

e-ISSN: 2319-8753 | p-ISSN: 2347-6710

TEDIA

International Journal of Innovative Research in SCIENCE | ENGINEERING | TECHNOLOGY

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 11, Issue 6, June 2022

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.118

9940 572 462

6381 907 438

 \bigcirc





| e-ISSN: 2319-8753, p-ISSN: 2320-6710| <u>www.ijirset.com</u> | Impact Factor: 8.118|

Volume 11, Issue 6, June 2022

DOI:10.15680/IJIRSET.2022.1106033

A Demand Forecasting Model using Machine Learning

Satyendra Kumar Bunkar¹, Dr. Jitendra Sheetlani²

Research Scholar, SSSUTMS, Sehore (M.P.), India¹ Associate Professor, SSSUTMS, Sehore (M.P.), India²

ABSTRACT: In the modern era business intelligence (BI) has a pivotal role in articulating a strategy and taking correct measures based on data. Business intelligence plays a pivotal role in an inevitable decision support system that enables the enterprise to perform analysis on data and throughout the process of business. Machine learning predicts the forecasting of future demands of the enterprises. Demand forecasting is one of the main decision-making tasks of enterprise. For demand forecasting first raw sales data is collected from the market, then according to data, the future sale/product demands are forecasted. This prediction is based on collected data that compiles through different sources. The machine learning engine executes data from different modules and determines the weekly, monthly, and quarterly demands of goods/commodities. In demand forecasting, its perfect accuracy is non-compromising, the more accurate system model is more efficient. Furthermore, we test the efficiency by comparing the predicted data with actual data and determine the percentage error. Simulation results show that after applying the purposed solution on real-time organization data, we get up to 92.38 % accuracies for the store in terms of intelligent demand forecasting.

KEYWORDS: Business intelligence, demand forecasting, prediction, machine learning, AWS sage maker, sale forecasting

I. INTRODUCTION

In this era of technological advancement, business intelligence plays a pivotal role in decision aspects of the company related to future endeavors. Business intelligence (BI) termed as the methods technique and concepts having a positive impact on the decision for business by excursing the support of fact-based systems. It is the architecture and technology that transforms raw and disparate data into meaningful full informative data. Business Intelligence (BI) is set up to play a decisive role in almost all kinds of business in the modern era and in the near future. Business Intelligence (BI) is inevitable for analytics and strong decision making for all sorts of businesses ranging up to all sectors. It is not only improving the efficiency and effectiveness of enterprise organizations, but it also reduces the cost and losses. It helps in retaining and attracting the customer, improving sales, and many other significant benefits. Business Intelligence (BI) predicts the future trends of the market. Machine Learning is used as onetool and technology another tool to implement a business intelligence (BI) Demand forecasting is the branch of predictive analytics [2] and become famous over time. There are traditionally two basic assessment methods used in demand forecasting. One is Qualitative assessment [3] and the other one is Quantitative assessment [4]. With time as research increases, these method sareenlargedin furthertypesandsomeothermethods forecasting ideas and combinations were introduced. Thus, by analyzing past data and current market data, we may predict the future demand and manufacture those goods whose more demanding in the near future. Consequently, we may produce the required products according to the demand of the market in advance. This will also determine the potential buyers to the company/production facility, besides the products that the company needs to manufacture [1]. Eventually, the right prediction may lead to the earning of the company. In other words, demand forecasting is an essential addition in efficient and effective management planning. In developed countries where industrially demand requirement is uncertain demand forecasting is also beneficial to them.

The remainder of this paper is organized as follows. Section II briefly describes the Literature Review. Section III presents the proposed system method in which carries out a comprehensive evaluation for Business Intelligence of



e-ISSN: 2319-8753, p-ISSN: 2320-6710 www.ijirset.com | Impact Factor: 8.118

Volume 11, Issue 6, June 2022

DOI:10.15680/IJIRSET.2022.1106033

Effective Demand Forecasting as output. Section IV discusses the simulation and results of the proposed model. Sections V discusses the conclusions from the study.

II. LITERATURE REVIEW

Different studies conducting on-demand forecasting models predicted sales calculated using Machine Learning (ML) regression models and methods with time series analysis for forecasting sales numbers using extended features. Azure Machine learning platform is used for that. Different regression techniques were applied to get a specific result [5].

The fuzzy-neural network [6] implemented for sales forecasting and demonstrated that this model's performance is better than traditional neural networks. An approach named Gray extreme machine learning with the Taguchi method [7] which demonstrates better system performance than the performance of artificial neural networks. Forecasting for month electricity sales purposed in china [8] uses clustering, regression, and time series analysis techniques. Time series analysis auto sales [9] also carried out in China. The periodic effects were calculated by using the exponential weighted moving average. After that, considered effects and the calculated frequency are merged for the linear regression technique. ARMIMA and neural networks are combined for forecasting [10]. Cloud computing-based forecasting [11] system and applied time series analysis with the moving average method are also implemented for forecasting. Systems are installed on Azure cloud, used PHP programming language and MySQL database. Moving average methods are being implemented to forecast the sales for a long time in the literature [12]. A forecasting engine based on genetic algorithm also embedded [13].

A customer model [14] created a which uses customer browsing behavior and verified the model on an e-commerce website. Another technique the merger of the SARIMA and wavelet transform method for forecasting. A hybrid model is demonstrated that delivers better performance than the single methods [15].

A hybrid model is designed as a hybrid model, which combines k-means clustering and fuzzy neural network for the prediction of circuit boards [16].

A model purposed which uses extreme learning machine and harmony search algorithm for prediction of retail supply chains and displayed that the new model provides better performance than the ARIMA models [17]. A fuzzy logic and Naïve Bayes classifier also used for forecasting [18]. Recurrent Neural Networks also implemented to forecast sales [19]. An extreme Machine Learning (ML) algorithm is used for prediction [20]. The Back Propagation Neural Network for forecasting is also implemented [21]. A hybrid method introduced based on MARS and SVR techniques for the prediction of IT products. They established that the new model provides better performance than the single SVR [22]. Numerous features such as fuel price, holiday, unemployment, temperature, store, and date are applied to forecast the weekly demand in Walmart and showed that Support Vector Machine delivers the best performance [23].

Forecasting was used in many fields and areas, as technology upgraded, we combine this field of the area with technology and nowadays Machine learning, Artificial Intelligence, Data Science play an important part.

The system discussed in this paper is to forecast future sale products. The distinction between classification accuracy and forecasting accuracy is important and some-times unappreciated [24]. For accuracy, we need accurate past and present data, for accurate estimation. In any case, if our collection of market data or lack of market person statement, we may miss our past data accuracy, and as a result, the prediction may be wrong which causes the forfeiture in business. We can compare our forecast data with real-time data and find the percentage of perfection and erroneous.

IV. PROPOSED WORK

Now let's discuss the purposed system in complete detail. The components in the purposed model and their interaction. Figure 1 shows the high-level overview of the proposed system and Figure 2, 3 & 4 shows the detailed interaction of each component. How every component proceeds. Let's discuss this in detail.Machine learning-based forecasting systems introduced to overcome the above hindrances. As shown in Figure 1 the system gets data from different sources to provide raw data to the Machine learning model.Model and Rule engine provides a forecast based on historical data. Forecasted values dumped in the database and used in front end application for processing. Front end application shows predicted data for the store every week then that data was aggregated to higher levels of hierarchy based on rules laid down by business. Front end application has the functionality to alter the numbers and approval workflow process in place. After alteration and approval data submitted to AX for further strategic decisions of sales and inventory.

e-ISSN: 2319-8753, p-ISSN: 2320-6710 www.ijirset.com | Impact Factor: 8.118



Volume 11, Issue 6, June 2022

DOI:10.15680/IJIRSET.2022.1106033



Figure 1: Proposed Model Overview

A. Data Sours

Data is the most important part of any BI centric application or model. Purposed model acquires data from different sources i.e sales inventory and calendar,.Data will be generated from these sources for forecasting, primary sources of data are sales, inventory, and calendar. Calendar acts as a metadata /timeline for time series based on The data generated is the real-time data of an organization. The inputs used for the purposed model are as follows, historic sales data of year, Calendar of year, holidays for sales spike, data from a marketing perspective includes discounted/promotional days. Input to model also includes historic share and contribution on each shop in with sector and subsector.

Data is dumped into the common database from all different sources. Data cleansing is performed before it processes and considered for the next stage. Data cleansing and preparation for Machine Learning (ML) input.

The grain of the data is shops * weeks as that is also the grain of perdition from ML. Data dumped is shopping wisely as the purposed system predicts the next 52/53-week sales shop wisely. So, all three data sources are important for forecasting. Data refinement activity is performed before pushing it to AWS S3 Storage.

B. Machine learning

Business Intelligence (BI) forecasting model using machine learning (ML) provides vital support in decision making. Purposed model for (ML) part takes data input from the data source, refined and preprocess the data. Refined and preprocess data used as input to the machine learning training model as shown in figure 3. The training model results and accuracy stored in data sources, these trained models are used for data prediction. The rule engine is also applied where we have shops with less data then it is used in combination with ML predicted model.

Figure 5 shows the working cycle of how Machine Learning engine works. First three steps are involved for in preprocessing of data that includes data fetching (Data from repositories that are stored in processed form from different sources) cleansing (That cleansing is with performed on processed data from data sources to improve the training results) and preparing before the model training then training evolution of models and then deployment plus monitoring

C. SALES/INVENTORY FORECAST WEB APPLICATION

Once all these prediction results are dumped into a database. Front end application built in Angular uses ASP.net Core Restful web services as backend come into action. Figure 4 shows a detailed overview of the architecture used for the application. Figure 6 describes the client-side architecture implemented using angular and angular material.



| e-ISSN: 2319-8753, p-ISSN: 2320-6710| <u>www.ijirset.com</u> | Impact Factor: 8.118|

Volume 11, Issue 6, June 2022

DOI:10.15680/IJIRSET.2022.1106033

IV. SIMULATION RESULTS

For forecasting the sales and inventory historic data has been analyzed. After the cleansing of historic data from 2015 onwards hyperparameters are fine-tuned to get the maximum forecasting results. Table 1, 2 and 3 shows week wise actual and predicted results for December 2019.

Table 1 shows the predicted and actual results of shop 1 in the north sector. The perdition for December is very effective as compared to the previous system where accuracy is around 50% as it is a manual process based on excel formula. As we have a fair amount of historic data which helps in predicting with great accuracy. The prediction varies from week to week or month to month as systems give accuracy with under perdition and over prediction.

Table 2 shows the accuracy of newly opened shops that do not have much sales and inventory history. We have use



FIGURE 7. The graph shows historical data of and future year 2020 prediction.

The X-axis shows weeks and the y-axis shows sales/ inventory is

converted in dollar \$. This is a representation of the north sector.

TABLE 2. Shop 12 (East Sector) comparison of actual and forecasted for December 2019 Weeks.

Shop#	Week#	Actual	Predicted	Accuracy
Shop 12 (East Sector)	Week1	5175	6521	73.99%
	Week2	3621	2821	77.99%
	Week3	6430	5120	79.62%



| e-ISSN: 2319-8753, p-ISSN: 2320-6710| <u>www.ijirset.com</u> | Impact Factor: 8.118|

Volume 11, Issue 6, June 2022

DOI:10.15680/IJIRSET.2022.1106033

Week4 9652 12250 73.08%		Week4	9652	12250	73.08%
-------------------------	--	-------	------	-------	--------

rule-based with machine learning prediction for shops of such a kind. As historic data grows for such shops Machine Learning (ML) prediction algorithm (Deep AR) will output better results based on time series and hyperparameters.

Table 3 shows the data of shop 5 of the eastern sector as we have a fair amount of historic data with good hyperparameters, the perdition results are excellent with over 90 % in this sector and sub-sector.

A. GRAPHICAL REPRESENTATION SECTOR WISE

Results are compiled sector-wise to show data graphically sector-wise as shown in Figure 7, Figure 8, Figure 9. Historic data have been mapped with the future year perdition as a model provides a prediction of 52/53 weeks of a complete fiscal year. The results are shown on the higher hierarchy as our front-end app shows the data based on hierarch levels, starting from shops to sub-sectors, sectors up to the highest level. For simulation, python is used with the Jupiter notebook.

TABLE 3. Shop 2 (East Sector) comparison of actual and forecasted for December 2019 Weeks.

Shop#	Week #	Actual	Predicted	Accuracy
Shop 5 (East Sector)	Week1	6621	7125	92.38%
	Week2	10253	8854	86.33%
	Week3	9851	11321	85.07%
	Week4	14232	15587	90.47%

Figure 7 represents the data spikes of a complete north sector where historic data has been considered from 2015-2019 and the year 2020 is predicted based on historical data. Data spikes show considerable good results that strengthen the fact that prediction will be accurate and near to reality as historic data improves.

Figure 8 represents the data spikes of a complete west sector where historic data has been considered from 2015-2019 and the year 2020 is predicted based on historical data.

Figure 9 represents the data spikes of the complete south sector where historic data has been considered from 2015-2019 and the year 2020 is predicted based on historical data. Data spike shows the accuracy of the predicted model.

V. CONCLUSION

As the modern era is the era of technological advancements.Business intelligence (BI) practices are also the need of the hour. As business intelligence (BI) practices are applied throughout the enterprise, these practices lead to accurate and effective decision support. BI helps in stabilizing the business, make it more sustainable, and increase productivity. For



| e-ISSN: 2319-8753, p-ISSN: 2320-6710| <u>www.ijirset.com</u> | Impact Factor: 8.118|

Volume 11, Issue 6, June 2022

DOI:10.15680/IJIRSET.2022.1106033

enterprises, the importance of demand forecast doubles as the day passes. Previously organizations do these calculations manually or some irrational techniques were there. As the market is becoming more dynamic and robust the forecasting has not only changed the organizational philosophy of the business and culture of an organization, it also increases executive support, cooperation, and transparency significantly. In this system, the demand forecasting enhances the operational productivity reduces the losses and wastages, as the company doesn't have the production Units they purchased items based on forecasting.

High forecast accuracy helps in formulating established market strategy, stock turn over increase, decrease in supply chain cost, and an increase in customer satisfaction. In this study effectiveness of time series and rule-base forecasting has been analyzed. As per forecasting calculations, the performance of Deep AR models is highly accurate and comparative. This concludes the percentage error values are relatively small so DeepAR models give a high percentage on accuracy for forecasting. As data size grows the model produces more accurate results. Depending upon accuracy new study can be related to stock optimization. So, the stock/product optimization point can be a new starting point.

REFERENCES

- [1] PlanetTogether. (2019). *The Advantages of Effective Demand Forecasting*. [Online]. Available: https://www.planettogether.com/blog/the-advantagesof-effective-demand-forecasting
- [2] L. Luce, "Deep learning and demand forecasting," in *Artificial Intelligence for Fashion*. Berkeley, CA, USA: Apress, 2019, pp. 155–166.
- [3] H. Stekler and H. Symington, "Evaluating qualitative forecasts: The FOMC minutes, 2006–2010," *Int. J. Forecasting*, vol. 32, no. 2, pp. 559–570, Apr. 2016.
- [4] V. M. Eguíluz, J. Fernández-Gracia, X. Irigoien, and C. M. Duarte, "A quantitative assessment of arctic shipping in 2010–2014," *Sci. Rep.*, vol. 6, no. 1, pp. 1–6, Aug. 2016.
- [5] C. Catal, K. Ece, B. Arslan, and A. Akbulut, "Benchmarking of regression algorithms and time series analysis techniques for sales forecasting," *Balkan J. Electr. Comput. Eng.*, vol. 7, no. 1, pp. 20–26, 2019.
- [6] R. J. Kuo, "A sales forecasting system based on fuzzy neural network with initialweightsgeneratedbygeneticalgorithm," *Eur.J.Oper.Res.*, vol.129, no. 3, pp. 496–517, Mar. 2001.
- [7] F. L. Chen and T. Y. Ou, "Sales forecasting system based on gray extreme learning machine with taguchi method in retail industry," *Expert Syst. Appl.*, vol. 38, no. 3, pp. 1336–1345, Mar. 2011.
- [8] J. Zhao, W. Tang, X. Fang, and J. Wang, "A novel electricity sales forecasting method based on clustering, regression and time-series analysis," in *Proc. 5th Int. Conf. Comput. Eng. Netw.*, vol. 259, Oct. 2015, p. 15.
- [9] Y. Tian, Y. Liu, D. Xu, T. Yao, M. Zhang, and S. Ma, "Incorporating seasonal time series analysis with search behavior information in sales forecasting," in *Proc. 21st Int. Conf. Companion World Wide Web*, 2012, pp. 615– 616.
- [10] G. P. Zhang, "Time series forecasting using a hybrid ARIMA and neural network model," *Neurocomputing*, vol. 50, pp. 159–175, Jan. 2003.
- [11] A. Pandey and R. K. Somani, "A cloud computing based sales forecasting system for small and medium scale textile industries," *Int. J. Eng. Innov. Technol.*, vol. 3, no. 4, Oct. 2013.
- [12] P. R. Winters, "Forecasting sales by exponentially weighted moving averages," *Manage. Sci.*, vol. 6, no. 3, pp. 324–342, Apr. 1960.
- [13] M. Vijayalakshmi, B. Menezes, R. Menon, A. Divecha, R. Ravindran, and K. Mehta, "Intelligent sales forecasting engine using genetic algorithms," in *Proc. 19th ACM Int. Conf. Inf. Knowl. Manage. (CIKM)*, 2010, pp. 1669– 1672.
- [14] J. Yeo, S. Kim, E. Koh, S.-W. Hwang, and N. Lipka, "Browsing2purchase: Online customer model for sales forecasting in an E-commerce site," in *Proc. 25th Int. Conf. Companion World Wide Web*, 2016, pp. 133–134.
- [15] T.-M. Choi, Y. Yu, and K.-F. Au, "A hybrid SARIMA wavelet transform method for sales forecasting," *Decis. Support Syst.*, vol. 51, no. 1, pp. 130–140, Apr. 2011.
- [16] P.-C. Chang, C.-H. Liu, and C.-Y. Fan, "Data clustering and fuzzy neural network for sales forecasting: A case study in printed circuit board industry," *Knowl.-Based Syst.*, vol. 22, no. 5, pp. 344–355, Jul. 2009.



| e-ISSN: 2319-8753, p-ISSN: 2320-6710| <u>www.ijirset.com</u> | Impact Factor: 8.118|

Volume 11, Issue 6, June 2022

DOI:10.15680/IJIRSET.2022.1106033

- [17] W. K. Wong and Z. X. Guo, "A hybrid intelligent model for medium-term sales forecasting in fashion retail supply chains using extreme learning machine and harmony search algorithm," *Int. J. Prod. Econ.*, vol. 128, no. 2, pp. 614–624, Dec. 2010.
- [18] V. Katkar, S. P. Gangopadhyay, S. Rathod, and A. Shetty, "Sales forecastingusingdatawarehouseandNaïveBayesianclassifier," in *Proc.Int. Conf. Pervas. Comput. (ICPC)*, Jan. 2015, pp. 1–6.
- [19] M. Muller-Navarra, S. Lessmann, and S. Voss, "Sales forecasting with partial recurrent neural networks: Empirical insights and benchmarking results," in *Proc. 48th Hawaii Int. Conf. Syst. Sci.*, Jan. 2015, pp. 1108– 1116.
- [20] M. Gao, W. Xu, H. Fu, M. Wang, and X. Liang, "A novel forecasting method for large-scale sales prediction using extreme learning machine," in *Proc. 7th Int. Joint Conf. Comput. Sci. Optim.*, Jul. 2014, pp. 602–606.
- [21] H. A. Omar and D.-R. Liu, "Enhancing sales forecasting by using neuro networks and the popularity of magazine article titles," in *Proc. 6th Int. Conf. Genetic Evol. Comput.*, Aug. 2012, pp. 577–580.
- [22] C.-J. Lu, T.-S. Lee, and C.-M. Lian, "Sales forecasting of IT products using a hybrid MARS and SVR model," in *Proc. IEEE Int. Conf. Data Mining Workshops*, Dec. 2010, pp. 593–599.
- [23] N.Stojanović, M.Soldatović, and M.Milićević, "Walmartrecruiting-store sales forecasting," in Proc. 14th Int. Symp. Symorg, 2014, p. 135.
- [24] R. A. Berk, S. B. Sorenson, and G. Barnes, "Forecasting domestic violence:Amachinelearningapproachtohelpinformarraignmentdecisions," J. Empirical Legal Stud., vol. 13, no. 1, pp. 94–115, Mar. 2016.
- [25] Amazon. (2019). *Machine Learning With Amazon SageMaker*. [Online]. Available: https://docs.aws.amazon.com/sagemaker/latest/dg/how-itworks-mlconcepts.html





Impact Factor: 8.118





INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY





www.ijirset.com