

Exploring the Profound Influence of Machine Learning on Business Intelligence: A Comprehensive Review

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Abstract: Businesses nowadays may save a significant amount of money by using technological solutions. It is impossible to deny this when considering the expenses of acquiring and training new personnel. When faced with such difficulties, technology is virtually always able to assist. Business Intelligence/Machine Learning (BI/ML) is an essential tool in today's decision-making process because of the many issues it has created for contemporary business decision-making. A comparative study of regression models, including linear regression, random forests, and gradient boosting, could unravel their effectiveness in predictive analytics within BI. Machine learning contribution in businesses is vital as it has a strong link with business intelligence, and it helps business decision-making in businesses. Without machine learning, business intelligence is not practical while making decisions, as business owners can't make decisions effectively. This paper will comprehensively review the noteworthy contributions of Machine Learning and its Impact on Business Intelligence. Further, it will discuss the challenges and opportunities of machine learning in business intelligence. Finally, the paper will discuss future correspondence about machine learning in businesses.

Index Terms: Business Intelligence (BI), Machine Learning (ML), Technology, Supervised Learning, Unsupervised Learning, Algorithm.

1. Introduction

In the dynamic landscape of data-driven decision-making, the intersection of Machine Learning (ML) and Business Intelligence (BI) has become a pivotal arena, propelling organizations toward more informed and strategic insights. The fusion of these two domains is characterized by a continuous evolution, marked by innovative trends that redefine how businesses extract value from their data. This synergy between ML and BI not only augments analytical capabilities but also transforms raw data into actionable intelligence, empowering organizations to navigate the complexities of the modern business environment. As we delve into the emerging trends in ML and BI integration, it is evident that the convergence of advanced analytics and business intelligence is ushering in a new era of efficiency, automation, and foresight. From augmented analytics and predictive modeling to the democratization of machine learning through automation tools, the landscape is evolving rapidly. This exploration will delve into key trends shaping this amalgamation, offering a glimpse into the future of data-driven decision-making where insights are not just discovered but dynamically generated, enabling businesses to stay ahead of the curve and make strategic decisions with unparalleled precision.

The preponderance of technology is focused on the creation of value in businesses. Technology is a tool that creates value, and companies exist to facilitate the exchange of value between people. Technology is a tool that allows businesses to trade values more effectively and efficiently and create new values that may be shared, as explained above. Technology has a significant impact since it is continuously developing. Several areas for different sectors enhance how they work, especially machine learning, which helps businesses enhance their business process [1]. Machine learning helps businesses make decisions as it has a strong relationship with business decision-making. The contribution of machine

learning in companies is essential since it has a strong relationship with business intelligence and helps organizations make better decisions when it comes to decision-making. Without machine learning, business intelligence is ineffective in decision-making, and company leaders cannot make successful decisions without machine learning [2].

Business intelligence (BI) is referred to as converting data into information, subsequently transformed into knowledge [3, 4, 5]. When it comes to business intelligence (BI), the goal is to make better, more informed choices. Business intelligence assists businesses in collecting and analyzing data to detect trends and patterns. This information may then be utilized to enhance strategic planning, operational efficiency, and marketing initiatives, among other things. One of the most significant advantages of business intelligence is that it may assist firms in reducing waste and optimizing resources [3]. An organization that determines that it is selling things that are not in great demand, for example, might change its inventory levels to reflect this information. Alternatively, suppose a company notices that a particular product is being returned at a higher rate than others.

In that case, it may look into what could be causing the issue and take appropriate action. Organizations may also benefit from business intelligence in terms of improving customer service. Businesses may better know what consumers are searching for by watching their activity over time and analyzing the data. If a firm notices that its consumers are unhappy with its service, it may rectify the situation and improve customer satisfaction. Business intelligence (BI) is now a critical component of many firms' day-to-day operations. Businesses benefit from it because it improves decision-making and helps them better understand their goods and services. The better fulfilling consumer wants, increasing sales, providing better service to customers, lowering expenses, maximizing resources, and minimizing waste improve firms' bottom lines [4, 5, 6].

Recently, we've observed integrating machine learning capabilities into business intelligence systems, making BI considerably more successful at uncovering hidden insights. BI solutions that can efficiently combine these skills in a user-friendly manner will soon become the standard. As consumers get used to this feature, they will expect it to be available at all times. GPS and other technology that we now can't fathom our lives without are examples of this. Combining these capabilities automates the process of unearthing insights that business users were not aware were available until they were discovered. For example, on a typical dashboard, a business user looking at their top-line sales would conclude that the trend seems to be in good shape and that there is no need to investigate deeper. However, there may be grounds for worry in the fine print, in the underlying makeup of the sales figures, which is difficult to discern. Some items may be doing well, while others may be exhibiting a deterioration in performance. This critical understanding is concealed from public view.

Additionally, automation of this process results in insights being supplied much more rapidly, enabling the company to respond quickly and with better information. It allows the business to act faster and with better information. Automating these procedures should allow the analyst to spend more time on other responsibilities in their organizations. Many analysts are engaged in regular chores such as variance analysis, the search for anomalies, and the creation of comments for inclusion in reports, among other things. The analyst will devote more time to higher-value activities [7].

In data analysis, machine learning models successfully uncover hidden patterns and insights. For many decades, data professionals have used these strategies to tackle technical and challenging business challenges. Because of improvements in computing power, it is now possible to construct and execute these complicated mathematical models on a more accessible platform. Models that used to need costly, high-end technology can now run on commodity platforms accessible to everyone, regardless of their financial situation [6]. Machine models are categorized into Supervised, Unsupervised, Semi-supervised Learning, and Reinforcement Learning models, and these models have several algorithms which can be used for Business intelligence (BI) such as Feedforward Neural Network (FNN), Artificial Neural Networks (ANN), Support Vector Machine (SVM) algorithm, KNN algorithm, etc. This paper will perform a comprehensive review of machine learning models used in business intelligence. Furthermore, we will review the impact of machine learning on business intelligence. The overall contribution of our paper is described following:

1. This paper has analyzed the impact of machine learning on business intelligence.
2. We have analyzed different machine learning models used for business intelligence.
3. Further, we have reviewed the current challenges and opportunities of machines for business intelligence, which can help transform the way work businesses.

Further proceeding of the paper, section 2 describes the paper's literature review. Section 3 is a discussion overview about the methodology in which we have discussed the machine learning model overview and business intelligence tools. Section 4 illustrates the interlink of machine learning and business intelligence and discusses the impact on business intelligence. Section 5 gives a conclusion and an overview of the opportunities and business intelligence towards machine learning and business intelligence. Section 6 discusses the conclusion and future work.

2. Literature Review

With the help of Machine Learning, business intelligence (BI) may significantly impact the insights that a company receives from its accessible data, making BI a true game-changer in helping organizations improve efficiency, quality,

customer service, and other aspects of their operations. Many researchers integrated machine learning models with business intelligence (BI) tools to enhance business operations. Khan et al. [3] discussed the impact of machine learning in business intelligence, and this paper uses the Feedforward Neural Network (FNN) to optimize business operations. It reviewed the different FNN techniques to optimize the business processes. Further, the article discussed the underfitting and overfitting for FNN used with business intelligence tools that combine BI and machine learning to enhance businesses.

A Feedforward Neural Network (FNN) consists of layers of interconnected nodes, where information flows in one direction, from the input layer to the output layer. The mathematical equations governing the behavior of a feedforward neural network involve the computation of weighted sums and the application of activation functions. For instance, we denote:

- x as the input vector.
- $W^{(i)}$ as the weight matrix for the i -th layer.
- $b^{(i)}$ as the bias vector for the i -th layer.
- $a^{(i-1)}$ as the output (or activation) of the i -th layer.
- f as the activation function.

The mathematical equations for a single layer (excluding the input layer) can be expressed as follows:

$$Z^{(i)} = W^{(i)} \cdot a^{(i-1)} + b^{(i)} \quad (1)$$

$$a^{(i)} = f(Z^{(i)}) \quad (2)$$

Here:

- $Z^{(i)}$ is the weighted sum of inputs plus bias for layer i .
- $a^{(i)}$ is the output (activation) of layer i after applying the activation function f .

The process is repeated for each layer in the network, propagating the information forward until the final output layer is reached. For the output layer ($i=L$, where L is the total number of layers), the final output y is often obtained without applying an activation function (or by using a specific one, depending on the task):

$$y = a^{(L)} \quad (3)$$

The learning process in a neural network involves adjusting the weights and biases during training to minimize the difference between the predicted output and the actual target values using techniques like backpropagation and gradient descent. The choice of activation function, loss function, and optimization algorithm also play crucial roles in training a feedforward neural network.

In the present day, business intelligence (BI) plays a critical role in formulating strategies and implementing appropriate measures based on data. A critical role in the future decision support system is played by business intelligence, which allows the firm to do data analysis at various stages of the business process and across the enterprise. Machine learning forecasts future needs for businesses by analyzing historical data. Demand forecasting is one of the most critical decision-making jobs an organization has. Demand forecasting begins with collecting raw sales data from the market, after which the future sale/product needs are anticipated based on the data received. This forecast is based on data that has been gathered from many sources and has been compiled. The machine learning engine runs the data from various modules and calculates the weekly, monthly, and quarterly wants for products and commodities in various markets. In demand forecasting, complete precision is unassailable, the more precise the system model, the more efficient the prediction. In addition, Khan et al. [3] evaluate the efficiency by comparing the projected data with the actual data and calculating the percentage error between the two. After applying the proposed solution to real-time organization data, simulation findings reveal that it can achieve up to 92.38 percent accuracy for the store in terms of intelligent demand forecasting when using the proposed solution. Patriarca et al. [8, 9] describes the process of creating a self-service BI and ML framework based on air traffic management system safety reporting data. In order to extract relevant information from many data sources, the suggested methodology begins by focusing on the development process of a BI architecture. The paper discussed how machine learning (ML) solutions might help us learn more about how a system works and provide particular safety recommendations.

The field of social informatics nowadays is confronted with the difficulty of dealing with the rapidly rising amount of data available on the internet. However, since this vast volume of data is accessible across various heterogeneous platforms, it is a complex undertaking, mainly when comprehending important information and using it effectively for business intelligence. Obtaining business intelligence using machine learning has emerged as one of the essential concerns in the modern day. Previously, outliers were seen as noisy data and were thus ignored, resulting in the loss of

essential information. The primary research problems in this mining subdomain are discussed by Sharma et al. [4]. It contains a thorough taxonomy collected from Business Intelligence techniques and information on current application industries. Future research areas and recommendations have been identified to close the anomaly gap and establish successful business strategies.

According to Chaturvedi's [6] research, sentiment analysis categorization may be used to effectively examine textual data obtained from a range of internet-based sites, including blogs and forums. In data mining, sentiment analysis is a methodology that analyses textual data using machine learning algorithms. Because of the vast amount of user opinions, reviews, feedback, and ideas accessible on the internet, it is necessary to locate, evaluate, and integrate their perspectives to make better decisions. Sentiment analysis is an effective and efficient way of obtaining customers' opinions in real-time, which may significantly impact the decision-making process in the corporate world. The amount of activity has increased significantly over the previous 10 years, with an increased emphasis on exploratory research methodologies being used. When authors looked at the pond of the Business Intelligence study, they observed that numerous processes were not paying attention. Aside from that, we identified prospective zones that need more investigation.

During the fourth industrial revaluation, a massive quantity of data is being generated, and this data is being generated at an exponential rate by many domains of the Internet of Things (IoT). Every second, businesses generate and store massive amounts of data onto data servers, known as data servers. Social media, sensors, tracking, websites, and online news items contribute to this data collection. The most notable firms are Google, Facebook, Walmart, and Taobao, responsible for creating most of the data stored online. Data is classified into three types: structured (text/numerical), semi-structured (audio, video, and picture), and unstructured (all other types of data) (XML and RSS feeds). According to the company, a firm generates income from analyzing 20 percent of such data, which is structured, but 80 percent of such data is unstructured. As a result, unstructured data contains valuable information that can assist an organization in a variety of ways, including increasing business productivity, better decision-making, extracting insights, developing new products and services, and understanding market conditions in a variety of fields, including shopping, finance, education, manufacturing, and health care. Unstructured data must be examined and disseminated in a structured way, which means that the necessary information must be acquired via data mining methods, which are used in the mining of the data. It is discussed by Yafooz et al. [11] how essential data analytics and data management are for the effective use of business intelligence, big data, data mining, machine learning, as well as data management. The numerous strategies that may be utilized to uncover knowledge and meaningful information from such data have also been examined in detail, as has their effectiveness. Several users are concerned with text mining and converting complex data into relevant information, which may be advantageous for academics, analysts, data scientists, and corporate decision-makers.

The rapid growth and widespread usage of digital technology in the contemporary world has resulted in an enormous volume of data generated in digital space. Because of the diverse nature of the data and the vast dataset, typical machine learning algorithms have a tough time dealing with such a significant amount of data. Using a hierarchical learning process, the deep learning technique is a breakthrough in machine learning research that allows researchers to cope with diverse data and enormous quantities while still extracting high-level representations of the data. In conjunction with a Stacked Auto-Encoder (SAE), a novel multilayer feature selection method is proposed by Singh et al. [12] to extract high-level features or representations from data while eliminating lower-level features or representations. Using the Farm Ads dataset, the proposed approach is validated, and the results are compared to those obtained using various conventional machine learning algorithms. Compared to standard machine learning methods, the suggested methodology beat them on the supplied dataset.

Although artificial intelligence (AI) and machine learning (ML) may save money and enhance the efficiency of business operations, these technologies have the potential to destroy corporate value, sometimes with disastrous results. Because of their incapacity to recognize and manage that risk, some managers may choose to postpone the implementation of new technologies, preventing them from attaining their full potential as a result. Canhoto et al. [13] present a new paradigm for mapping the components of an AI solution and identifying and managing the value-destructive potential of artificial intelligence and machine learning for organizations. The author demonstrates how the defining properties of artificial intelligence and machine learning (AI and ML) might jeopardize the integrity of the AI system's inputs, processes, and outputs. Using the notions of value-creation content and value-creation process, we demonstrate how these risks may inhibit value creation or even result in value destruction. After that, the author provides an example of the deployment of an AI-powered chatbot in customer service to demonstrate the use of our framework. We explore how to address the issues that occur due to the deployment.

3. Objective and Methodology

This paper aims to delve into the symbiotic relationship between ML and BI, with a specific focus on uncovering and highlighting novel insights and findings that contribute to the existing body of knowledge. As organizations increasingly rely on data-driven strategies, understanding the nuanced impact of integrating ML into BI becomes imperative for informed decision-making. By scrutinizing recent advancements, emerging trends, and notable applications at the intersection of ML and BI, this review seeks to shed light on unique contributions that extend beyond conventional understandings. The objective is to provide a comprehensive and up-to-date perspective on how ML is shaping the landscape of BI, offering fresh insights that contribute to a deeper comprehension of the transformative potential inherent

in this amalgamation. Through meticulous analysis, this paper endeavors to identify key takeaways and novel findings that advance our understanding of the evolving dynamics between ML and BI, paving the way for more effective utilization of these technologies in the contemporary business environment.

The methodology section will overview the machine learning models and business intelligence tools and sees how the machine learning model can be used for business intelligence for the decision-making process.

3.1 Machine Learning and its Models

Machine learning is one of the sorts of artificial intelligence, which allows systems/applications/computers to go into self-learning mode without being explicitly designed. Whenever the computer is subjected to new data, it conducts data analysis and learns and expands the data in a meaningful manner. The same data may be presented in numerous ways as per necessity. There are many different algorithms in the machine learning field, with hundreds being authored day after day. They're typically classified according to their learning style (supervised learning vs. unsupervised learning vs. semi-supervised learning, for example), as well as their similarity in form or function (i.e., classification, regression, decision tree, clustering, deep learning, etc.) [15]. There are three forms of machine learning.

- i. **Supervised:** This encompasses all forms of models that produce predictions that are based on models trained on data that has been tagged, e.g., by the analyst him- or herself.
- ii. **Unsupervised:** Models are mainly used for classification and pattern recognition. Unsupervised machine learning models are models that employ techniques that do not require tagged data.
- iii. **Reinforcement:** Models that are built on iterative techniques. The theory of such models is that a learning agent builds a decision-making policy. This decision-making policy outlines the agent's choice in a specific scenario. After iteration, the agent will alter his decision-making policy depending on the incentives gained.

3.2 Artificial Neural Networks (ANN)

In data analytics, Artificial Neural Networks (ANNs) are a collection of techniques that attempt to replicate the human brain's learning process. Artificial Neural Networks, like neural connections in the human brain, operate in a multi-layered environment. They accept input data and expel out an output after passing through one or multiple hidden levels. (Fun fact: consciousness seems to be a massive neuronal connection in the brain.) Therefore, after the fake network has ejected an output, it compares the output to the actual value in the real world. If the fault is significant, the team returns to the drawing board and revises the design even more. If the mistake is smaller, the revision is more minor. Backpropagation is the technical term for this. As a result, an artificial neural network attempts to predict an output from input data collection. Depending on how big the mistake is, it adjusts its design to provide a better output the following time. When you think about it further, this learning process is quite similar to how human brains operate, which makes it interesting [16]. Figure 1 illustrates the artificial neural networks.

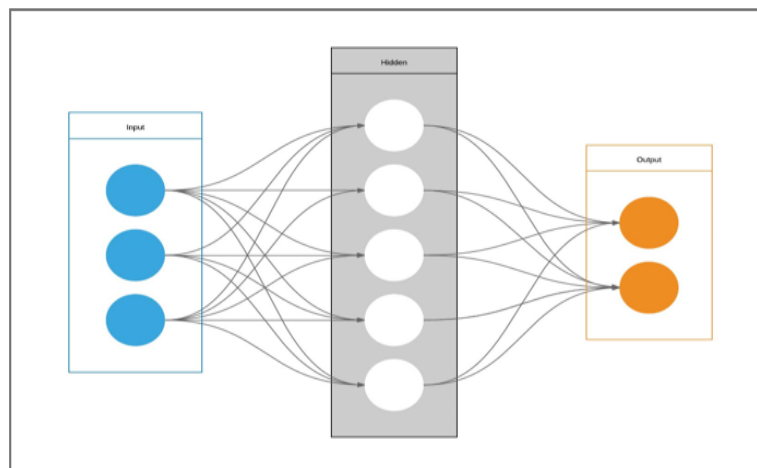


Fig. 1. Artificial Neural Networks illustration

3.3 Feedforward Neural Network (FNN)

If the connections between the neural network units do not form a cycle, this is referred to as a feedforward neural network or multilayer perceptrons (MLPs). Flows of information pass from the function being evaluated from x , through the intermediate calculations needed to define f , finally to the result y . There are no feedback links in the model, which means that the model's outputs are not sent back into the model. When feedforward neural networks are expanded to incorporate feedback connections, the result is a kind of neural network known as a recurrent neural network. Figure 2 describes the primary illustration of the Feedforward Neural Network (FNN).

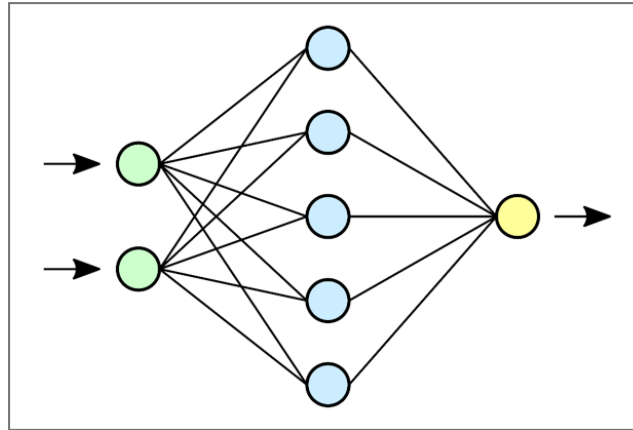


Fig.2. Feedforward Neural Network (FNN) illustration

The following qualities may be found in feedforward networks:

- Unlike neurons, which are organized in layers, perceptrons are organized in rows, with the first layer receiving inputs and the final layer creating outputs. Hidden layers are layers with no link to the outside world and are not visible to the naked eye.
- In the first layer, each perceptron is coupled to every other perceptron in the following layer. In this way, information is continually "fed forward" from one layer to the next. This is why these networks are referred to as feedforward networks in the first place.
- Perceptrons in the same layer do not communicate with one another in any way.

3.4 Support Vector Machine (SVM)

The Support Vector Machine (SVM) is a binary classification technique that requires supervision. Given a collection of points of two kinds in an N -dimensional space, SVM creates an $(N-1)$ dimensional hyperplane to divide the points into two groups, then splits the points into two groups [25].

It is a supervised machine learning technique known as "Support Vector Machine" (SVM) that may be used for classification and regression problems in machine learning. In practice, it's most often employed in categorization difficulties. Each data item is plotted as a point in n -dimensional space (where n is the number of features you have), with the value of each feature being the value of a specific coordinate in the n -dimensional space. After that, we classify by identifying the hyper-plane that most clearly distinguishes between the two groups (Fig. 3 Shows the illustration of Support Vector Machine (SVM)) [17].

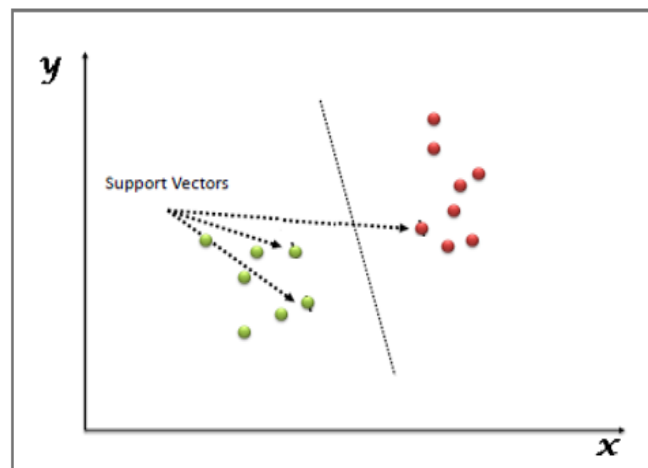


Fig. 3. Illustration of Support Vector Machine (SVM)

3.5 Decision Trees

A Decision Tree is a supervised learning approach used for classification and regression problems regarding classification difficulties. However, it is most often employed for classification problems. A decision tree is a simple structure that asks a question and then divides the tree into subtrees depending on the response (yes or no). Depending on

the choice criteria, a decision tree may graphically depict all potential answers to the problem at hand. Decisions taken can be simply communicated to a third party. Following fig. 4 illustrates the example of the decision tree [24].

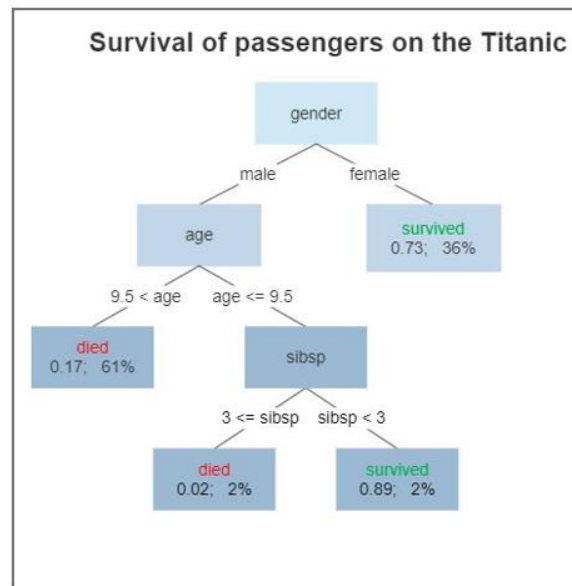


Fig. 4. Decision Tree example

3.6 Business Intelligence (BI) and its models

When it comes to business intelligence (BI), the goal is to make better, more informed decisions. Business intelligence assists firms in collecting and analyzing data to detect trends and patterns. This information may then be utilized to enhance strategic planning, operational efficiency, and marketing initiatives, among other things [23]. One of the most significant advantages of business intelligence is that it may assist firms in reducing waste and optimizing resources. An organization that determines that it is selling things that are not in great demand, for example, might change its inventory levels to reflect this information. Alternatively, suppose a company notices that a particular product is being returned at a higher rate than others. In that case, it may look into what could be causing the issue and take appropriate action. Organizations may also benefit from business intelligence to improve customer service [22]. Businesses may better know what consumers are searching for by watching their activity over time and analyzing the data. If a firm notices that its consumers are unhappy with its service, it may rectify the situation and improve customer satisfaction. Business intelligence (BI) is now a critical component of many firms' day-to-day operations. Businesses benefit from it because it improves decision-making and helps them better understand their goods and services. The better fulfilling consumer wants, increasing sales, providing better service to customers, lowering expenses, maximizing resources, and minimizing waste improve firms' bottom lines [18].

Business intelligence solutions are becoming more popular and embraced by firms worldwide to get better insights. They assist businesses of all sizes, from SMEs to multinational corporations, in keeping their data structured. It facilitates quick access to data in reports, dashboards, and graphics for easy comprehension, assisting in making well-informed choices. Data maintenance has changed from paper-based and digital records with shifting trends. The following are a few additional particular ways in which the usage of business intelligence may assist your firm in optimizing its operations:

1. Performance Benchmark for business intelligence (BI)

Benchmarking industry KPIs are a common feature of BI systems and may be used to assess your company's overall performance on several levels. Tracking your company's performance over time using performance measurements and benchmarking tools can help you make incremental changes.

2. Business Intelligence (BI) Analytics

Several business intelligence solutions allow you to gather and analyze data from various sources, including many systems and tools at once. Many analytics tools are available, but BI solutions enable you to execute analysis in a single spot. You won't need an expert to do so since the BI analytics are simple to run, to begin with. Analytical data may be more understandable via visualization (and, therefore, easy to act on). One may get the following three kinds of analysis from a BI solution.

- A dataset is described using central tendency metrics and spread in descriptive analytics.
- With accessible data, prescriptive analytics determines what should be done to get the best possible results.
- In predictive analytics, statistical methods are used to build models to foresee future occurrences or trends.

4. The Impact of Machine Learning on Business Intelligence (BI)

As the name implies, Machine Learning is what it sounds like—making it possible for the machine to learn from its own experiences. Machine Learning may be found in any action that has an eye toward the future, i.e., wherever "Predictive" is used. As a result, tasks like estimating sales for the next week or detecting fraudulent insurance claims are classic Machine Learning problems. Chabot's powered by Cognitive Computing often offer L1 help to clients, which is a similar but distinct topic. Business intuition may be explained using Machine Learning, which strives to provide better scientifically grounded insights. There are patterns in the data that a person cannot see, and this tool helps a business user make better judgments. Real-time intelligent decision-making is also possible. For example, consider a recommendation engine for e-commerce sites or a system for flagging fraudulent activities in real-time.

Businesses increasingly rely on algorithms like autoencoders, which can uncover data points that were previously impossible to quantify. Machine learning aids in transforming experience into knowledge and extracting relevant patterns from massive datasets. Business intelligence is enhanced by this technology, which complements it and performs activities that are impossible for humans to do on their own. Machine learning systems can detect patterns beyond human study because of their capacity to process and analyze large datasets. According to an example, the job of statistics is to verify the integrity of a doctor's premise that bad eating habits and diabetes are related. On the other hand, machine learning aims to build a description of diabetes based on medical data.

Machine learning makes predictive models possible by using aggregated data and the individual unit characteristics of each occurrence. If we look at the interactions and synergy of current systems like production databases, data purification, and data collecting, we can now access and understand certain future behaviors. Predictive analytics enhance business intelligence's objective, moving from retrospective responses to a targeted performance prediction and recommending particular actions based on it. Sore points or occurrences in the crucial KPIs are flagged by machine learning as anomalies in the business intelligence pipeline. Scaling operations to meet consumer needs based on market demand or historical data may be better understood in this way so that lucrative possibilities aren't lost. Interactive dashboards and real-time analytics enable firms to have a descriptive view based on the gathered visual data in Business Intelligence (BI). In Power BI, learn how to create your data visualizations. A hypothesis may be tested using machine learning algorithms applied to datasets, which can assist in determining whether it is true or not. Algorithms for fundamental machine learning can identify patterns in data that would be impossible to identify manually [21].

4.1 Ways that Machine Learning can be used for Business Intelligence

1. Data Presentation: Many dashboards fall short when usability and emphasize the essential signals within the given data. Without the continued work of a data scientist, most cannot automatically highlight what's important. Here ML could support the data scientist or BI engineer through recognizing important patterns or irregularities within the stream of information.
2. Data Exploration: Shifting through vast piles of data - yes, your classic Big Data problem - is all about finding patterns and new exciting connections between the multiple data sources. This is a classic ML problem.
3. Predictive Analytics: Lastly, ML will directly be used to quickly understand a given data set - if it may be unstructured and messy or highly cleaned and optimized. This is where predictive analytics comes into play.

4.2 Machine Learning for Business Challenge and Opportunities

Machine learning's primary goal is to reduce complexity on a large scale. The particular purpose of this collection of tools is to discover the underlying order in chaotic systems, resulting in indefinitely complicated decision-making frameworks. And it does it at a low cost, continuously, and without fail. Using an algorithm, you can make a choice quicker than your screen refreshes, thousands of decisions in less time than it takes a human to analyze visual information, and millions in the time it takes you to click your mouse. There is a limit to how much an analyst can learn and evaluate each day in machine learning. A machine learning algorithm can repeat a million times a second. The rate at which you may improve by a minuscule amount is equal to the rate of one repetition [19]. As many as a million generations are passed each day, and the high frequency of those generations means that even a modest improvement may make a noticeable effect. Rather than vetoing experiments deemed "wasteful," the machine allows sub-optimal parameters to yield sub-optimal results because the common wisdom is wrong, the ecosystem shifts, and the machine adapts without its manager vetoing experiments for being "wasteful." It solves the problem that humans are biased. It attempts things we wouldn't since we assume we're more knowledgeable than the algorithm, which needs to learn everything from the ground up because we assume we are [20].

5. Conclusions

In order to understand more or to enrich the discussion surrounding the integration of ML models in various BI contexts, a comprehensive examination of the effectiveness of different ML models becomes essential. This analysis will delve into the nuanced intricacies of how specific models perform within diverse BI scenarios, shedding light on their strengths, limitations, and potential synergies. One facet of this examination involves dissecting the performance of

classification models such as logistic regression, decision trees, support vector machines, and neural networks across BI applications. Understanding the nuances of how these models handle different types of data, ranging from structured to unstructured, and their ability to discern patterns within varied business datasets, provides invaluable insights into their applicability within BI frameworks. Moreover, a comparative study of regression models, including linear regression, random forests, and gradient boosting, could unravel their effectiveness in predictive analytics within BI. By scrutinizing their accuracy, robustness, and adaptability to changing business environments, we can discern the most suitable models for forecasting and trend analysis. An exploration of clustering algorithms such as k-means, hierarchical clustering, and DBSCAN within the BI landscape could uncover their utility in identifying patterns and segments in large datasets. Understanding how these models contribute to data segmentation and enable more granular insights could prove instrumental in enhancing BI capabilities. Additionally, the analysis will extend to anomaly detection algorithms and their role in outlier identification, offering a deeper understanding of their effectiveness in enhancing data quality and reliability within BI systems.

People, Process, and Technology are the three most essential components in today's corporate environment. If you have gaps in these areas, you will have difficulty making money and growing your business. Technology is essential for business success, but you should never throw technology at a problem or assume that technology will solve all of your company's problems on its own. It is necessary to integrate technology solutions with People and Processes for the technology solutions to be successful and to assist your firm in achieving success and driving revenue. Due to the many challenges, it has caused for modern corporate decision-making, BI/ML has become a vital tool in today's decision-making process. When making business decisions, machine learning plays a crucial role in helping firms better use their business information. Without machine learning, business intelligence is useless because business leaders cannot make good decisions. An in-depth examination of the significant contributions to machine learning and its impact on business intelligence will be presented in this article. It also covered the difficulties and possibilities presented by machine learning in the context of enterprise intelligence. Last but not least, the paper explored how machine learning will be used in business.

Future Work

As a concern to future work, in our following study, we will use the Technology Acceptance Model (TAM) to survey machine learning from different businesses to use in their companies and how their business got affected by the use of Machine Learning. Basically, TAM uses a model called UTAUT. With the help of UTAUT, we will survey the use of machine learning models for business. The model UTAUT uses the different variables for hypothesis analysis to survey to adopt any technology with different sectors.

References

- [1] Apte, C. (2010, January). The role of machine learning in business optimization. In ICML.
- [2] Reshi, Y. S., & Khan, R. A. (2014). Creating business intelligence through machine learning: An Effective business decision-making tool. In *Information and Knowledge Management* (Vol. 4, No. 1, pp. 65-75).
- [3] Khan, W. A., Chung, S. H., Awan, M. U., & Wen, X. (2019). Machine learning facilitated business intelligence (Part II): Neural networks optimization techniques and applications. *Industrial Management & Data Systems*.
- [4] Sharma, R., & Srinath, P. (2018, March). Business intelligence using machine learning and data mining techniques-an analysis. In *2018 Second International Conference on Electronics, Communication and Aerospace Technology (ICECA)* (pp. 1473-1478). IEEE.
- [5] Jourdan, Z., Rainer, R. K., & Marshall, T. E. (2008). Business intelligence: An analysis of the literature. *Information systems management*, 25(2), 121-131.
- [6] Chaturvedi, S., Mishra, V., & Mishra, N. (2017, September). Sentiment analysis using machine learning for business intelligence. In *2017 IEEE International Conference on Power, Control, Signals, and Instrumentation Engineering (ICPSCI)* (pp. 2162-2166). IEEE.
- [7] Brad Scarff, 2021, the Impact of Machine Learning on Business Intelligence, Yellowfin BI.
- [8] Khan, W. A., Chung, S. H., Awan, M. U., & Wen, X. (2019). Machine learning facilitated business intelligence (Part II): Neural networks optimization techniques and applications. *Industrial Management & Data Systems*.
- [9] Patriarca, R., Di Gravio, G., Cioponea, R., & Licu, A. (2022). Democratizing business intelligence and machine learning for air traffic management safety. *Safety Science*, 146, 105530.
- [10] Khan, M. A., Saqib, S., Alyas, T., Rehman, A. U., Saeed, Y., Zeb, A., ... & Mohamed, E. M. (2020). Effective demand forecasting model using business intelligence empowered with machine learning. *IEEE Access*, 8, 116013-116023.
- [11] Yafooz, W. M., Bakar, Z. B. A., Fahad, S. A., & Mithun, A. M. (2020). Business Intelligence through Big Data Analytics, Data Mining, and Machine Learning. In *Data Management, Analytics and Innovation* (pp. 217-230). Springer, Singapore.
- [12] Singh, V., & Verma, N. K. (2018). Deep learning architecture for high-level feature generation using a stacked autoencoder for business intelligence. In *Complex systems: solutions and challenges in economics, management and engineering* (pp. 269-283). Springer, Cham.
- [13] Canhoto, A. I., & Clear, F. (2020). Artificial intelligence and machine learning as business tools: A framework for diagnosing value destruction potential. *Business Horizons*, 63(2), 183-193.
- [14] Baştanlar, Y., & Özuysal, M. (2014). Introduction to machine learning. *miRNomics: MicroRNA Biology and Computational Analysis*, 105-128.

- [15] Sharma, V., Rai, S., & Dev, A. (2012). A comprehensive study of artificial neural networks. *International Journal of Advanced research in computer science and software engineering*, 2(10).
- [16] Jakkula, V. (2006). Tutorial on support vector machine (svm). School of EECS, Washington State University, 37.
- [17] Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS quarterly*, 1165-1188.
- [18] Dean, J. (2014). *Big data, data mining, and machine learning: value creation for business leaders and practitioners*. John Wiley & Sons.
- [19] Kratsch, W., Manderscheid, J., Röglinger, M., & Seyfried, J. (2020). Machine learning in business process monitoring: a comparison of deep learning and classical approaches used for outcome prediction. *Business & Information Systems Engineering*, 1-16.
- [20] Saura, J. R., & Bennett, D. R. (2019). A three-stage method for data text mining: Using UGC in business intelligence analysis. *Symmetry*, 11(4), 519.
- [21] Tavera Romero, C. A., Ortiz, J. H., Khalaf, O. I., & R ós Prado, A. (2021). Business intelligence: business evolution after industry 4.0. *Sustainability*, 13(18), 10026.
- [22] Cvitaš, A. (2010, May). Information extraction in business intelligence systems. In *The 33rd International Convention MIPRO* (pp. 1278-1282). IEEE.
- [23] Rokach, L., & Maimon, O. (2005). Decision trees. In *Data mining and knowledge discovery handbook* (pp. 165-192). Springer, Boston, MA.
- [24] Yan, K., & Shi, C. (2010). Prediction of elastic modulus of normal and high strength concrete by support vector machine. *Construction and building materials*, 24(8), 1479-1485.

Authors' Profiles



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