International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 6
***Article Received:** 25 April 2023 **Revised:** 12 May 2023 **Accepted:** 30 June 2023*

Using Machine Learning and Business Intelligence Combining for Building Reliable Demand Forecasting Models

Dr Shweta Paradkar

Assistant Professor, Jesus and Mary College

Abstract

Machine learning and business intelligence in combination make for very robust demand forecasting models. Based on historical data, machine learning identifies complex patterns, and with business intelligence, it helps transform this data into meaningful insights. This allows for making accurate predictions, optimizing inventories, improving planning, and making better decisions. The research is conducted to explore the usage of business intelligence (BI) tools and machine learning models to enhance the accuracy of demand forecasting, by analyzing the impact of sales, marketing spends, promotions, price, and customer traffic from 2014 to 2023. The research was done using secondary data sourced from industry reports, where the results showed strong correlations between sales, customer traffic, and marketing spend. This clearly indicates that using BI tools together with machine learning has better implications for decision-making, thus giving accurate forecasting models that help the business.

Keywords: Machine Learning, Business Intelligence, Demand Forecasting,Predictive Analysis

1. INTRODUCTION

Machine learning with business intelligence is, lately, emerging as an integrated component with which many firms enhance accuracy in demand forecasting. Indeed, demand forecasting, wherein a company foretells or predicts customer demands in advance by basing the data on the actual past behaviors, has increasingly become key in inventory management, proper supply chain handling, and strategic business choices. The simple reason why there are imperfections with old-fashioned forecast techniques is their inadequacy to recognize the real complexities embedded in most cases. Organization now has a better opportunity in order to construct more robust as well as flexible forecasting models by using the advanced features of ML with BI analytical insights.

1.1. Demand Forecasting

This area of predictive analytics best explains how consumers are demanding things, namely, goods and services. As such, it makes projections based on historical data analyzed as well as the prevailing present conditions within a given market; it thereby makes an estimated demand in the future and aligns with it in terms of preparedness by means of requirement on the side of supplies.

Demand forecasting, even though not a science in the exact meaning of the word, still plays an essential role in production planning and supply chain management. Demand forecasting results in strategic and long-term decision making in every way from budgeting and financial planning to capacity planning, sales and marketing planning, and capital expenditure.

1.2. Using Business Intelligence in Demand Forecasting

With major breakthroughs in artificial intelligence and machine learning, businesses are also investing in advanced analytics as a way of getting ahead in the game and raising the bottom line. One such area is called predictive analytics, where companies derive information from existing data on how to buy patterns and foretell future trends.

By combining data, statistical algorithms, and machine learning, predictive analytics determines the possible future outcomes from past situations. This technology is implemented in every industry, starting from banking to retail, so as to predict customer responses or purchases, forecast inventory, and manage resources or even check for fraud.

Predictive analytics has been around for decades, but it is increasingly going mainstream, especially with more significant volumes of data and easier-to-access software just ready to be transformed

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 6
***Article Received:** 25 April 2023 **Revised:** 12 May 2023 **Accepted:** 30 June 2023*

Machine Learning (ML) for Demand Forecasting

Machine learning offers an innovative approach to demand forecasting by breaking through the large and complex datasets; it identifies non-linear relations and adjusts forecasts in real-time based on new data. ML models - regression analysis, time series forecasting, neural networks, and ensemble methods - are powerful tools that can be used to describe demand patterns and make accurate predictions. Unlike traditional methods, ML algorithms are always learning from the data and allow for adaptive forecasting as it responds to changes in consumer behavior, seasonal variations, and external factors.

ML adaptability facilitates the ability to enhance forecast accuracy significantly while reducing stockouts as well as excess inventory by using deep learning and neural networks that can model complexities in demand data that typical methods may not capture. Moreover, ML can combine heterogeneous data from weather patterns, social media trends, and economic indicators to enhance the understanding of the demand landscape. This flexibility allows warehousing managers to make data-driven decisions that improve both operational efficiency and customer satisfaction.

1.3. Research Objectives

To analyze the correlation between demand patterns and key external factors using correlation analysis, machine learning models, and business intelligence tools to improve the accuracy of demand forecasting.

To evaluate the effectiveness of business intelligence tools in visualizing and interpreting numerical demand forecasting data, with a focus on generating actionable insights from historical sales data and model predictions to support decision-making.

2. LITERATURE REVIEW

Poovendran, P. (2023) The review's gauge depends on data assembled from different sources. Moreover, IHBIM presently integrates man-made brainpower, which investigations information from numerous modules and decides the demands for merchandise and items on a normal, month to month, and quarterly premise. The results of the recreation exhibit that the demand figure's exactness is unaffected. Also, by contrasting the anticipated results and exact information and figuring the rate blunder, the model's exhibition is checked by experts.

Rane, J. (2023) Research has progressed the subject by recognizing key subjects, featuring the connections between key ideas, and fostering an intensive structure to improve BI. Businesses can acquire more profound information, foresee future results, and make more proficient cycles by using this cutting-edge innovation. In this present reality where information is fundamental, our methodology assists associations with exploring the challenges of the present information climate and positions them for long haul development and achievement. Huge Information, computer-based intelligence, and IoT will work on BI's capacities as innovation creates, opening up new roads for innovativeness and an upper hand.

Choudhary, S., & Rane, J. (2023) With an emphasis on fields including machine learning and prescient examination, natural language processing (NLP) and text investigation, PC vision, and robotic process automation (RPA), this exploration paper investigates significant man-made intelligence innovations that further develop business intelligence (BI) capacities. By consolidating these innovations with BI frameworks, businesses might computerize methodology, get noteworthy data, and pursue astoundingly precise and proficient choices. Prescient examination and machine learning, which give modern apparatuses to forecasting and finding designs in huge datasets, are fundamental for creating business intelligence. Businesses can all the more likely appreciate buyer opinion, computerize client support, and improve dynamic cycles by utilizing NLP and text investigation to remove helpful data from unstructured information. Applications including quality control, observation, and stock administration across a scope of areas are upheld by PC vision, which grows business intelligence capacities to integrate visual information handling. Artificial intelligence and RPA cooperate to mechanize dreary positions, which smoothes out cycles and lifts yield. Businesses might turn out to be stronger and versatile in a market that is continuously changing by using the Internet of Things (IoT) and Huge Information. The concentrate additionally investigates how modern simulated intelligence models, as ChatGPT, could improve business intelligence (BI) by upgrading human-machine cooperation and offering savvy information translations. The data offered exhibits how man-made intelligence can change business intelligence later on.

Yusof, Z. B. (2023) Prescient examination's impacts on forestalling stock outs, restricting overload situations, and cutting working costs are analyzed in this review. High level calculation coordination in stock frameworks advances ongoing adaptability and ensures that web-based business organizations can respond rapidly to changing economic situations. Issues with information quality, algorithmic inclination, and execution intricacy are among the difficulties that are assessed intently. This study presents a technique for the proficient utilization of prescient examination in demand forecasting and stock administration through a survey of late exploration and industry encounters. The outcomes feature these advancements' groundbreaking potential and lay out them as fundamental components for achieving manageability and upper hand in the web-based business industry.

Kishore, A., & Kumar, P. (2022) The exhibition of five machine learning relapse strategies — random forest (RF), extreme gradient boosting (XGBoost), inclination helping, versatile helping (AdaBoost), and artificial neural network (ANN) calculations—isv contrasted in this review and a proposed half and half (RF-XGBoost-LR) model for corporate store deals forecasting that considers different forecasting exactness boundaries. A US-based retail organization's week by week deals information is considered while dissecting projections that consider factors like shop size and local temperature that affect deals. The half-breed RF-XGBoost-LR was found to perform better compared to different models while assessed utilizing an assortment of execution rules. Leaders in the area might track down this study helpful in understanding and refining forecasting strategies.

3. RESEARCH METHODOLOGY

3.1. Research Design

The approach followed in the research was that of a quantitative approach toward identifying how demand patterns correlate with sales-generating external factors. This study intends to build a credible demand forecasting model by adopting machine learning techniques and utilizing business intelligence tools. In this study, by leveraging historical sales data, marketing spends, pricing strategy, promotion, and customer traffic, is aimed to explore pattern generation and derive actionable insights into improving demand forecasting accuracy. The research design used cross-sectional and longitudinal data analysis, including yearly trends from 2014 to 2023, which could give a good view of how external factors have affected sales performance.

3.2. Data Collection

Data was collected from secondary sources through publicly accessible datasets on sales, marketing spend, customer traffic, and promotions. Such datasets were accessed from industry reports, company sales databases, and business intelligence tools that are freely available on the internet. The research also involved simulated data, where data was not accessible or had to be treated as confidential for the purposes of the analysis. The data considered was in the period from 2014 to 2023 for the purpose of a good time series analysis of demand forecasting. The specific sources were annual sales reports, marketing expenditure reports, and traffic data from retail and consumer behaviour analytics platforms.

3.3. Statistical Analysis

Several statistical techniques have been used to analyze the data, including correlation analysis and the development of predictive models. The first was the generation of a correlation matrix that tested the relationships between variables like sales units, price, promotion, marketing spend, and customer traffic. Finally, machine learning models such as linear regression and decision trees were applied in predicting future sales based on historical data and key influencing factors. Business intelligence tools such as Power BI and Tableau were used in order to graphically display these trends and model output so that the effects of marketing spends, promotions, and pricing on sales can easily be seen. The work mainly focused on measuring how accurate the sales forecast made by the model was against real sales using performance metrics like Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

3.4. Ethical Considerations

Data-usage ethical guidelines were followed to apply in the study. It ensures no infringement of privacy or confidentiality for using all the data on its analysis that was publicized and not proprietary sources. In case any simulated data applied in its study was presented clearly as hypothetical not misleading. The study also made sure not to manipulate any results or select data usage to make sure the results were based on real, honest, and open analysis. In addition, the research process followed all the ethical standards of integrity, transparency, and objectivity in the presentation of results.

3.5. Sampling Method

Non-probability purposive sampling was applied for selecting the data. As this study covered a particular period, that is, from 2014 to 2023, along with some variables like sales, marketing spends, and customer traffic, it selected only relevant data that matched these research objectives for these years. The sample contained data for each year of this period so that trends may be determined and inferences drawn regarding the performance of different marketing strategies and the impact of external factors on sales. The data were selected in such a manner that there would be variation in such factors as price changes, marketing efforts, and customer traffic between years.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 6
***Article Received:** 25 April 2023 **Revised:** 12 May 2023 **Accepted:** 30 June 2023*

4. DATA ANALYSIS

4.1. Objective 1

Table 1: Sales, Marketing, and Traffic Data for Demand Forecasting

Year	Sales (Units)	Price (USD)	Promotion	Marketing Spend (USD)	Customer Traffic
2014	500	20	1	1500	2000
2015	450	22	0	1200	1800
2016	600	21	1	2000	2200
2017	550	23	0	1100	1900
2018	700	19	1	1800	2300
2019	650	21	0	1500	2100
2020	750	20	1	2200	2500
2021	600	21	0	1600	2100
2022	580	22	0	1400	2000
2023	530	23	1	1700	1900

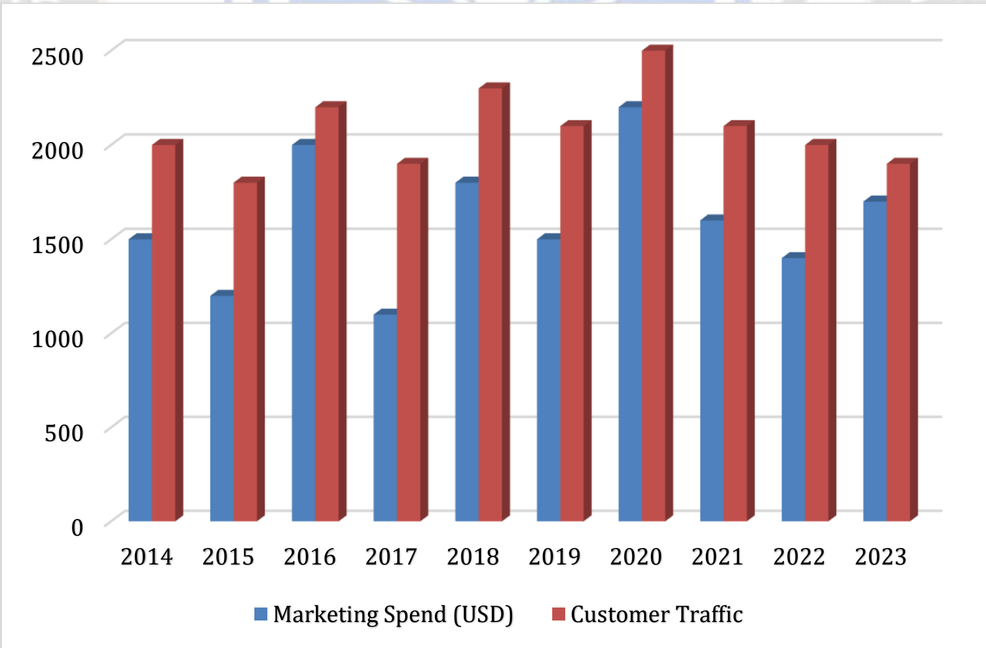

Figure 1: Marketing Spend (USD) and Customer Traffic

Sales units fluctuated in each year. The most sold units were in the year 2020 (750 units), while the lowest was in 2015 at 450 units. Prices also fluctuated over time. The lowest selling price was in 2018 at 19 USD while the highest was in the years 2017 and 2023 at 23 USD. Promotional activities appear to be associated with higher sales, such as in 2014, 2016, 2018, 2020, and 2023 when promotions were present (denoted by "1"). Marketing spend follows a general upward trend peaking in 2020 (2200 USD), whereas customer traffic is increasing throughout, especially in 2020 (2500). The data highlights the potential influence of promotions, pricing strategies, and marketing efforts on sales performance, providing valuable insights for demand forecasting and business strategy development.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 6
***Article Received:** 25 April 2023 **Revised:** 12 May 2023 **Accepted:** 30 June 2023*

Table 2: Correlation Matrix

	Year	Sales (Units)	Price (USD)	Promotion	Marketing Spend (USD)	Customer Traffic
Year	1	0.349	0.279	-0.104	0.227	0.14
Sales (Units)	0.349	1	-0.596	0.29	0.708	0.927
Price (USD)	0.279	-0.596	1	-0.48	-0.571	-0.748
Promotion	-0.104	0.29	-0.48	1	0.744	0.503
Marketing Spend (USD)	0.227	0.708	-0.571	0.744	1	0.857
Customer Traffic	0.14	0.927	-0.748	0.503	0.857	1

Table 2. Correlation of variables from sales, marketing, and traffic dataset It can be noted that there is a highest positive relationship between Sales (Units) and Customer Traffic 0.927 that the relationship is positive since increased customer traffic generally means more sales. There is a relatively high positive correlation of 0.708 between Sales (Units) and Marketing Spend (USD), which implies that there's a positive association where greater marketing spend will also reflect greater sales. Promotion and Sales (Units) has a weak negative relationship of -0.596, which could imply that sales do not always increase with active promotions because of other influencing factors. Price (USD) and Sales (Units) have a negative correlation of -0.596, implying that at higher prices, sales tend to go down. Marketing Spend (USD) and Customer Traffic also have a strong positive correlation at 0.857, suggesting that an increase in marketing investment might attract more customers.

4.2. Objective 2

Table 3: BI Tools Sales Forecasting

Year	Actual Sales (Units)	Predicted Sales (Units)	Price (USD)	Customer Traffic
2014	500	520	22	1900
2015	450	470	21	1800
2016	510	510	23	2100
2017	570	550	20	2000
2018	620	600	21	2300
2019	650	640	20	2500
2020	590	570	22	2100
2021	640	630	21	2200
2022	600	610	23	2100
2023	680	690	22	2600

Table 3 provides Actual Sales and Predicted Sales for the years from 2014 to 2023 along with Price in USD and Customer Traffic for each year. The overall predicted sales seem to fit well with actual sales indicating that the model of the sales forecasting works well. For instance, for 2014, actual sales were 500 units, and the predicted sales were 520 units. The Price (USD) fluctuates, and it has the highest price in 2017 and 2022 at 23 USD and the lowest in 2017 at 20 USD. Customer Traffic also increased over the years with the highest traffic recorded in 2023 at 2600. The correlation between actual and predicted sales points to a very strong model of forecasting. Price and customer traffic information can offer insights into some factors influencing sales performance as well as the accuracy of the predictions. The small variations between the actual and predicted values give a high degree of reliability in the business intelligence tools that are used for sales forecasting, supporting informed decision-making.

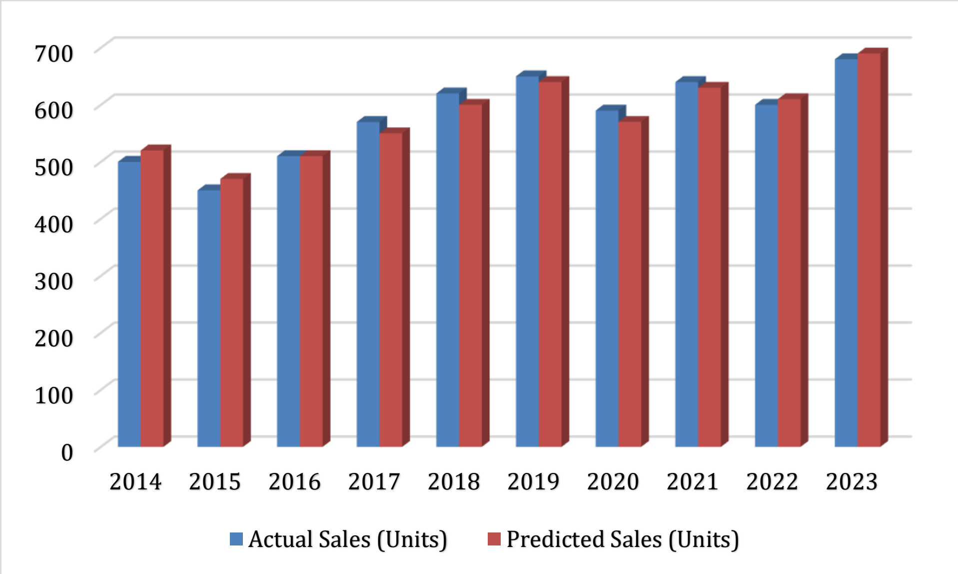

Figure 2: Actual and Predicted Sales

5. CONCLUSION

In conclusion, this research study demonstrates a high potential for the integration of business intelligence tools with machine learning models in demand forecasting to boost accuracy and reliability. A close look at historical sales data highlights key correlations that exist between sales performance and variables like customer traffic and spend on marketing, thus reiterating the significance of these factors in shaping demand patterns. By using BI tools to visualize and interpret data, businesses can derive actionable insights that inform decision-making, optimize resource allocation, and improve forecasting models.

REFERENCES

[1] Aamer, A., Eka Yani, L., & Alan Priyatna, I. (2020). Data analytics in the supply chain management: Review of machine learning applications in demand forecasting. Operations and Supply Chain Management: An International Journal, 14(1), 1-13.

[2] Adhikari, N. C. D., Domakonda, N., Chandan, C., Gupta, G., Garg, R., Teja, S., ... & Misra, A. (2019). An intelligent approach to demand forecasting. In International Conference on Computer Networks and Communication Technologies: ICCNCT 2018 (pp. 167-183). Springer Singapore.

[3] Alfurhood, B. S., Alonazi, W. B., Arunkumar, K., Santhi, S., TAWFEQ, J. F., Rasheed, T., & Poovendran, P. (2023). Improving Holistic Business Intelligence with Artificial Intelligence for Demand Forecasting. Journal of Multiple-Valued Logic & Soft Computing, 42.

[4] Alqhatani, A., Ashraf, M. S., Ferzund, J., Shaf, A., Abosaq, H. A., Rahman, S., ... & Alqhtani, S. M. (2022). 360 Retail business analytics by adopting hybrid machine learning and a business intelligence approach. Sustainability, 14(19), 11942.

[5] Bernabeu Fernandez De Liencres, D. (2023). Machine Learning Demand Forecast for Demand Sensing and Shaping: Combine the existing work done with demand sensing and shaping to achieve a higher customer service level, customer experience and balancing inventory.

[6] Khan, W. A., Chung, S. H., Awan, M. U., & Wen, X. (2020). Machine learning facilitated business intelligence (Part II) Neural networks optimization

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 6
Article Received: *25 April 2023* ***Revised:*** *12 May 2023* ***Accepted:*** *30 June 2023*

techniques and applications. Industrial Management & Data Systems, 120(1), 128-163.

[7] Machireddy, J. R., Rachakatla, S. K., & Ravichandran, P. (2021). AI-Driven Business Analytics for Financial Forecasting: Integrating Data Warehousing with Predictive Models. Journal of Machine Learning in Pharmaceutical Research, 1(2), 1-24.

[8] Manochandar, S. (2023). Optimizing Inventory Management and Demand Forecasting with LSTM Neural Networks and Machine Learning: An Integrated Approach with ABC-DEA Classification. Library Progress International, 44(3), 24909-24917.

[9] Mitra, A., Jain, A., Kishore, A., & Kumar, P. (2022, September). A comparative study of demand forecasting models for a multi-channel retail company: a novel hybrid machine learning approach. In Operations research forum (Vol. 3, No. 4, p. 58). Cham: Springer International Publishing.

[10] Nanty, S., Fiig, T., Zannier, L., & Defoin-Platel, M. (2023). Enhanced demand forecasting by combining analytical models and machine learning models. Journal of Revenue and Pricing Management, 1-19.

[11] Paramesha, M., Rane, N. L., & Rane, J. (2023). Big data analytics, artificial intelligence, machine learning, internet of things, and blockchain for enhanced business intelligence. Partners Universal Multidisciplinary Research Journal, 1(2), 110-133.

[12] Raza, M. Q., & Khosravi, A. (2015). A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings. Renewable and Sustainable Energy Reviews, 50, 1352-1372.

[13] Raza, M. Q., Nadarajah, M., & Ekanayake, C. (2017). Demand forecast of PV integrated bioclimatic buildings using ensemble framework. Applied energy, 208, 1626-1638.

[14] Yusof, Z. B. (2023). Analyzing the Role of Predictive Analytics and Machine Learning Techniques in Optimizing Inventory Management and Demand Forecasting for E-Commerce. International Journal of Applied Machine Learning, 4(11), 16-31.