

Analysis of ANN, (Artificial Neural Network) based Simulation Model for Predicting the Stock Market

Mr. Iswar Singh, Mr. Aneesh Kumar Mishra²

¹M. Tech Scholar, Department of Computer Science Engineering, Dr.K.N. Modi University, Newai, Tonk, Rajasthan, India, iswar2singh@gmail.com

²Assistant Professor, Department of Computer Science Engineering, Dr.K. N. Modi University, Newai, Tonk, Rajasthan, India hod.cse@dknmu.org

Abstract: Because many economic, political, and psychological variables affect stock prices, forecasting stock market movements is a difficult undertaking. Existing techniques including technical analysis, fundamental analysis, time series analysis, and statistical analysis have not always shown to be reliable instruments for making predictions. A stock market prediction model based on artificial neural networks is presented in this research. As a result, this study investigates the usage of artificial neural networks, which have benefits as a tool for data analysis and are capable of capturing complicated and non-linear correlations without making firm assumptions about the distribution of the data.

Keywords: Artificial Neural Network, market prediction model, Back Propagation network

Introduction: Accurate prediction of stock market movements is crucial in various fields, including commerce, mathematics, engineering, finance, and science, as it provides valuable insights for potential investment returns. It also aids shareholders in making informed decisions and avoiding unexpected surprises. However, the stock market is inherently uncertain and volatile, making it challenging to predict accurately. Artificial neural networks, as a form of soft computing, have the potential to be employed for stock market prediction. These networks may simulate complicated and non-linear interactions without depending on tight assumptions about the distribution of the data since they have effective implementation techniques, and take computation speeds and memory needs into account.

1. Stock Market Intentions and Roles

- Stock market intentions:
- Facilitating the country's capital structure
- Maintaining active trading
- Enhancing liquidity of resources
- Assisting in the process of price revival

The stock market provides a platform for buyers and sellers to engage in fair, fast, and impartial transactions. Modern stock markets coordinate buyers and sellers electronically, ensuring immediate execution of trades. Rules and regulations are in place to facilitate fair trading, and detailed transaction data is made available

to the public by stock exchanges. However, stock market investments always carry risks.

2. Artificial Neural Network

Artificial neural networks aim to replicate the efficiency of biological systems by densely interconnecting basic processing elements, or neurons. These networks operate based on knowledge rather than purely data-driven approaches. The main building components of neural networks are an input layer, one or more hidden layers, and an output layer. One well-liked type is the Back Propagation (BPN) network. Because of characteristics like the capacity to grasp intricate links and nonlinear patterns, neural networks are highly suited for the prediction of the stock market.

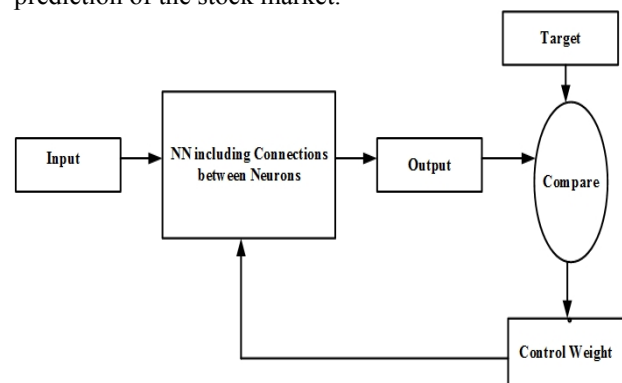


Figure 1: Block Diagram of Artificial Neural Network

3. Layer of Output

The output layer of a neural network is the top layer that generates the network's overall response to the inputs. It has a big impact on how well the network performs. The activation functions applied to the inputs determine the output of the output layer. Due to the connections between each neuron and its neighbours, the neural network is frequently referred to as a completely linked network. Synaptic weights, which measure the strength of the connections between neurons, are used to quantify those connections. The signal corresponding to the input of neuron K at the synaptic junction is multiplied by the synaptic weight. If the synapse is excitatory, the synaptic weight (w_{kj}) is positive, while it is negative for inhibitory synapses. A neuron in the artificial neural network functions similarly to a neuron in the brain, acting as a basic processing unit. These neurons are interconnected through synaptic weights, forming a

network. During the learning process, the network of neurons acquires information and adjusts the synaptic weights to improve performance.

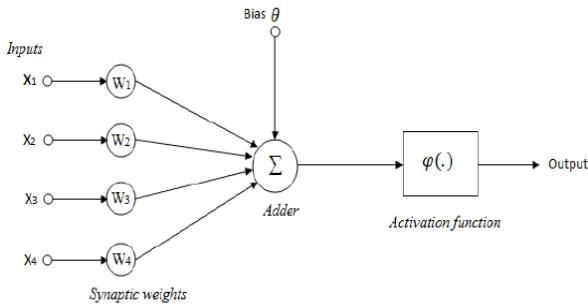


Figure 2 Different layers in Neural Network

4. Neural Network Back Propagation

Two of FFI Cult's issues were resolved with success via multi-layer awareness. The back-propagation algorithm is one of the most popular ways to track errors since it is called by the algorithm. On error-correction principles, the algorithm is built. Two FF erroneous network layer forward and backward steps are necessary for error recovery. Move directly, perform. When there is positive input, the model is implemented via input propagation.

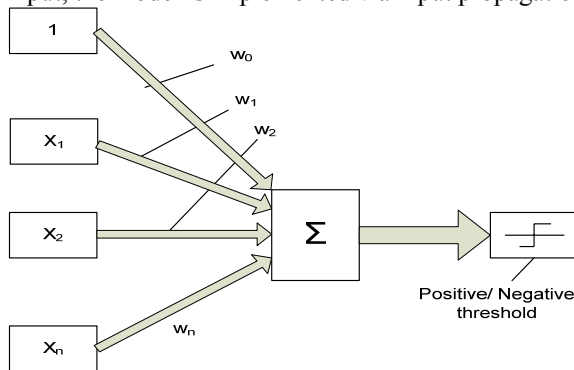


Figure 3 Multi-Layers Feed-Forward ANN

BP rule derivation:

- Message of error:

$$E_d(\vec{w}) \equiv \frac{1}{2} \sum_{k \in \text{outputs}} (t_k - o_k)^2 \quad \dots\dots\dots(1)$$

- Gradient descent:

$$E(\vec{w}) \equiv \frac{1}{2} \sum_{d \in D} \sum_{k \in \text{outputs}} (t_{kd} - o_{kd})^2 \quad \dots\dots\dots(2)$$

- Chain rule:

$$\Delta w_{ji} = -\eta \frac{\partial E_d}{\partial w_{ji}} \quad \dots\dots\dots(3)$$

- Notations

$$\frac{\partial E_d}{\partial w_{ji}} = \frac{\partial E_d}{\partial net_j} \frac{\partial net_j}{\partial w_{ji}} = \frac{\partial E_d}{\partial net_j} x_{ji} \quad \dots\dots\dots(4)$$

Rule for Output Unit Weights:

- Step 1:

$$\frac{\partial E_d}{\partial net_j} = \frac{\partial E_d}{\partial o_j} \frac{\partial o_j}{\partial net_j} \quad \dots\dots\dots(5)$$

- Step 2:

$$net_j = \sum_i w_{ji} x_{ji} \quad \dots\dots\dots(6)$$

- Step 3:

$$\frac{\partial o_j}{\partial net_j} = \frac{\partial \sigma(net_j)}{\partial net_j} = o_j(1 - o_j) \quad \dots\dots\dots(7)$$

- All together:

$$\Delta w_{ji} = -\eta \frac{\partial E_d}{\partial w_{ji}} = \eta(t_j - o_j)o_j(1 - o_j)x_{ji} \quad \dots\dots\dots(8)$$

Rule for Hidden Unit Weights :

- Step 1:

$$\begin{aligned} \frac{\partial E_d}{\partial net_j} &= \sum_{k \in \text{Downstream}(j)} \frac{\partial E_d}{\partial net_k} \frac{\partial net_k}{\partial o_j} \frac{\partial o_j}{\partial net_j} \\ &= \sum_{k \in \text{Downstream}(j)} -\delta_k \frac{\partial net_k}{\partial o_j} \frac{\partial o_j}{\partial net_j} \\ &= \sum_{k \in \text{Downstream}(j)} -\delta_k w_{kj} \frac{\partial o_j}{\partial net_j} \\ &= \sum_{k \in \text{Downstream}(j)} -\delta_k w_{kj} o_j(1 - o_j) \quad \dots\dots\dots(9) \end{aligned}$$

$$\Delta w_{ji} = \eta \delta_j x_{ji}, \text{ where } \delta_j = o_j(1 - o_j) \sum_{k \in \text{Downstream}(j)} \delta_k w_{kj} \quad \dots\dots\dots(10)$$

- E = minimization of error parameters
- wij = weight of the input unit I to the output j-th
- and the pace and momentum of learning

$$E''(w_k) p_k = \frac{\dot{E}(w_k + \sigma_k p_k) - \dot{E}(w_k)}{\sigma_k} + \lambda_k p_k \quad \dots\dots\dots(11)$$

The first and second derivative information is E 'and E Pk = direction of search
 μk = second derivative weight shift
 μk = Hessian's governing indefinity

The dataset, which includes statistics on stock performance over the last five years, was gathered in CSV format from Kaggle and Yahoo Finance. This statistical study set out to look at any possible

relationships between various price indicators and the closing price of shares. A neural network model was used to achieve this. There is evidence to support the claim that the opening, high, and low prices are accurate predictors of the closing price. It's interesting to note that the number of trades has no statistical bearing on the closing price. Obtaining a daily stock dataset, model fitting, cross-validation, and visualization were the steps in the procedure. The conclusion of the evaluation of the model's performance was a visualization of the projected pricing.

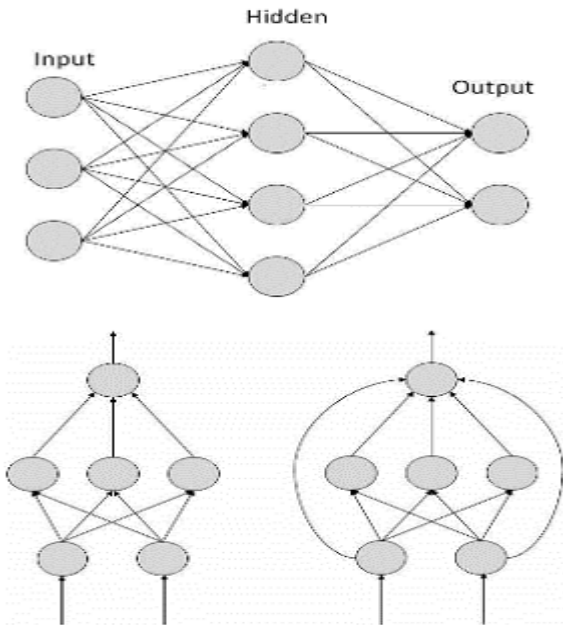


Figure 4 ANN Model for Implementation of Proposed Work

The architecture of the neural network model used in the suggested system is shown in Figure 4. In order to create the network, a feed-forward architecture with specialized layers was used. Its goal was to assess how accurately the suggested system performed.

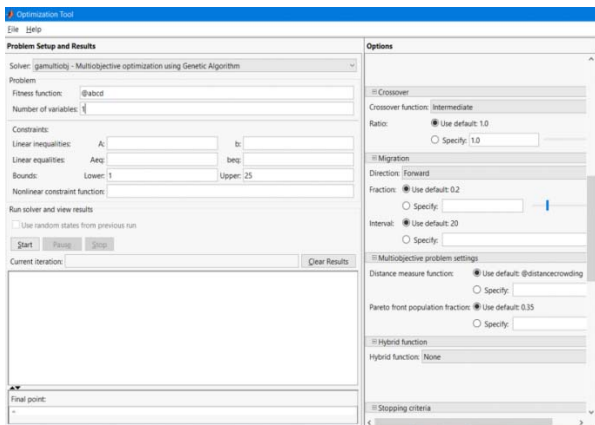


Figure 5: Training Algorithm Configuration

Sr. No.	Date	FII inflow	FII outflow	Exchange rate	Daily Closing
1	4-Jan-10	1614.83	1001.41	46.296	5232.2
2	5-Jan-10	3337.48	2367.19	46.135	5277.9
3	6-Jan-10	3380.3	2719.75	45.73	5281.8
4	7-Jan-10	2579.68	2487.47	45.695	5263.1
5	8-Jan-10	3240.2	3170.82	45.526	5244.75
6	11-Jan-10	5973.59	2932.03	45.366	5249.4
7	12-Jan-10	2903.43	3266.19	45.625	5210.4
8	13-Jan-10	3530.52	3816.36	45.495	5233.95
9	14-Jan-10	3592.26	3904.27	45.57	5259.9
10	15-Jan-10	2010.27	2940.36	45.811	5252.2
11	18-Jan-10	2577.75	2424.85	45.646	5274.85
12	19-Jan-10	2123.88	2485.55	45.855	5225.65
13	20-Jan-10	2655.82	2927.15	46.125	5221.7
....
....
....
....
1537	30-Mar-16	5866.32	4423.85	66.375	7735.2
1538	31-Mar-16	11230.72	7174.1	66.255	7738.4

Figure 6 Screenshot of Selected Data Fields

Independent Variables (FII inflow, FII outflow, Exchange rate)					Dependent Variable (Here we used roundup value of Daily closing field)	
Sr. No.	Date	FII inflow	FII outflow	Exchange rate	Daily Closing	Daily Closing (Round up)
1	4-Jan-10	1614.83	1001.41	46.296	5232.2	5233
2	5-Jan-10	3337.48	2367.19	46.135	5277.9	5278
3	6-Jan-10	3380.3	2719.75	45.73	5281.8	5282
4	7-Jan-10	2579.68	2487.47	45.695	5263.1	5264
5	8-Jan-10	3240.2	3170.82	45.526	5244.75	5245
6	11-Jan-10	5973.59	2932.03	45.366	5249.4	5250
7	12-Jan-10	2903.43	3266.19	45.625	5210.4	5211
8	13-Jan-10	3530.52	3816.36	45.495	5233.95	5234
9	14-Jan-10	3592.26	3904.27	45.57	5259.9	5260
10	15-Jan-10	2010.27	2940.36	45.811	5252.2	5253
11	18-Jan-10	2577.75	2424.85	45.646	5274.85	5275
12	19-Jan-10	2123.88	2485.55	45.855	5225.65	5226
13	20-Jan-10	2655.82	2927.15	46.125	5221.7	5222
....
....
....
....
1537	30-Mar-16	5866.32	4423.85	66.375	7735.2	7736
1538	31-Mar-16	11230.72	7174.1	66.255	7738.4	7739

Figure 7 Screenshot of Selected Data with Independent and Dependent Variable

Results Analysis: The dataset, which was downloaded in CSV format from Kaggle and Yahoo Finance, comprises stock performance information over the last five years. The objective of this statistical analysis was to investigate any potential relationships between various price indicators and the closing price of the stock

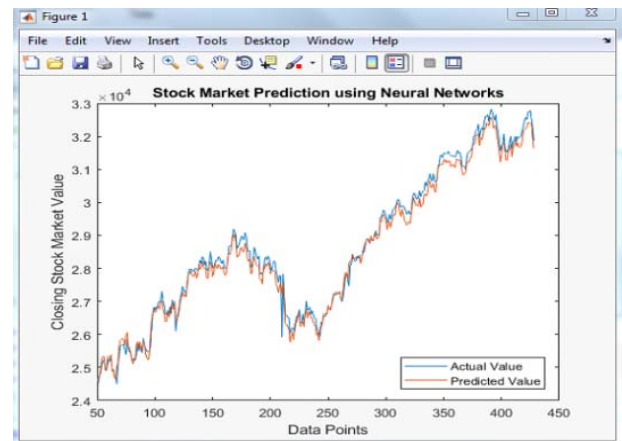


Figure 8: Actual Value and Predicted Value Relationship

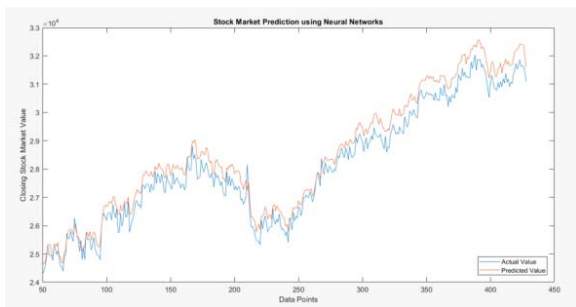


Figure 9 Actual and Predicted Value Relationship Phase 1

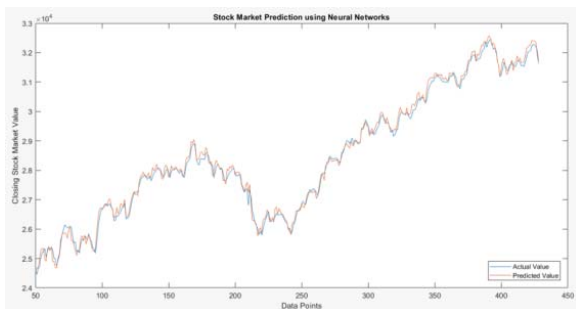


Figure 10: Actual and Predicted Value Relationship for an Improved Network

Conclusion

The study employed artificial neural networks (ANN) to accurately anticipate the daily closing price movements of the NSE Nifty 50 Index in India. A three-layered feed-forward neural network model trained with the backpropagation technique using MATLAB produced a prediction accuracy of 89.46% by experimenting with various ANN parameters and training patterns. The test dataset, which contained the most recent 20% of the data, was used to evaluate the model's performance using Root Mean Square Error (RMSE). The findings show that ANN is an extremely successful technique for predicting stock market movements and can be used to precisely predict the Nifty 50 index's closing price every single day. For investors and regulators, this predictive power offers considerable advantages for making wise judgments.

REFERENCES

1. Abdullah, M.C., Elias, H., Mahyuddin, R., & Uli, J. (2004). Emotional intelligence and academic achievement among Malaysian secondary students. *Human Resource Management Papers*, Islamabad: National Institute of Psychology.
2. Abraham, R. (2000). The Role of Job Control as a Moderator of Emotional Dissonance and Emotional Intelligence - Outcome Relationships. *The Journal of Psychology*, 134 (2), 169-184.
3. Alhashmei, E. Sushaila., & Hajee, R. Zahra. (2013). The relationship between leadership,

educational level, and emotional intelligence: A case study in Bahrain. *Prabhandan: Indian Journal of Management*, 6, 24-32.

4. Ashforth, B.E., & Humphrey, R.H. (1995). Emotion in the workplace: A reappraisal. *Human Relations*, 48(2), 97-125.
5. Ayoko, O. B., Callan, V. J., & Hartel, C. E. J. (2008). The Influence of Team Emotional Climate on Conflict and Team Members' Reactions to Conflict. *Small Group Research*, 39 (2), 121-149.
6. Iqbal, Mohammad Asif, and Sunil Kumar Gupta. "Comparative analysis between numerical simulation of PPV/PCBM and InGaN based solar cells." *Materials Today: Proceedings* 30: 168-173.
7. M. A. Iqbal and S. Sharma, "Analysis and comparison of various control strategy of hybrid power generation a review," 2014 1st International Conference on Non-Conventional Energy (ICONCE 2014), 2014, pp. 184-189, doi: 10.1109/ICONCE.2014.6808717.
8. Salovey, P. (1995). EQ-I: The emotional quotient inventory Manual. A test of emotional intelligence. New York, NY: Multi-Health Systems, Inc.
9. Bar-On, R. (1997). Bar-One Emotional Quotient Inventory: Technical manual. Toronto: Multi-Health Systems.
10. Mayer, J. (2002). Bar-On Emotional Quotient Inventory (EQ-I): Technical Manual. Toronto, Canada: Multi-Health Systems.
11. Bar-on, R.(2000). Emotional and social intelligence: Insights from the Emotional Quotient Inventory (EQ-IQ). In R.B.Bar-on & J.D.A.
12. Boyatzis, R. E., & Ratti, F. (2009). Emotional, Social, and Cognitive Intelligence Competencies Distinguishing Effective Italian Managers and Leaders in a Private Company and Cooperatives. *Journal of Management Development*, 28 (9), 821-838.
13. Bryant, D. (2000). The components of emotional intelligence and the relationship to sales performance. In K.P. Kuchinke (Ed.), *Proceedings of the annual conference of the Academy of Human Resource Development*. Baton Rouge, LA.
14. Callahan Fabian, J.L. (1999). Emotion management and organizational functions: A study of action in a not-for-profit organization. In K. P. Kuchinke (Ed.), *Proceedings of the annual conference of the Academy of Human Resource Development*, 1030-1037.
15. A. Alesna and M. G. Venturini, "Analysis and design of optimum-amplitude 9-switch direct AC-AC converters," in *IEEE Transactions on Power Electronics*, vol. 4, no. 1, pp. 101-112, Jan. 1989, doi: 10.1109/63.21879.
16. Yan, Fan. (2012). MC Based on Asymmetric Regular Sampling Method SPWM Control Strategy. *Procedia Engineering*. 29. 10.1016/j.proeng.2012.01.266.

17. Gupta RA, Kumar R, Sangtani V. Direct torque controlled MC fed induction motor drive. In 2014 International Conference on Circuits, Power and Computing Technologies [ICCPCT-2014].
18. Iqbal, Mohammad Asif, and Sunil Kumar Gupta. "Comparative analysis between numerical simulation of PPV/PCBM and InGaN based solar cells." *Materials Today: Proceedings* 30: 168-173.
19. M. A. Iqbal and S. Sharma, "Analysis and comparison of various control strategy of hybrid power generation a review," 2014 1st International Conference on Non-Conventional Energy (ICONCE 2014), 2014, pp. 184-189, doi: 10.1109/ICONCE.2014.6808717.
20. Dr. Mohammad Asif Iqbal. Performance Optimization Assessment of Different Polymer-based PV Cells. *International Journal of Modern Agriculture*, 10(2), 3983 - 3989.
21. Chimnani, Mayank, et al. "Efficiency Improvement Approach of InGaN Based Solar Cell by Investigating Different Optical and Electrical Properties." *Proceedings of International Conference on Sustainable Computing in Science, Technology, and Management (SUSCOM)*, Amity University Rajasthan, Jaipur-India. 2019.
22. Iqbal MA, Dwivedi AD. Modeling & efficiency analysis of ingap/gaas single junction PV cells with BSF. *Int. J. Eng. Adv. Technol.* 2019;8(6):623-7.
23. Iqbal, M.A. and Dwivedi, A.D.D., 2017. A comparative study of microgrid load frequency control techniques with the incorporation of renewable energy. In *Published in International Conference on Recent Innovation and Trends in Engineering, Technology, and Research (ICRITETR-2017)* December (pp. 23-24).