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# AI-Based Sales Forecasting Model for Digital Marketing

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## ABSTRACT

Sales prediction with minute accuracy plays a crucial role for an organization to sustain amidst the global competitive business environment. The use of artificial intelligence (AI) on top of the existing information technology environment has become one of the most exciting and promising area for any organizations in the current era of digital marketing. E-marketing provides customers to share their views with other customers. In this paper, the authors proposed a model which will be helpful to the digital marketers to find out the potential customers to extract value from customer feedback. The proposed model is based on artificial neural network and will make it possible to identify the customer demand depending on previous feedback and to predict the future sales volume of the product. The authors tried to utilize AI, mainly neural networks (NNs), to construct an intelligent sales prediction and also to apply ANNs for prediction regarding sales of mobile phone (Redmi, Note 6 Pro) one month ahead depending on customer feedback on two e-commerce platform, namely Amazon.in and Snapdeal.in.

## KEYWORDS

Artificial Neural Network, Digital Marketing, Sales Prediction

## 1. INTRODUCTION

Sales forecasting is a well-known domain in the existing literature (Sun, Choi, Au, & Yu, 2008, p. 411). The challenge is that, till date, recent literatures cannot ensure any definite prescribed predictive model with guaranteed success rate. Even very few literatures can ensure a reasonable level of error margin during modeling anticipated sales. Three remarkable literatures confirming this challenging issue in this respect are (Mitra, Jain, Kishore, & Kumar, 2022,p.1), (Kantasa-ard, Nouiri, Bekrar, Ait el cadi, & Sallez, 2020, p. 7491) and (Seyedan &Mafakheri, 2020, p. 1). Researchers across the globe attempted various techniques ranging from elementary multiple linear regressions to advance non-linear Artificial Neural Network (ANN) with a view to improve accuracy from the literature available. However, very few studies are available which are optimal or near optimal in the predictive performance. Thus methodological research gaps exist in this area of research.

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There are many factors that influence sales and the exact nature of this influence could not be predicted by using any single model (Liu, Ren, Choi, Hui, & Ng, 2013, p. 1). Modeling such a mathematical function with several variables seems to be next to impossible due to high degree of dependency and auto-correlation among them. Here the challenge motivates the researchers to investigate into a deeper to unfold the said burning issue. Such mathematical modeling of sales function is well addressed in many recent studies of which two important are (Saraswathi, Renukadevi, Nandhinidevi, Gayathridevi, & Naveen, 2021, p. 14) and (Penpece, & Elma, 2014, p-435).

Artificial Neural Network (ANN) is commonly used in recent time for the above said sales forecasting for its inherent advantages. ANN is basically non-linear statistical regression model with feedback loop. It is named so became of its similarity with biological neural system of human brain. This is why ANN is called biologically inspired technique. This ANN can process information and updates its model parameters (i.e regression coefficients in non-linear case) for the next step from the error resulted in the previous step. This updation is technically known as learning. As ANN works learning from mistakes (i.e error minimization aspect of the model), it is also called machine learning in the recent literature. In this paper ANN and NN are used interchangeably without loss of generality.

The research work has shown that ANN technology is one of the appropriate techniques for solving the complex problems on sales forecasting (Frank, Garg, Sztandera, & Raheja, 2003, p. 107). The forecasting model based on ANN systems may be a suitable tool for enabling managers in the preparation of any sales forecast. The uniqueness of this paper is to shift the computing paradigm of sales forecast from traditional linear models in inferential statistic towards a world of non-linear dynamics based on ANN based predictive models. This paper is an attempt to investigate the suitability of using such ANN based methodologies for sales forecasting in the present era. The paper is a footstep towards the development of a mobile App to be used by manufacturers as well as retailers & customers to view the sales pattern of a product as emerged from the feed backs from e-commerce sites.

This research paper is organized as follows section 1. Depicts Introduction followed by section 2 as Literature Reviews of the work, section 3 as Proposed work and Research Goal, section 4 as Methodology, section 5 as Results and Interpretations, section 6 as Conclusions section 7 as Managerial Implications section 8 Limitations and Future Directions section 9. Acknowledgement.

## 2. LITERATURE REVIEWS

In the present century of Indian digital market, Amazon, Flipkart and Snapdeal are playing a major role to expand the e-commerce market share. In this study authors used feed forward ANN to analysis the customer's feedback which influences the potential customers for their purchase decisions (Biswas, Sanyal, & Mukherjee, 2021, p-78) Online review systems take an important role for any e-commerce business to analyze their customer's satisfaction and consequently up gradation of their products. It helps the retailers and manufacturers to make decision on their inventory management.

The use of Business Intelligence techniques (B.I) have become one of the most exciting and promising application areas for any business organizations. Drawing an optimal prediction at right time for the sales of each manufactured products is most important game changer for an enterprise. If an appropriate sales forecasting is not drawn at time, the enterprise can have face severe damage due to disruption of whole supply-chain pipeline. With the help of Artificial Neural Networks (ANNs), one of well-known Artificial Intelligence techniques, it's possible to draw optimal sales prediction of a product for an organization (Baba.and Suto, 2000, p.565).

If the sales forecasting is not done accurately then the manufacturers or retailers may fall in stock out or over stock. It may lead to increase of inventory cost, lost the loyal customers and miss the opportunity to catch ne new customers. There is a direct relation between demands forecasting and supply chain management. But the marketers are confronted with dynamic markets and uncertain. Always the conventional statistical methods are not suitable and applicable for a reliable sales forecasting. To remove the uncertainty and get better accuracy of statistical result AI is used presently. A straightforward demand forecasting empowers the marketers to increase the supply chain elasticity. AI and statistical method jointly give more significant result in customer demand forecasting (Mediavilla, Dietrich & Palm, 2022, p.1126). ANN suggests a way for making better intelligent decision. In this study authors used ANN for demand forecasting.

Intelligent business analytical system involves integration of decision analysis and predictions. Most of the organizations depend on their knowledge base along with the total sales data collected in their information system in pasts (Cheriyan, Ibrahim, Mohanan & Treesa,2018,p.53).There are many cases where business faced significant problems due to their year-old product forecasting methods and models, applied on the historical data of business. Many times human decisions or intuitions cause problems to integrate the historical data and decision due to a number of biased considerations (Bazerman & Moore, 2012). To solve such kind of predictive problems, Artificial Intelligence (AI) mainly ANN outperformed year-old forecasting tools. In many situations, the conventional human expert system is not capable of taking a unanimous decision and is often inconsistent in judgment. The literatures like (Collins, Ghosh, & Scofield, 1988) and (Jagielska, 1993) started initially to emphasize the superiority of ANN over traditional linear predictive statistical models and subsequently this point has been confirmed by many recent literatures like (Yuan & Lee, 2019, p. 2033), (Biswas, Sanyal, & Mukherjee, 2021, p-78) and (Aydin, 2022, p.1).

ANN model for sales prediction level can be developed for optimal predictions. The outcome of that model and the actual number of sales volumes can be compared. The accuracy of the result so obtained may indicate that the prediction performance (Jagielska.l, 1993) and (T., Choudhary, & Prasad, 2018) developed a sales prediction model with the help of Linear Regression for input data they collected (sales data from the year 2011-2013) and predict for 2014. In 2014, they also collected the real data and then calculated the prediction's accuracy and it was found that their result was validated with actual one (T., Choudhary, & Prasad, 2018) Organizations can take better tactical and strategic decisions on sales volume, if the forecasting is done by an intelligent process, may be the game changer for an organization. Organizational goal depend on improvement of forecasting quality. It can be possible using AI with the help of ANN (Yuan & Lee, 2019, p. 2033). Independent predictive variables, like discount rate, review sentiments, are required to be analyzed to determine the trend of sales volume, which can be controlled by the marketers to influence the sales volume. It is found that the accuracy of prediction of ANN based model is better than the regression analysis, or the decision tree based model (Sharma, Chakraborti, & Jha, 2019, p. 261). Now days, organizations can analyze the real-time online data, those are available in the online marketing platforms and it is easy to predict the product sales, customers' demands by analyzing the customer reviews available on online (Floyd, Freling, Alhoqail, Cho, & Freling, 2014, p. 217). Now e-commerce sites allow consumers to view the products reviews shared by the other consumers before taking their buying decisions. It is shown that UGC (User Generated Content) plays an important role on product sales. The social Media report 2012, found out with a survey report that 70% of customers kept faith on UGC for making their buying decisions (Chong, and Zhou, 2014, p.48). Users are requested by e-commerce portal to share their feedbacks after purchases products either in numerical rating or textual comments. The "Sales Assistance" of consumers is influenced by these sub-sequent online feedbacks. The web-analytical models are helpful for an organization to make their blueprint for new launching products or modifying features of the existing products. The Indian e-commerce market leader like Amazon, Snapdeal and Flipkart take customers' feedbacks in a regular basis and analyze those feedbacks. The ANN plays a pivotal role in Digital Media Marketing to minimize the time in converse the best solution from the collected huge feedbacks from the customers (Biswas and Sanyal, 2019, p.432).

The reason of using smart phone as a case study in our paper is also emerged from our literature review. As evident from literature, almost all retail shops have been changed their nature in the line of digital environment, in particular during post covid era. Smart mobile phones take an important role in this respect for using smart payments for the customers. As a consequence, smart mobile phones have been turned into an essential commodity in our daily life (Aydin, 2022, p.1). It is the only commodity which was luxury goods few years back while rapidly shifted into the central part of our life, being transformed into an essential commodity. This enhanced the importance of smart phones in our society & hence selection of such a product in our research community is completely justified. Authors chosen the mobile phone (Redmi Note 6 pro, 64GB, 4GB AM) for an example in this study. However, users of the developed model can chose any other product from the e-commerce sites to get the benefit of this research study. This has a direct implication of revolution of digital technology. It ensures that smart phones have a strong effect on the customer shopping decision& shopping execution (Jensolin Abitha Kumari & Gotmare, 2022, p. 1).

## 3. PROPOSED WORK AND RESEARCH GOAL

Authors proposed to construct an intelligent sale prediction system utilizing ANN computing model with the help of ANN tool box of SPSS. The input variables of this model are quantitative reviews (ratings) of the past users who actually bought the product. They are the only eligible to write feedback. The output of our newly constructed model is the expected change in sales in one month ahead. The primary advantage of using ANN for such sales forecast is that, here computation is distributed our several computational nodes of ANN which can capture several independent variable simultaneously which influence future sales. Due to such distributive way of computation, negative error from one variable may be balanced by the positive error of other variables.

## 4. METHODOLOGY

The numbers of e-commerce customers are growing on daily basis and the customer reviews have become an important source of information. The most important drive of this work is to understand the present demand or acceptance of the specific e-commerce product. Authors used the ANN feature in SPSS for analyzing the reviews. In this research work, authors mainly focused on concerning the influences of positive and negative feedbacks on sales outcomes.

### 4.1 Descriptive Steps in SPSS to Build ANN Predictive Model

Artificial Neural Networks are the models of choice in many data classification tasks in the present era (Dreiseitl & Ohno-Machado, 2002, p. 352). These models are algorithmic implementations of ideas from statistical learning theory (Vapnik, 2000, p. 1).It analyzed almost 72 papers for issues of concern like - parameter selection and over fitting avoidance for ANN, whether unbiased estimates of the generalization error are reported by using test sets, whether measures of discriminatory power were given, and whether calibration information is included. Mistakes in model building and evaluation can have disastrous consequences in some applications. Special care must therefore be taken to ensure that the models are validated, preferably by using an external data set (Altman and Royston, 2000, p.453).

The most effective literature that authors found for describing the way to build ANN based predictive model using SPSS is (Al-Imam, 2019). It is clearly mentioned in the said research study that ANN features in SPSS does not require any pre-programming for task-specific rules. SPSS do “learn” to perform tasks by considering examples, i.e. Training vs. Testing. For creating a predictive model using ANN feature of SPSS, the authors use its Data Editor View to reach to Analyze module to Neural Networks portion. There are two commonly used ANN models functions are available there as 1. Multilayer Perceptron and 2. Radial Basis Function. The authors are this study used the multilayer perceptron feature of SPSS. The authors used number of numerical ratings during last 10 days for fitting the input data into the only input layer while the ANN feature of SPSS generates the

Sum of Squares Error, Relative Error, Stopping Rule Used, Training Time in the only output layer of that predictive model.

### 4.2 Product Validation and Recalibration

Total 120 review data is collected from two well-known e-commerce sites of a specific product that shown in Table 2 and the details of the product shown in Table 1 the customer's views categories or data categories are shown in Tables 4 and 5. The rationale of using smart mobile phone is that it's a common commodity in our daily life and it becomes essential goods from its initial status of luxury goods. This idea of choosing smart phone as a product in our paper is nicely presented and many authors used mobile phone for an example of their research works (Kreutzer, 2009, p.903), any other product e-commerce product may be chosen for an example.

### 4.3 Data Collection

The required data is collected two eminent e-commerce web-sites (Amazon.in and Snapdeal.in) in a regular interval of time and the duration was six months (February to July, 2019). The total numbers of reviews are shown in Table 2.

### 4.4 Data Preparation

The collected data set are posted in a metric which are shown in Table 3. In the table, all the features of the data set are mentioned for both e-commerce sites and the reviews are classified as positive or negative based on their features.

### 4.5 Data Training

See Tables 4 and 5.

**Table 1. Product Dimension**

| Feature | Description | Remarks |
|---|---|---|
| Name of the Product | Model of the specific product (mobile phone. | Note 6 pro (64GB,4GB AM) |
| Name of the Product brand | Manufacturer of the specific product | Redmi |
| Product price | Price of the specific product in Rs. | Price is not considered in this stage of study. |
| Review rating | E-commerce site's allow the existing customer to give their satisfaction level in a scale rating 1 to 5. | Bellow 3* ratings it is negative and above positive where 3* ratings is the neutral point. |
| Review or feedback | Customers have given reviews for the specific product in the e-commerce site. | Only the numerical ratings is considered |

**Table 2. Sampling Cardinality**

| Review Data source | Review Metrics | No. of review Data items |
|---|---|---|
| Amazon.in | Numeric Value (rating) | 60 |
| Snapdeal.in | Numeric Value (rating) | 60 |

Table 3. Metric forSnapdeal.in andAmazon.in

| Metrics | Snap deal.in | Amazon.in |
|---|---|---|
| Initial Ratings | 120 | 10 |
| Last Ratings | 293 | 370 |
| Positive Ratings | 236 | 299 |
| Negative Ratings | 37 | 50 |
| Neutral Ratings | 20 | 21 |
| 5 Stars (*) Ratings | 179 | 223 |
| 4 Stars (*) Ratings | 57 | 76 |
| 3 Stars (*) Ratings | 20 | 21 |
| 2 Stars (*) Ratings | 8 | 9 |
| 1 Star (*) Ratings | 29 | 41 |

Table 4. Case Processing Summary for Amazon.in

| | | Number | Percentage (%) |
|---|---|---|---|
| Sample | Training | 3 | 50.0% |
| | Testing | 3 | 50.0% |
| | Valid | 6 | 100.0% |
| | Excluded | 0 | |
| | Total | 6 | |

Table 5. Case Processing Summary for Snapdeal.in

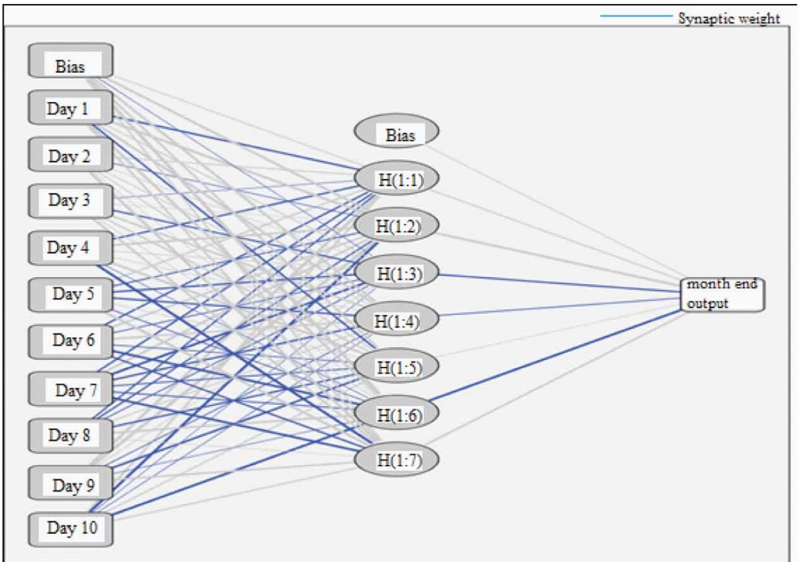
| | | Number | Percentage |
|---|---|---|---|
| Sample | Training | 4 | 66.7% |
| | Testing | 2 | 33.3% |
| | Valid | 6 | 100.0% |
| | Excluded | 0 | |
| | Total | 6 | |

## 5. RESULTS AND INTERPRETATIONS

Following two logical block diagrams (Figure 1 and 2) are respectively representations of Amazon & Snapdeal neural networks including the error correction bias nodes. Ten input nodes are for first day to tenth day. The only output node is the forecasted node. The connection updation weights are dynamically adjusted after each iteration & on completion of training, their converging values are depicted by H (p,q), where p is number of layer& q is number of node within that layer for deep learning. Details of results are depicted in tabular forms from Table 6 to Table 10.

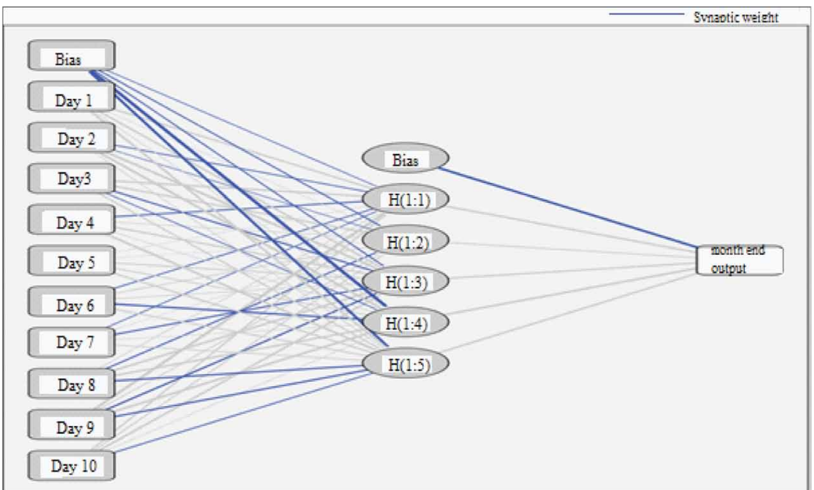
Authors attempted in this paper a lead-lag relationship across the customer feedback over two predetermined e-commerce websites. All the tables are nearly self-explaining their merits. Authors

Figure 1. Logical Diagram of Neural Network for Amazon.in




Hidden layer activation function Hyperbolic tangent output layer activation function identity

Figure 2. Logical Diagram of Neural Network for Snapdeal.in




Hidden layer activation function Hyperabolic tangent Output layer activation function Identity

collected two e-commerce sites numerical feedbacks (rating only without taking text feedback) present in the specific product page. Depending on ten randomly selected daily feedbacks during a given month, this paper has attempted to forecast the possible feedback for next month last day sales volume and compared that with the actual volume after one month. The said process is followed for accumulation across six months for the given e-commerce sites. Authors calculated the average accuracy level of our predictive model and it has been observed that the accuracy is fairly high &

**Table 6. Parameter Estimates for Amazon.in**

| Predictor | | Predicted | |
|---|---|---|---|
| | | Hidden Layer 1 | Output Layer |
| | | H(1:7) | Month End Output |
| Input Layer | (Bias) | .146 | |
| | Day1 | .230 | |
| | Day2 | .424 | |
| | Day3 | .317 | |
| | Day4 | -.410 | |
| | Day5 | .502 | |
| | Day6 | -.242 | |
| | Day7 | -.451 | |
| | Day8 | .050 | |
| | Day9 | .405 | |
| | Day10 | .239 | |
| Hidden Layer 1 | (Bias) | | .092 |
| | H(1:1) | | .210 |
| | H(1:2) | | .577 |
| | H(1:3) | | -.305 |
| | H(1:4) | | -.139 |
| | H(1:5) | | .041 |
| | H(1:6) | | -.440 |
| | H(1:7) | | .305 |

satisfactory. However, with the increase in prediction horizon, the accuracy may be in a downward trend, which is quite natural due to uncertainty in future.

Authors have shown the details of the predictive analysis for the two e-commerce sites in Table 9 and Table 11. The predictive outputshavealso shown in visual representation in Figure 3 and Figure 4. It is observed from Table 9 and Table 11 and from Figure 3 and Figure 4 that the actual data and the machine predicted output are nearly equal. The errors are negligible, now it may say that the model is working well.

## 6. CONCLUSION

ANN model has been used in this paper to judge its suitability for sales forecast. As a case study sales prediction of smart phone (which is turned to be an essential commodity status from earlier status of luxury commodity) has been investigated. The study shows a significant improvement over traditional statistical linear models line multiple regressions. Consequently, this study unfolds the secret to success for mathematical prediction modeling in the context of demand forecasting.

## 7. MANAGERIAL IMPLICATIONS

The manufacturers can use this newly developed computational framework as depicted in this paper to plan their upcoming production schedules as a function of product demanded. The newly

**Table 7. Parameter Estimates for Snapdeal.in**

| Predictor | | Predicted | | | | | |
|---|---|---|---|---|---|---|---|
| | | Hidden Layer 1 | | | | | Output Layer |
| | | H(1:1) | H(1:2) | H(1:3) | H(1:4) | H(1:5) | Month End Output |
| Input Layer | (Bias) | -.118 | -.177 | -.166 | -.567 | -.380 | |
| | Day1 | .365 | .038 | .306 | .083 | .316 | |
| | Day2 | -.208 | -.103 | .451 | .401 | .087 | |
| | Day3 | .437 | .388 | -.271 | -.120 | .232 | |
| | Day4 | -.293 | .152 | .383 | .099 | .411 | |
| | Day5 | .067 | .033 | .301 | .263 | .335 | |
| | Day6 | -.194 | .205 | .181 | -.387 | .313 | |
| | Day7 | -.118 | .058 | -.300 | .110 | .231 | |
| | Day8 | .103 | -.229 | .415 | .425 | -.376 | |
| | Day9 | .494 | .126 | -.295 | .470 | -.342 | |
| | Day10 | .231 | .172 | .337 | .084 | -.220 | |
| Hidden Layer 1 | (Bias) | | | | | | -.498 |
| | H(1:1) | | | | | | .409 |
| | H(1:2) | | | | | | .239 |
| | H(1:3) | | | | | | .392 |
| | H(1:4) | | | | | | .729 |
| | H(1:5) | | | | | | .386 |

**Table 8. Model Summary for Amazon.in**

| | | |
|---|---|---|
| **Training** | Sum of Squares Error | .005 |
| | Relative Error | .009 |
| | Stopping Rule Used | 1 consecutive step(s) with no decrease in error[a] |
| | Training Time | 0:00:00.001 |
| **Testing** | Sum of Squares Error | 3.351 |
| | Relative Error | .01048 |

Dependent Variable: End of Month Actual
a. Error computations are based on the testing sample.

developed ANN based predictive framework of this paper will result in a mobile Application software as a consequence. The analyzed information from that mobile Application software will directly influence retailers to take their strategic decision regarding inventory and other logistics. Finally potential customers also will be influenced for their purchasing decision making from the compact analysis of the reviews given by the existing users of the concerned product. Thus the present study has managerial implications in a three level hierarchy starting from manufactures to retailers and potential Customers.

**Table 9. Accuracy Comparisons for Amazon.in**

| Month | Feb 19 | March 19 | April 19 | May 19 | June 19 | July 19 |
|---|---|---|---|---|---|---|
| **Day 1** | 10.00 | 138.00 | 175.00 | 241.00 | 316.00 | 345.00 |
| **Day 2** | 10.00 | 138.00 | 184.00 | 252.00 | 323.00 | 347.00 |
| **Day 3** | 18.00 | 143.00 | 192.00 | 257.00 | 330.00 | 347.00 |
| **Day 4** | 14.00 | 144.00 | 193.00 | 262.00 | 330.00 | 348.00 |
| **Day 5** | 14.00 | 145.00 | 194.00 | 268.00 | 336.00 | 349.00 |
| **Day 6** | 15.00 | 153.00 | 200.00 | 269.00 | 339.00 | 350.00 |
| **Day 7** | 127.00 | 158.00 | 223.00 | 270.00 | 340.00 | 356.00 |
| **Day 8** | 131.00 | 167.00 | 231.00 | 273.00 | 345.00 | 360.00 |
| **Day 9** | 131.00 | 168.00 | 238.00 | 276.00 | 344.00 | 361.00 |
| **Day 10** | 132.00 | 171.00 | 238.00 | 298.00 | 344.00 | 365.00 |
| **Next Month** | **March 19** | **April 19** | **May 19** | **June 19** | **July 19** | **Aug 19** |
| **End of Month Actual** | 171.00 | 238.00 | 298.00 | 344.00 | 365.00 | 370.00 |
| **MLP_Predicted Value** | 178.91 | 236.66 | 296.92 | 345.04 | 368.10 | 369.98 |
| **Percentage of Prediction Error** | 4.62 | -0.56 | -0.36 | 0.30 | 0.85 | -0.01 |

**Table 10. Model Summary for Snapdeal.in**

| | | |
|---|---|---|
| **Training** | Sum of Squares Error | .017 |
| | Relative Error | .011 |
| | Stopping Rule Used | 1 consecutive step(s) with no decrease in error[a] |
| | Training Time | 0:00:00.001 |
| **Testing** | Sum of Squares Error | .298 |
| | Relative Error | .222 |

Dependent Variable: End of Next Month Actual

## 8. LIMITATIONS AND FUTURE DIRECTIONS

To construct a more reliable and valid sales forecasting system, it is necessary to take into a count of many other variables line Gender, Territory, Occupation, Price discount etc. In the present study, only review and feedback of quantitative form have been considered. Future researchers may also include the other untouched demographic variables as stated above in their study.

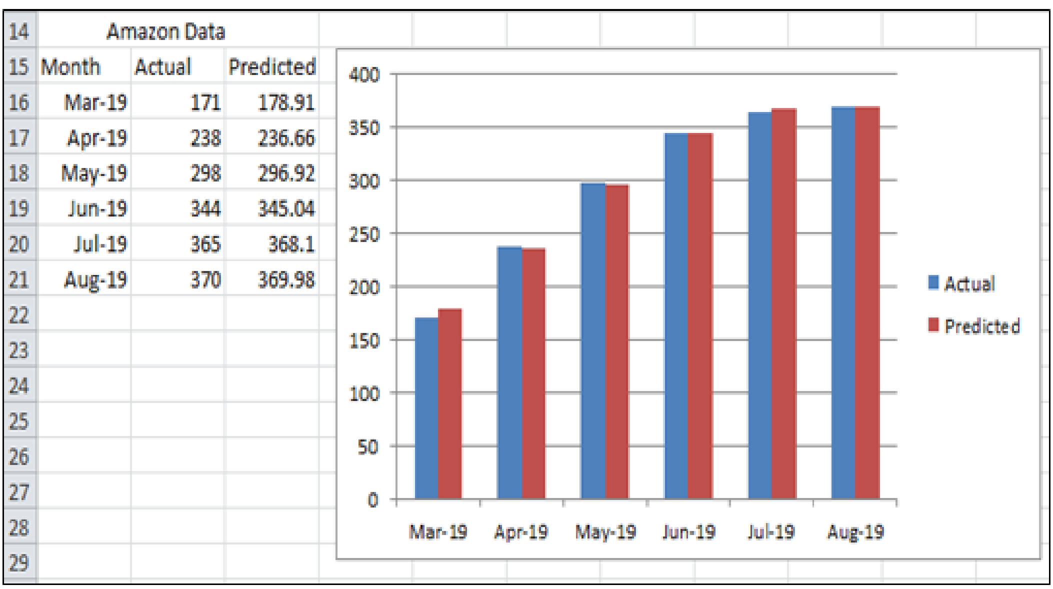
As the reviews have been collected from e-commerce sites only (which are online in nature), so the feedbacks of customers who bought the product in offline mode have not been considered in the present study. Future researchers may club the online feedback with available offline feedback to improve the accuracy of the prediction.

The present study only uses Amazon and Snapdeal to collect online reviews as these two are commonly used e-commerce sites in Indian context. But in future other such e-commerce sites can also be considered for review collection.

Table 11. Accuracy Comparisons for Snapdeal.in

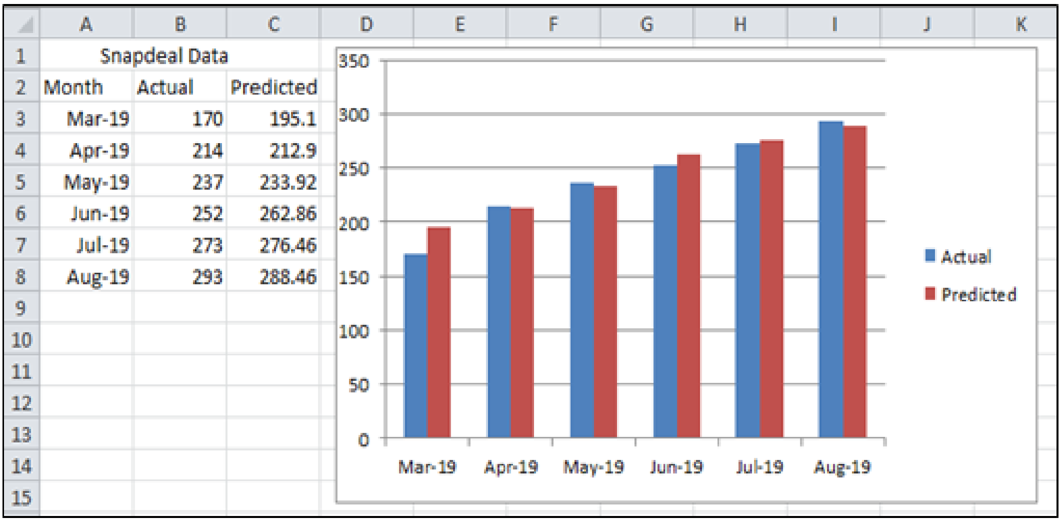
| Month | Feb 19 | March 19 | April 19 | May 19 | June 19 | July 19 |
|---|---|---|---|---|---|---|
| **Day 1** | 12.00 | 152.00 | 172.00 | 214.00 | 240.00 | 260.00 |
| **Day 2** | 123.00 | 154.00 | 176.00 | 217.00 | 242.00 | 262.00 |
| **Day 3** | 124.00 | 159.00 | 179.00 | 223.00 | 245.00 | 265.00 |
| **Day 4** | 127.00 | 159.00 | 181.00 | 224.00 | 245.00 | 268.00 |
| **Day 5** | 131.00 | 160.00 | 184.00 | 225.00 | 246.00 | 269.00 |
| **Day 6** | 132.00 | 162.00 | 193.00 | 230.00 | 247.00 | 271.00 |
| **Day 7** | 137.00 | 162.00 | 200.00 | 231.00 | 243.00 | 273.00 |
| **Day 8** | 146.00 | 166.00 | 203.00 | 232.00 | 249.00 | 279.00 |
| **Day 9** | 147.00 | 167.00 | 204.00 | 234.00 | 250.00 | 281.00 |
| **Day 10** | 149.00 | 170.00 | 214.00 | 237.00 | 252.00 | 282.00 |
| **Next Month** | **March 19** | **April 19** | **May 19** | **June 19** | **July 19** | **Aug 19** |
| **End of Month Actual** | 170.00 | 214.00 | 237.00 | 252.00 | 273.00 | 293.00 |
| MLP_Predicted Value | 195.10 | 212.90 | 233.92 | 262.86 | 276.46 | 288.46 |
| **Percentage of Prediction Error** | 14.77 | -0.51 | -1.30 | 4.31 | 1.27 | -1.56 |

Figure 3. Actual vs. Predicted chart for Amazon.in




There are so many buyers who are very satisfied with the product but do not give any review. This study misses their but sentiment and only considered sentiments for those who have given reviews. In future we need to explore the other way to capture the sentiment of those untouched buyers too.

Figure 4. Actual vs. Predicted chart for Snapdeal.in




In addition to the above limitations, there is another future scope of new exploration. Other methods of sales forecasting can also be explored to compare the predictive performance with the present study.

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