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Research Article

Bi-objective sales planning using machine learning for industrial valves

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Abstract

Accurate prediction and forecasting of industrial products' consumption, enables up-to-date and efficient supply, replacement of worn-out items, and prevention of resource wastage. Planning and forecasting the usage of industrial products can help often based on historical years' performance and environmental factors, using either traditional methods or smart systems. However, the instability of some sales behavior in certain products and the lack of previous data for new products or sales offices can create problems in intelligent systems. In this paper, we present a hybrid and bi-objective model in the form of a business intelligence system that first fits an appropriate function to the products, providing a new estimated combination for the type and sales amount of all products, while taking into account the profit margin. This new intelligent system allows for flexible planning for the company, generating a special scenario for each new input strategy.

Furthermore, using machine learning and based on similarity measurements and the company's previous data, we predict the sales behavior for new products and sales offices in their first year of operation. Finally, the model announces the sales trend of each product in different time periods, separately for each sales office, taking into account the previous two stages. The current investigation outlines the integration of the proposed model into the business intelligence system of Mirab Valves Company, a reputable manufacturer of industrial valves, and its subsequent effective application as an exemplar. The model's efficacy in forecasting sales of new products and sales offices is established at 79% and 92%, respectively.

Introduction

Intelligence, speed, and sharpness of the mind are often associated with machine learning, computers, and algorithms. However, problem-solving is also an essential component of intelligence. While the speed of the mind is critical in interacting with the ecosystem, more is expected from it in today's world. For businesses, quick processing of existing data, learning from previous data, and providing solutions and decision support systems are vital aspects of business intelligence. Expert suggestions and the ability to use Machine Learning (ML) and Extract Secret Knowledge (ESK) from available data are other essential expectations of a complete business intelligence system. The scope of these needs varies depending on the organization's extent.

These AI approaches can be used for industries related to the control of water resources and sustainable water management. This can be facilitated by implementing appropriate pricing mechanisms in water supply infrastructure and enhancing the efficiency of valve production.

Organizations often face challenges and inconsistencies when transitioning from traditional systems to new ones. Introducing new methods can be disruptive and may not yield positive results due to inconsistency with the system and resistance to change. The same is true for implementing

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business intelligence systems. To achieve good results, it is mandatory to have at least one expert from the field of application or industry desired by the employer in the business intelligence team. However, this may create contradictions in the results due to factors that are outside of the data behavior, such as relationships that govern the organization and cannot be found in previous data. The question arises, which traditional planning method should be used based on business intelligence? Should the expectations of the New Year be defined by increasing the growth factor of the previous year's budget or by applying the increase coefficients to the performance of the previous year? In stable organizations with integrated systems and fewer unexpected events, the focus is on discovering hidden knowledge in data. However, in organizations with special products and sales affected by environmental disturbances, traditional methods may be preferable. This article proposes a method that combines both possibilities and is particularly useful for organizations that use both methods at the same time.

This paper utilizes machine learning methods to analyze sales data for future planning and consider environmental factors and company policies. The artificial intelligence department is responsible for analyzing all sales details by product, sales manager, and time periods to identify patterns and trends. In cases where new expectations arise, such as the removal of a sales manager or the creation of a new branch or product, the lack of previous data is overcome through the use of machine learning. The most similar products are identified using classification algorithms, and sales modeling is conducted by calculating the profit margin of each product and applying the company's policies on price adjustments. The system's fitting function continuously does suggest new, quantities, and prices for each product, maximizing the total annual profit of the company. The main contribution of this research can be summarized as the successful application of machine learning algorithms to resolve the lack of previous data, while also continuously trying to optimize sales modeling to maximize the company's profit margin. In general, the main contributions can be addressed as follows:

- Modeling the sales process and planning it with details and separately by product, time period, and sales office
- Sales forecasting for new products and sales offices
- Providing a continuous linear function to influence the profit margin to determine the price of products to maximize the company's profit
- Providing different scenarios and flexible sales planning that models the organization's various strategies.

Literature review

As mentioned before, effective forecasting and planning of a company's sales volume and the future way can significantly affect production [1].

This issue has been addressed in too many articles, highlighting the significance of accurate sales forecasting and planning to maximize a company's total yearly profit margin [2,3]. It is also noted that such forecasting can have an effect on a company's modeling method [4,5]. and promote its marketing role.

Accurate forecasting and planning of sales not only maximize the company's total yearly profit but also increase the efficiency of logistics, supply chain, and manufacturing processes [6-8]. It can have a significant impact on customer satisfaction by enabling responsiveness to their needs [6]. While old methods have been used for a long time in sales forecasting or planning, this paper focuses on applying artificial intelligence-based methods to achieve the aforementioned values.

Numerous algorithms have been contributed to artificial intelligence and machine learning, that have been applied in different businesses with real data. Some of these algorithms and methods, which are related to the topic of this paper, are addressed in [9]. In recent years, the use of AI algorithms for sales forecasting and planning has become increasingly important, as evidenced by the increasing trend of scientific articles in this field. For example [10], explains one of the common algorithms called CART, which uses AI for sales planning and forecasting.

In [11], financial planning and forecasting methods for the oil and gas industry have been investigated. This research employs advanced statistical techniques, historical data analysis, and industry-specific indicators to predict market trends, optimize budget allocation, and enhance financial decision-making processes.

Moreover [12] analyzed sales data using artificial neural networks for ten years and found them to be very effective in predicting sales. Another study by [13] used artificial neural networks to forecast sales during time windows, such as seasonal data.

In [14], researchers investigated the relationship between data science techniques and business planning. The article explores the application of big data analytics and budget modeling, highlighting the crucial role of data science in enhancing business strategies and financial planning processes.

In another study, B2B sales forecasting in the spare parts sector of an after-sales service provider was investigated using supervised machine learning techniques. This research focused on implementing advanced algorithms to predict sales patterns, emphasizing the practical application of machine learning in business forecasting [15].

Also, in [16], an enhanced Sales and Operations Planning (S&OP) with Artificial Intelligence in an Engineer-to-Order (ETO) structure has been explored. This article investigates sub-areas of the S&OP process in ETO environments and leverages Artificial Intelligence, specifically Machine Learning (ML), to optimize planning efforts and align the dimensions of the company effectively.

In [17], a comparative analysis method was used to compare the performance of conventional sales forecasting and machine learning-based sales forecasting in selected industries. The

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results indicate that the use of machine learning-based sales forecasting has higher accuracy and precision compared to conventional methods.

In [18], AI was used to plan sales for women's clothing, by considering sales behavior during all seasons. Additionally, [19] developed a hybrid machine learning method to predict product sales in a store, allowing for quick replacement of sold goods to maintain optimum inventory and capital levels.

In a study by Au [20], various neural networks were explored for sales planning and forecasting, and the method's effectiveness was demonstrated. Pan [21] suggested another combined approach called EMDNN, which uses past experiences and ANN simultaneously to forecast sales. This method was found to be more efficient than previous neural networks and experimental methods. Dwivedi [22] compared different methods, including the ANN method, linear regression model, fuzzy neural modeling, and ANFIS (Fuzzy Inference System Based on Adaptive Network), and found that ANFIS was the most reliable method for sales forecasting.

Sajawal et al. [23] uses machine learning techniques to forecast retail sales by collecting sales data and training a model to predict future sales, which can improve production planning, inventory management, resource allocation, and business performance while reducing costs.

Aye [24], compared the performance of 26 different models (ARIMA, ANN, etc.) for forecasting seasonal sales in South Africa and showed that the nonlinear ANN model performed better than other models. Ramos [25] also compared various artificial intelligence and learning-based methods for predicting sales of women's footwear products and reported their results. Kolassa [26] used discrete predictive distributions to forecast daily sales, while Ma [27] presented a four-step method for predicting stock sales that demonstrated good progress in forecasting sales.

Uncertain and probable data is also, a fundamental aspect of real-world models. Researchers often prioritize these types of data. Data Envelopment Analysis (DEA) is a method frequently used to rank suppliers, aiding in better decision-making when selecting them. Zahedi-Seresht, et al. [28,29] have proposed a methodology combining the Monte Carlo Method, DEA, and Multi-Criteria Decision-Making (MADM) methods. This approach aims to handle uncertain data by using simulations, evaluate supplier efficiency through DEA, and improve decision-making via MADM techniques. This integrated approach offers a more comprehensive framework for dealing with uncertain data, assessing supplier efficiency, and making informed decisions in supplier selection processes. The effectiveness of these methods depends on the specific context and the quality of the data used.

In the upcoming section of this paper, we will introduce machine learning. Specifically, the Sales Planning Model section will discuss the general aspects of sales planning and forecasting and will explore machine learning methods and problem-solving approaches while presenting the model. In the Implementation section, we will present computer programs' experimental results and output. The Final section will summarize the topics covered and introduce avenues for future research to interested readers.

Machine learning

Machine learning is a technique where, instead of programming and making decisions for every situation, a general algorithm is fed with data, and it builds its logic based on the given data. There are various methods in machine learning, including supervised learning, unsupervised learning, and reinforcement learning.

Supervised learning is a type of machine learning where both the input and output are specified, and an observer provides information to the learner. In this method, each pattern has a label, which is the desired output of that pattern. This label is properly prepared by an expert, and it is used to train the algorithm so that the machine can learn from the expert's experiences. The aim of this method is to learn a function that maps input patterns, also known as feature vectors, to their corresponding labels or classes. This process involves both training and testing phases where the machine is tested as a learner. In the testing phase, the system is given patterns whose labels are unknown, and the system predicts their output or labels using a learned function. If the learning system is discrete, it is called a classification problem, and the mapping function to the output is referred to as the classifier.

Decision trees are one of the most commonly used rule-based supervised algorithms in machine learning for both classification and regression problems. The decision tree structure generates antecedents expressed in the form of a series of rules. Each path from the root to a leaf of the decision tree represents a rule, and the leaf is labeled with the class to which the largest number of records belongs (Figure 1). Decision trees are used to partition the input space into regions based on the input features, and then assign a class or regression value to each resulting region.

The decision tree algorithm can predict both quantitative and qualitative variables and attempts to minimize the diversity of nodes. The heterogeneity of nodes is evaluated using impurity criteria, with the most commonly used measure

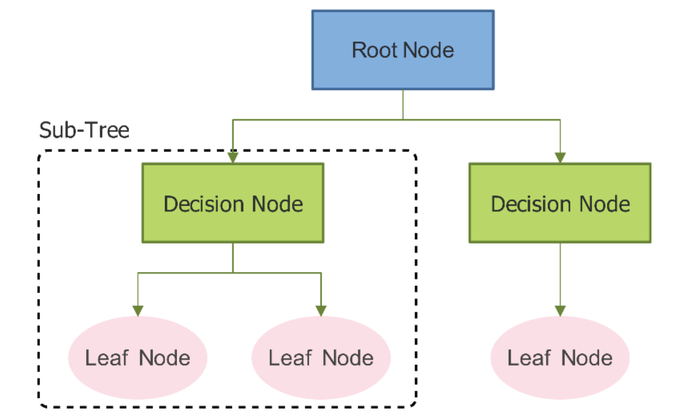

Figure 1: The structure of a decision tree.

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being the Gini index. There are various decision tree algorithms available, differing in how they measure impurity, branch, and prune tree nodes. Examples of these algorithms include MARS, CHAID, CART, C4.5, and ID3.

CART algorithm

The CART algorithm, presented by [1], creates binary trees in such a way that two branches are removed from each internal node. The obtained trees are pruned by the Gini index. Equation 1 shows how to calculate the index.

$$Gini\left(X\right)=1-\sum_{i=1}^{n} p_i^2, \tag{1}$$

Where p_i is the probability that a sample in a subset of X belongs to class i and n is the number of classes. The Gini index considers a binary distribution (X_1, X_2) for each feature F_j. Therefore, according to this division, the Gini index is expressed as the total weight of impurity of each part according to Equation 2.

$$Gini_F\left(X\right)=\frac{X_1}{X}Gini\left(X_1\right)+\frac{X_2}{X}Gini\left(X_2\right), \tag{2}$$

Where X_1 and X_2 are the subsets obtained from dividing the original set X using the feature F_j, and X is the total number of samples in X. The amount of impurity reduction is also calculated from the following equation.

$$\Delta Gini\left(F\right)=Gini\left(X\right)-Gini_F\left(X\right), \tag{3}$$

Therefore, the subset that obtains the minimum Gini index for feature F is selected as its dividing subset. The Gini index considers the degree of impurity of a feature compared to classes. The lower the value obtained in this index, the better the result, as higher impurity corresponds to higher irregularity.

First, the decision tree is built using a top-down method, and in the next step, the branches of the tree will be removed by using a pruning algorithm. The purpose of pruning is to reduce the height of the tree to prevent overfitting and remove noisy data. Pruning involves removing branches from the tree that have branched off from less important features. This method reduces the complexity of the tree and increases the predictive power of the model. Pruning can be applied in two ways: post-pruning and pre-pruning and can start from either roots or leaves.

Pre-pruning: In this method, pruning is performed before the complete construction of the tree. The tree that is growing is not allowed to grow too much, as continued growth increases the probability of overfitting.

Post-pruning: In this method of pruning, the tree is fully grown before pruning begins. The pruning operation starts from the bottom of the tree or the leaves and works towards the root by turning a series of middle nodes into leaves. This method of pruning is a little slower than pre-pruning, but it is more accurate. To avoid overfitting, the maximum depth limit (Max-depth) or the split limit (Min-Sample-split) can be used.

In order to choose the best feature at each node, it is necessary to pay attention to the degree of purity in the distribution of records based on classes. The branch that increases the data purity the most is the best branch, and the desired node is placed at the root of the tree. The Gini criterion is used in this article for purity measurement. Determining the stopping condition is also one of the most important issues in recursive algorithms. The stopping conditions in different applications are diverse. In this article, the condition of reaching the maximum allowed depth of the tree is used as the stopping condition.

Evaluation of the classification algorithm

When a classifier is built, measuring its accuracy is of great importance. To measure the accuracy of a classifier, it is better to use test data (usually 20% to 30% of the data set). After building the model on the training data, the accuracy of the model in determining the class label of the samples on the test data can be calculated using the following equation:

$$Accuarcy=\frac{TP+TN}{TP+TN+FP+FN}, \tag{4}$$

Where:

TN (number of true negatives): the number of records whose real category is negative and the algorithm correctly recognized them as negative.

TP (number of true positives): the number of records whose real category is positive and the algorithm correctly recognized them as positive.

FP (number of false positives): the number of records whose true category is negative, but the algorithm mistakenly recognized them as positive.

FN (number of false negatives): the number of records whose real category is positive, but the algorithm has mistakenly recognized them as negative.

For some applications, there are other accuracy evaluation criteria that are not considered in this article, and therefore, for the sake of brevity, their introduction is omitted. According to the calculations performed on the real data set, the method introduced in the next section has an accuracy of 79% for the new product and 92% for the new sales office, both of which are reliable in the industrial beverage industry. It can be used directly in sales planning. In the next section, the details of the method are discussed.

Sales planning model

This section presents a method that is in accordance with the real behavior of an organization, specifically Mirab Company. The method has two types of inputs. The first type of data is related to previous years, including information about products, sales offices, and all other relevant details. The second type of data comes from the organization itself and includes information about new products or sales offices, as well as any new policies. It is important to note that due to the confidentiality of the data, the values have been changed or the names have been anonymized.

The general model of the business intelligence system for budgeting and calculating the monthly sales plan follows (Figure 2). First, some manual adjustments are made by the management, by considering the features of the New Year and special restrictions. These adjustments may be by considering the creation of new branches, integration of some activities, design, and production of a new product or removal of a product, new national policies or new export facilities and restrictions, etc.

Entering new information: At the beginning of using the system, new information is provided to it. This information may pertain to the removal of a product in the new year, the addition of a new product, changes to the representatives and sales offices, fundamental changes in the costs and policies of the company, as well as external factors such as unusual increases in wages, the continuation or lifting of sanctions, and new export licenses, among others. These various pieces of information are not provided to the system separately, and initially, only an estimate of them is given to the system in the form of forecasted prices and volumes of future sales.

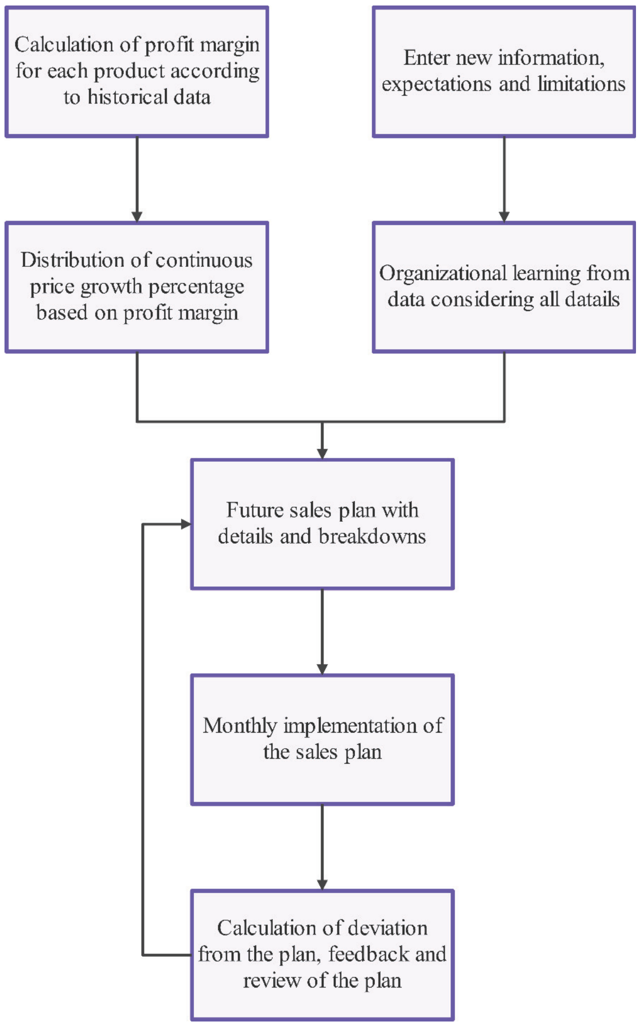

Figure 2: General sales planning model.

Organizational learning from data: Learning from the previous year's sales data, especially the budget year, is one of the most important steps included in the system. By separating all the effective components in the sales process (product, product family, and sales manager), it is possible to extract data from the current year and model the previous behavior and performance of each customer. This conclusion is not only about the total annual sales and the knowledge; it also includes the sales behavior of each product. The function that the sales of a particular product follow throughout the year is the result of this part of the system. The learning system at this stage learns the sales details and the patterns hidden in the data and uses them in the planning of the coming year. The system includes answers to questions such as the following questions in the planning:

- What pattern does a particular product follow throughout the year? The sales pattern of product A may be different from the sales pattern of product B in different months of the year, and the learning system considers these behaviors and the sales volume of each product separately in forecasting and planning.
- What kind of pattern does a particular sales manager use in terms of sales time? If the way of interaction of a particular sales manager or the type of customers is such that, for example, they are able to sell more at the end of the hot season of the year, the new planning system learns and uses this behavior for that particular sales manager, and it is natural that the system learns a different behavior for each customer.
- According to old data, this system learns the possibility of changing sales rates, discounts, the behavior of sales representatives, etc., in detail, and includes them in its final planning models.

To calculate the profit margin, the system considers the cost of production for each product and subtracts it from the sale price. The difference between the selling price and the cost of production is the gross profit for the product. Then, the system takes into account indirect costs such as overhead expenses, taxes, and other expenses that are not directly related to the production of a particular product. By finding the gap between these costs from the gross profit, the system calculates the net profit margin will be concluded. The system also analyzes the sales data to identify the products that have the potential to increase their profit margin by adjusting their prices or reducing their production costs. By considering the profit margins of each product and the overall sales volume, the system optimizes the price and quantity of each product to achieve the highest possible profit margin while maintaining a balance in the product portfolio.

Calculating the Percent of growth and continuous decrease in price: Increasing the price of products by a constant factor in time intervals is different from the simplest common decisions. But more right methods lead to more profit for the organization and do not induce a large increase in prices to customers are the methods in which the price of the number of products with

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a higher profit margin is increased more than normal, and on the other hand, the price of the same number of products with the lowest margin is increased. The profit increases slightly or the price even decreases.

In the proposed model, the step is taken further and the percentage of price change is continuous and proportional to the profit margin of each product. In this method, if the average price increase of the $GR = \%\alpha$ budget year (for example 20 percent), the profit margin of the *i'th* product is equal to P_i and the average profit margin of all products is equal to P_{mean}, then the price increase of each product is calculated as follows:

$$GR_i = \left(\frac{P_i}{P_{mean}}\right) \times GR \quad (5)$$

In this regard P_{mean}, is obtained in a weighted manner and includes the volume and amount of sales as a weight along with the profit margin. With this method, we can be sure that in the end, the increase in the total sales budget will be the same amount as $GR = \%\alpha$. In this way, there is no need to group products and discrete behavior between them, and each product will have a special increase or decrease percentage individually. Therefore, this method can be called the continuous method.

The future sales plan: After incorporating feedback from unit performance and receiving information from management, the organization undergoes a process of continuous price optimization. As a result, the product pricing offer and the company's sales budget are calculated. Sales managers, product families, and individual products can be examined in detail at every step of the process. This budget calculation method takes into account possible problems from previous years and places greater weight on the company's previous sales performance than other factors. Additionally, upstream information is used to make predictions about events that have not yet been recorded in the system.

In the stage of learning the monthly sales behavior and entering into the calculation of the company's monthly sales plan, it is avoided to divide the budget by the number of working months. Because the sales behavior of the company is different in different months. At this stage, even the constant increase of the learning rate in different months is not implemented, and in the proposed method, the budget is determined for different months, exactly according to the previous behavior of the company and using the partial information of product sales. It is possible that product A had the highest sales in the months of June, July, and February in the past years. Suppose that product B had the highest sales every year in the last four months of the year. All these behaviors are learned by the system from the data of the past years and separated by month. For example, you can understand the percentage of sales of a certain product in different months based on the data of the last three years separated by month. These ratios, along with the calculated sales volume and budget, determine the expected sales volume for that product each month.

Monthly implementation of the program: The actual sales data for every single month are chosen and compared with the expected sales volume found by the system. Any gap between the expected sales volume is analyzed and the reasons for this gap are found. The system also monitors the sales performance of each sales manager and product family each month and makes reports to the management team. This feedback helps the manager to identify the strengths and weaknesses of the sales team and take appropriate actions if needed. The system also creates reports and dashboards to provide an overview of the sales performance of the company, which helps the management to make appropriate decisions about the future direction of the sales of the company.

Calculation of program deviation and providing feedback: The final stage of the system involves calculating the deviation of the implemented monthly sales plan from the actual performance and providing feedback for future planning. This review can be conducted dynamically at the end of every month or at longer intervals of three months to establish stability in the program and measurement indicators. The outcome of this review can update the plan for the coming months by utilizing the knowledge obtained through learning from the previous data.

Implementation and results

The used data set in this paper is related to the sales records of a recent year, which includes 1000 samples, based on the previous year's sales of Mirab company (including name, price, and profit margin of products, sales office, Date, and etc). In Figure 3, the planned budget by month can be displayed as follows. In which the column charts from left to right are related to the planned budget for the New Year and the sales for the last year. One of the features of this method is that you can present this diagram in any detail. The same chart can be drawn exactly for each sales office or for a specific product. However, due to the special nature of the products, calculating detailed forecasts does not seem logical. If the same method is implemented in the case of another commercial company that has popular and popular products, it would be reasonable for the new method to provide its prediction even for questions such as "product *X* that will be sold by sales office *Y* in month *Z*".

In the next part, we use the CART decision tree algorithm to predict the sales budget of new products. The data set used for this purpose includes 229 samples with four attributes, namely "price", "size", "pressure" and "weight", and is categorized into 6 classes based on sales office and product. To account for the difference in the unit of each feature, the data has been normalized in the interval between zero and one. Similarly, the same normalization operation has been performed on the data set of the sales office, which includes 150 samples with three attributes, namely "sales office size", "sales office", and "sales product", and is categorized into two classes. The decision tree algorithm has been implemented with a maximum of three levels and the Gini index on the product data set. The output of this algorithm is shown in Figure 4, where the price feature has been identified as the root node and the main distinguishing feature.

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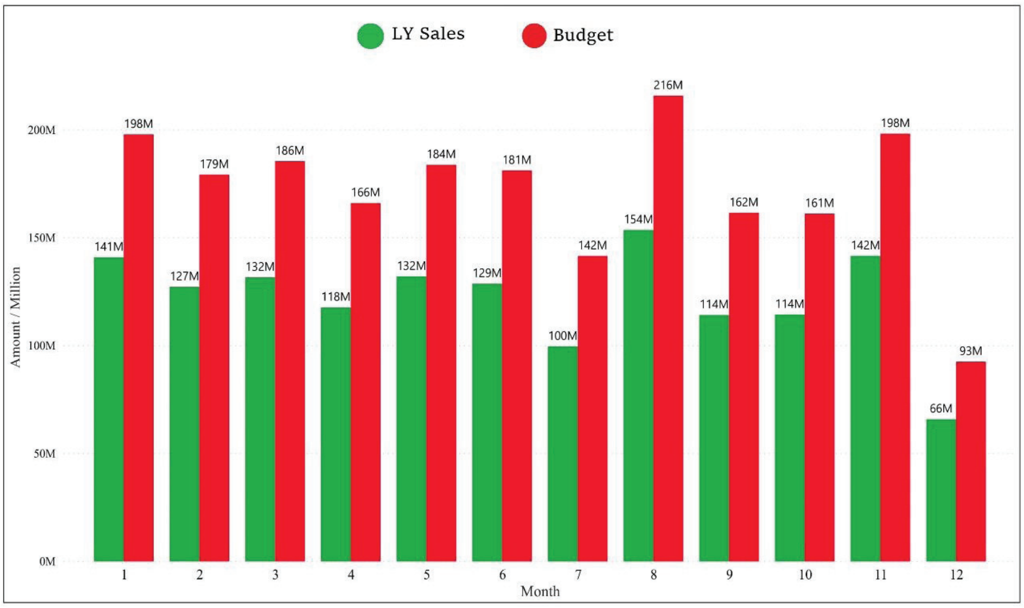

Figure 3: Right: planning budget, left: last year's sales (LY Sales).

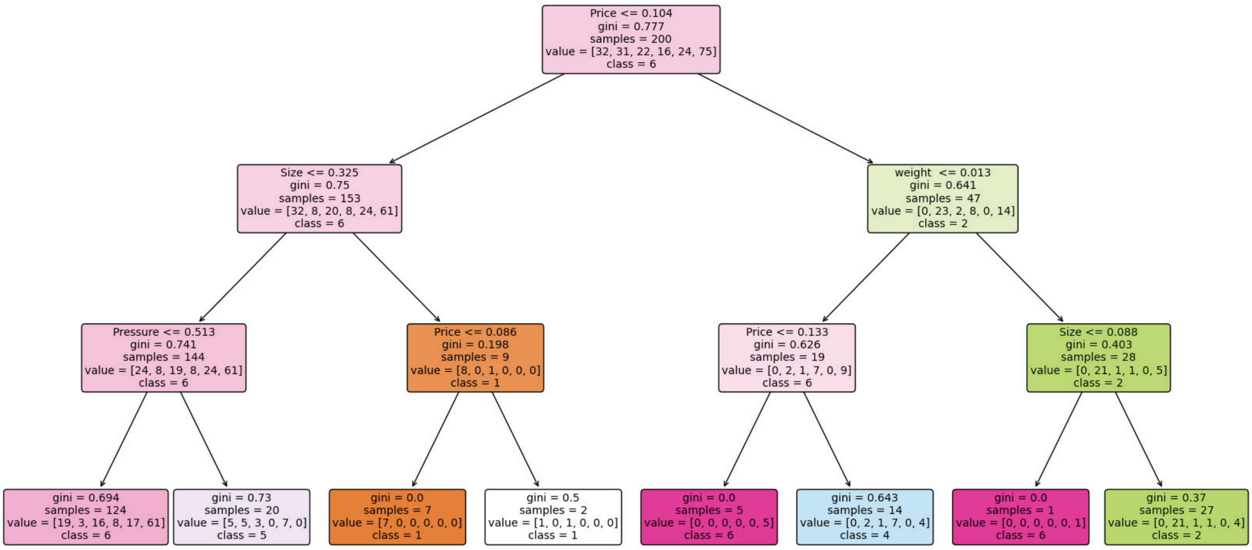

Figure 4: The output of the decision tree algorithm with three levels to classify products.

To assess the model's performance and efficiency, we used the accuracy metric and compared the results on both the product and sales office data sets against their training and test sets respectively. Table 1 summarizes the findings.

Table 1: Accuracy of the proposed method on training and test data in two new product and sales office data sets.

Dataset		Accuracy (%)
Product	Train Data	81
	Test Data	79
Sales Office	Train Data	93
	Test Data	92

Conclusion and future work

In this article, we combined machine learning methods and the profit margin of products, along with the company's historical data, to estimate the type and sales amount of products in Mirab company. This estimation is the result of a continuous linear function that ended up increasing the company's profit margin. Moreover, we contributed a model that predicts the sales behavior of new products and sales offices using both machine learning methods and data classification. The model uses the similarity of new data (product or sales office) with the company's past data. Eventually, we mixed the previous two stages and used modeling to present the sales process of each product in different time windows, for each sales office separately. This method allows us to monitor

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the difference between the plan and goal at all times for all parts of the company's sales. We proposed the model using the company's three-year sales data and the present study reports the accuracy of a novel machine learning-based approach for predicting the performance of a new product and sales office, yielding success rates of 79% and 92% respectively. These results are deemed satisfactory within the context of valve companies.

As a future direction, it is recommended to incorporate other additional factors such as inflation rates into the machine learning model. The same approach can also be applied to other areas such as procurement, inventory, logistics, and supply chain management, where it can be utilized to prepare purchasing plans for various time windows.

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