (India VIX)	Shahani and Bansal (2020)

Source: author's elaboration.

Artificial Neural Networks (ANN) can create a prediction model for the dependent variable based on the operation of predictor or explanatory elements. The BSE Sensex is a proxy for the stock market and is regarded as the dependent variable (Baranidharan, Dhivya, 2020; Giri, Joshi, 2017). This study's explanatory factors are the Consumer Price Index (CPI), Index of Industrial Production (IIP), Foreign Exchange (FX), Long-Term Interest Rates (LTINT), Morgan Stanley Capital International World Index (MSCI-WI), Morgan Stanley Capital International Emerging Market Index (MSCIEF), gold, crude oil, and India Volatility Index (India VIX). These are the most common macroeconomic and international stock market factors identified as affecting the stock market in the literature (see Table 1).

2.1. Process of deploying an Artificial Neural Network Model

1. Data Preparation:
   - Load dataset into MATLAB. Used functions like csvread, xlsread, or import data from various formats.
   - Pre-process data for the purpose of data cleaning, normalization, and feature scaling.
   - Split data into training, validation, and test sets.
2. Neural Network Design:
   - Define the architecture of your neural network. This includes specifying the number of layers, neurons in each layer, the activation functions, and the network's topology.
   - Use MATLAB's Neural Network Toolbox to create, configure, and visualize the network. The feedforwardnet function is commonly used for feedforward neural networks.
3. Data Formatting:
   - Organize data in a format suitable for MATLAB's neural network functions. Typically, input and target matrices were created.
   - Use functions like con2seq or tonndata to format data into sequences or time series.
4. Training:
   - Choose a training algorithm. MATLAB provides various optimization algorithms like stochastic gradient descent (trainscg), or Levenberg-Marquardt (trainbr).
   - Train the neural network using the training data and the selected algorithm. Use the train function for this.

- Monitor the training process by specifying performance metrics and plotting training progress.

5. Validation and Hyperparameter Tuning:
   - Use the validation set to prevent overfitting. Adjusted hyperparameters like the number of hidden layers, neurons, and learning rate based on validation performance.
   - Use techniques like cross-validation to fine-tune your model.
6. Testing and Evaluation:
   - Evaluate the trained ANN using the test dataset to assess its generalization performance.
   - Calculate relevant metrics such as accuracy, mean squared error, or any domain-specific metric suitable for your problem.
7. Deployment:
   - Since ANN meets the desired performance criteria, it can be further deployed to predict new, unseen data.
   - Save the trained model using the save function to use it later without retraining.
8. Visualization and Interpretation:
   - Visualize the network's performance, such as training and validation curves or confusion matrices.
   - Also visualize the weights and activations of the neurons in the network for better understanding.
9. Fine-tuning and Optimization:
   - Depending on the results and real-world feedback, it is further required to fine-tune your ANN by adjusting hyperparameters, collecting more data, or modifying the network architecture.

2.2. Scaled Conjugate Gradient (SCG)

SCG Algorithm is a supervised, fully automated algorithm designed by Møller (1993). It does not require prior user-dependent critical parameters. This algorithm can be used on any data set if the weights, input, and activation functions have a derivative function. The most significant advantage of SCG is that it does not line search iteration-wise, unlike other conjugate algorithms. In the line search, the responses of each network of all training inputs are computed for every computationally expensive search. Therefore, to avoid the time-consuming line search, a scaled conjugate algorithm was employed (Selvamuthu *et al.*, 2019).

2.3. Bayesian Regularization (BR)

Bayesian Regularization Neural Networks (BRANNs) perform more robustly than conventional Backpropagation Neural Networks (BPNNs) as it does not require a lengthy cross-validation process (Selvamuthu *et al*., 2019). Bayesian Regularization is a mathematical technique developed to convert a nonlinear problem into a "well-posed" statistical problem (Burden, Winkler, 2008; Mackay, 1992; Selvamuthu *et al*., 2019; Ticknor, 2013). The training function generally aims to lower the sum of a squared error.

The key advantage of the Bayesian regularization algorithm over the traditional backpropagation algorithm is that it considers the probabilistic nature of network weights about the data set. Bayesian regularized networks calculate the non-trivial weights that converge to a constant as the network grows. Also, as the network's number grows, i.e., more neurons are added in the hidden layer, and the problem of overfitting increases significantly. Therefore, the validation data set is required to determine the stopping point. In BRANNs, all unreasonable models are penalized by assigning extra weights to zero.

Moreover, the noise and volatility of stock markets lead to the probability of overfitting. However, Bayesian Regularization is more economical than conventional backpropagation algorithms, as the algorithms reduce the problem of overfitting by eliminating the need for validation steps. Thus allowing more data for training purposes (Ticknor, 2013).

3. Results and discussion

Table 2 shows the descriptive statistics of all the select variables during the COVID period (March 2020–June 2021). The value of kurtosis reveals that all the chosen variables are not normal. Also, the Jarque Bera probability test results confirm that the variables are not normal, as the null hypothesis of normality is rejected at a 5 percent level of significance. However, all the variables except long-term interest rate are found to be expected as the null hypothesis cannot be rejected at a 5 percent level of significance.

The Bayesian regularized algorithm is well known to take both training and validation datasets for training purposes. The same data set has been used for both of the algorithms, i.e., SCG and BR algorithms. The training is done on 70 percent of the data set, whereas 15 percent has been used for validation purposes, and the remaining 15 percent has been used for testing purposes. Therefore, 85 percent of the data set was used for training, and the remaining 15 percent was used for testing. The testing, training, and validation datasets were chosen at random.

Table 2. Descriptive Statistics

	LIVIX	LFX	LIIP	LCPI	LLTINT	LMSCI_WI	LCRUDEOIL	LGOLD
Mean	1.220	1.795	2.076	1.995	0.887	3.231	3.637	4.431
Median	1.212	1.807	2.074	2.009	0.892	3.234	3.647	4.430
Maximum	1.504	1.869	2.307	2.101	0.954	3.373	3.841	4.572
Minimum	1.036	1.645	1.975	1.859	0.815	3.043	3.302	4.335
Std. Dev.	0.100	0.050	0.055	0.064	0.038	0.082	0.127	0.046
Skewness	0.707	–1.032	1.196	–0.374	–0.233	–0.344	–0.409	0.675
Kurtosis	3.155	3.480	5.774	2.238	2.115	2.237	2.347	3.763
Jarque-Bera	8.858	19.630	58.705	4.991	4.380	4.616	4.787	10.531
Probability	0.012	0	0	0.082	0.112	0.099	0.091	0.005

Source: author's elaboration.

Figure 1 represents the architecture of the ANN model. It is visible that the ANN model consists of 3 consecutive layers: output layer, Input layer, and Hidden layer. The input layer has nine nodes, implying nine input or predictor variables (macroeconomic variables identified from the literature). The hidden layer comprises ten nodes, which are chosen at random. In this case, the target or dependent variable is one of the nodes in the output layer, BSE Sensex.

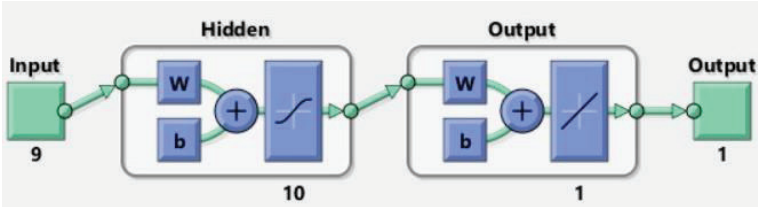


Figure 1. The architecture of the Artificial Neural Network

Source: author's elaboration.

The performance plot helps to interpret the total number of epochs or iterations at which the performance function, i.e., sum squared error (SSE) and mean squared error (MSE), becomes least or stops changing. The number of epochs does not represent the time required to train the network. Figure 2 reveals that the SCG algorithm gives the best validation performance in 14 iterations in the case of SSE and 25 iterations in the case of MSE. Similarly, the Bayesian Regularization algorithm provides the best validation performance in 1,000 iterations in the case of SSE and 405 in the case of MSE. Moreover, Figure 2 also reveals that the Bayesian

regularized algorithm gives the least mean squared error compared to the scaled conjugate algorithm. However, the time taken by SCG is less than the BR. Also, the scaled conjugate algorithm gives the best results compared to the test dataset. Moreover, MSE provides better performance than SSE on both algorithms.

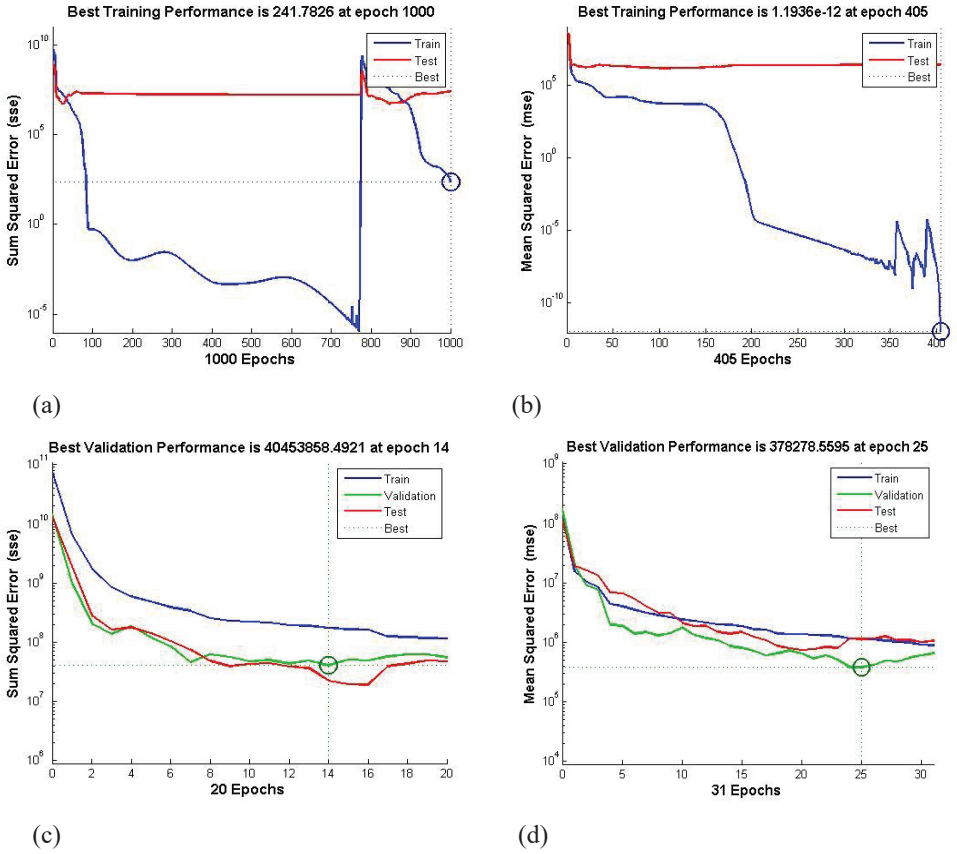


Figure 2. Performance plots. (a) BR in SSE (b) BR in MSE (c) SCG in SSE (d) SCG in MSE

Source: author's elaboration.

The network performance is validated using the regression plots shown in Figure 3. The regression plots show the accuracy percentage of training, validation, testing, and validation datasets. However, the BR algorithm uses training and validation datasets for training purposes. Only training, testing, and overall datasets are displayed for the BR algorithm. Moreover, the performance of both algorithms was measured by two performance measures, i.e., SSE and MSE. Here also, the Bayesian regularized neural network outperforms

the scaled conjugate algorithm as 100 percent accuracy was observed in the training dataset on both SSE and MSE. However, BRANN took more time to train the model.

Moreover, the BR algorithm achieved 99.66 percent accuracy when measured by SSE and 99.55 percent when measured by MSE. However, the scaled conjugate algorithm outperformed BR when the accuracy percentage is compared in the testing dataset, as SCG achieved 99.07 when measured by SSE and 97.92 when measured by MSE. Similarly, Table 1 depicts the accuracy percentage comparison between SSE and MSE. Table 1 also clearly shows the superiority of the BR algorithm over SCG in predicting the Indian stock market. Similar results are reported by Selvamuthu *et al.* (2019).

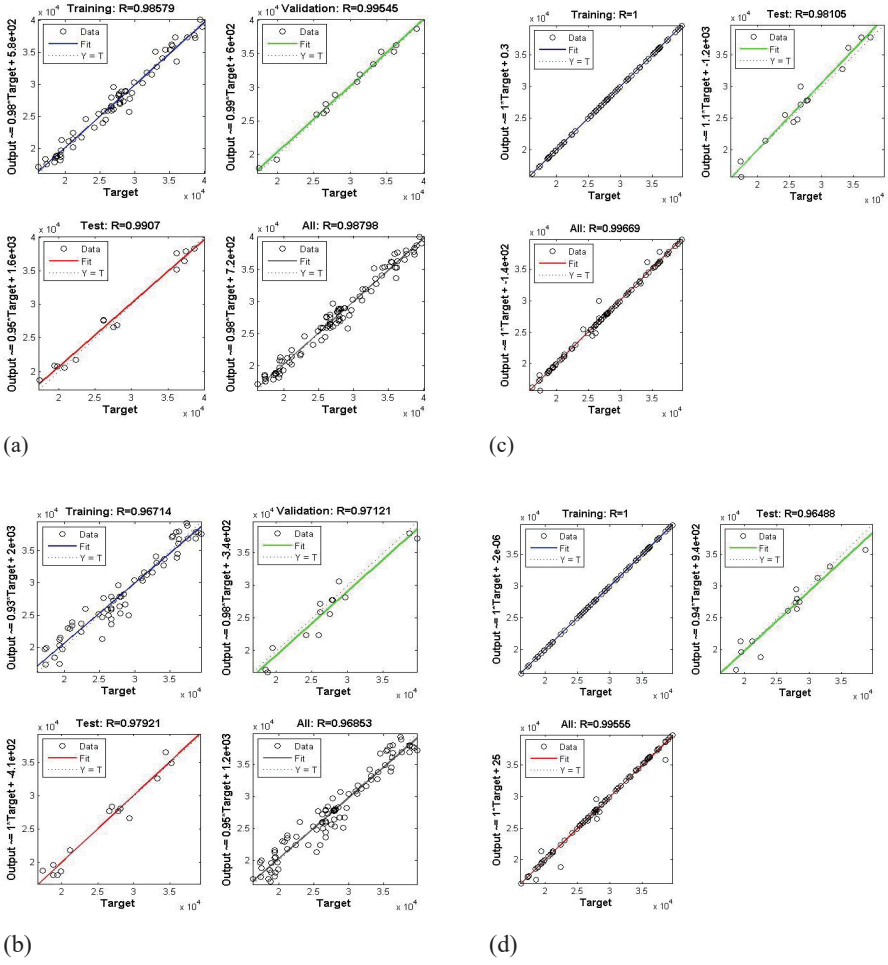


Figure 3. Regression Plots. (a) SCG in MSE (b) SCG in SSE (c) BR in SSE (d) BR in MSE

Source: author's elaboration.

Table 3. Comparison of MSE and SSE accuracy (in percent)

No.	Algorithms	Mean Squared Error				Sum Squared Error			
		"Train"	"Valid"	"Test"	"All"	"Train"	"Valid"	"Test"	"All"
1	SCG	98.57	99.54	99.07	98.79	96.71	97.12	97.79	96.85
2	BR	100.00	–	96.48	99.55	100.00	–	98.10	99.66

Source: author's elaboration.

Figure 4 presents the error histogram plots. The error range, i.e., the maximum positive to the maximum negative, is divided into 20 bins. Error histogram helps us to identify the outliers in the dataset. Outliers are, hence, data points where fit is noticeably worse than the other data points. Moreover, the error histograms are made for two performance metrics, i.e., SSE and MSE. It is visible from Figure 4 that the Bayesian regularized ANN outperformed the ANN model trained with the SCG algorithm as the errors in the BR algorithm are divided into smaller bins in comparison to the errors in SCG that are scattered over bigger bins in both cases (SSE and MSE). Therefore, the study concludes that the BR algorithm is a better approach for

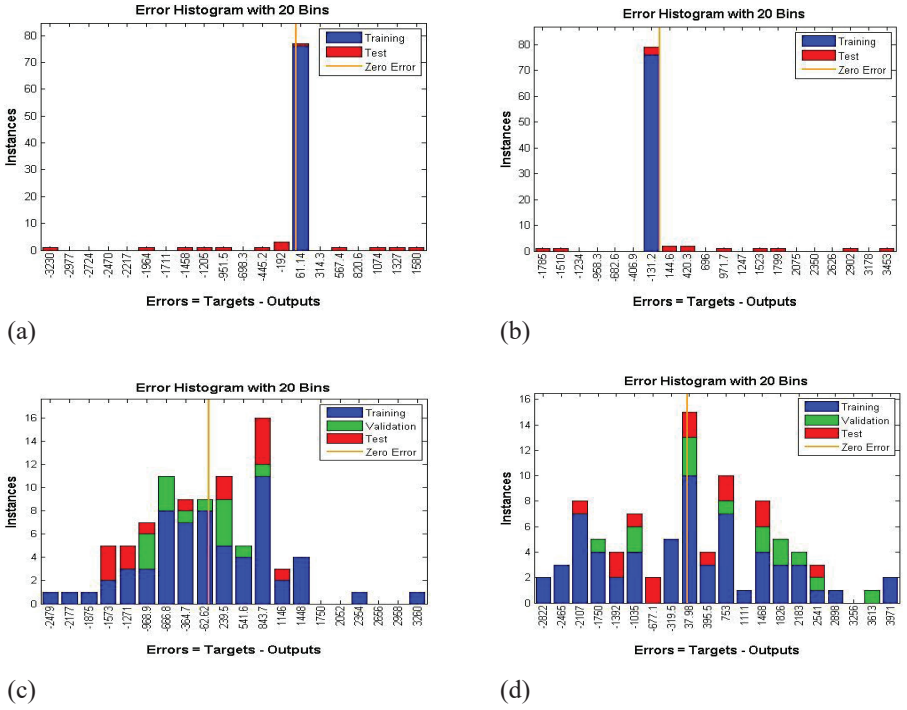


Figure 4. Histogram Plots. (a) BR in SSE (b) BR in MSE (c) SCG in SSE (d) SCG in MSE

Source: author's elaboration.

training the ANN model for predicting the stock market (Selvamuthu *et al.*, 2019; Ticknor, 2013). However, one major disadvantage of the BR algorithm is that it takes longer than other algorithms, such as Levenberg Marquardt (LM) and SCG.

Conclusions

The present study employs the artificial neural network using two algorithms, i.e., SCG and BR algorithms, to predict the BSE Sensex. The following macroeconomic factors: CPI, LTINT, IIP, FX MSCIEF, Gold, Crude oil, IVIX, and MSCI-WI are identified from the literature. Monthly data spanning the past eight years, from 2012 to 2019, has been used for analysis. Firstly, the ANN model was trained using a scaled conjugate algorithm. SCG differs from other conjugate algorithms because it does not line search after each iteration. Therefore, SCG is computationally inexpensive, reducing the time for training the network.

On the contrary, the BR algorithm is more robust than the conventional backpropagation algorithms as it reduces the problem of overfitting by eliminating the validation step. The findings reveal that the ANN model trained with SCG can achieve higher accuracy with minimum error. However, the ANN model trained with the BR algorithm achieved maximum accuracy (99.66%) and the slightest error measured by MSE and SSE. Our model's prediction accuracy outperforms earlier research like Chen, Daouk, and Leung (2001) and Alonso, Batres-Estrada, and Moulin (2018). The novelty of this study lies in the fact that none of the studies in the literature has employed macroeconomic variables to predict the Indian stock market. Studies quoted in the literature have employed technical indicators used by traders for predicting the stock market. Therefore, this study is one of its kind, which employs macroeconomic indicators as input variables for predicting the Indian stock market.

The study's findings will assist all types of investors in making more accurate stock price estimates, including investment companies, high-net-worth individuals, portfolio managers, domestic institutional investors, etc. Additionally, Machine learning algorithms may be more reliable for forecasting stock market values since fundamental analysis and technical analysis applied by investors and traders are more time-consuming and unreliable. Additionally, the results reveal that the ANN model may assist traders and investors in making exact predictions to make more profits quickly. Future research can concentrate on including more macroeconomic variables such as Treasury bills, foreign portfolio investment, etc. In addition, the study could be extended for a longer duration, or better findings could be obtained using intraday data.

A comparative analysis could also be performed using machine learning methods like Long-Short Term Memory.

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