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Management Decision Making in a Retail Establishment Using Machine Learning Methods

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ABSTRACT

Management decisions about store atmosphere, such as temperature, or light intensity in retail establishments can be made based on solutions from machine learning methods. These conditions determine whether the customer will stay in the store longer and whether his shopping cart will reach the desired high value. Previous literature research associates certain atmospheric factors with customers' propensity to make purchasing decisions and allows us to identify what influences the customer during shopping and to what extent. The article aims to reveal the feasibility of using machine learning methods to make management decisions based on store atmosphere parameters. When deciding on the conditions in a retail establishment, applicable health and safety regulations should also be considered. This was used to set limits on the input parameters for the model. The authors identified 3 atmospheric factors and, based on them, proposed two types of models: regression and classification models, predicting how long customers stay in an establishment and can classify it into categories: short, medium and long. These models can then be used to create a model that optimizes the parameters in the facility to achieve a minimum given time a customer stays in the facility.

Keywords: machine learning, neural network, decision trees, support vector machines, decision making, customer.

INTRODUCTION

Managing a retail establishment, especially one such as a large-format store or a shopping mall, requires making many decisions daily. Owners and managers of such establishments can encourage customers to purchase through various means. In 1986, Baker believed that the design of a business environment could create a unique emotional impact in customers' minds and increase purchasing opportunities. He distinguished, among other things, ambient cues, i.e., environmental conditions potentially affecting customers, such as attributes of temperature, music, noise and lighting [1]. Also Utami in 2010 suggested store atmosphere is the character of the state of the store, such as architecture, layout, markers, displays, colours, lighting, temperature, music and aromas, which as a whole will create an image in the minds of consumers [2]. It was found that there is a correlation between three elements in a customer's purchase decision: commitment, mood, and the experience of purchasing goods. The store atmosphere in a retail establishment affects the customer's mood. Foremost, it can affect their experience of purchasing goods in the store, their expenditure levels, the time and frequency of the customer's stay at the point of sale, or their evaluation of the information available there [3]. The conditions in the store can therefore multi-channelly inspire the customer to make purchasing decisions and stay in the store.

Inspiring customers allows retailers to increase purchase intention and customer loyalty. Customers employ multiple channels for shopping, and they can be inspired to buy products both online and offline throughout the customer journey [4]. With the appropriate conditions in the retail establishment (such as temperature), customers may decide to stay longer or shorter. The duration of a customer's stays in an establishment is directly related to the quality and quantity of their purchasing decisions.

Shopping malls and large-format stores care about customer retention for as long as possible. This is important, especially at a time when online shopping is displacing traditional forms of purchasing goods. For example, research conducted in 2024 after the Covid-19 pandemic reveals that perceived usefulness, consumer psychology, ease of payment, budget considerations, health issues, and cultural and traditional values significantly and positively impact the e-shopping behavioral intention of consumers. However, product variety does not significantly influence the e-shopping behavioral intention [5]. In 2020, as lockdowns forced consumers to move much of their spending online, a golden age for e-commerce appeared to be dawning [6]. Nevertheless, it can be concluded that customers are just as likely to use offline stores, and it is necessary to ensure their loyalty and appropriately attract them to these establishments. The advantage of offline over online shopping is provided by sensory marketing.

The atmospheric parameters adopted precisely refer to the theory of this marketing. Sensory marketing, also known as five senses marketing, is a concept based on: hearing, taste, sight, smell and touch [7]. The issue of sensory marketing is a relatively new concept in management science [8]. The human perception and subjectivity factor is emerging in companies' business strategies through sensory marketing. Sensory marketing mainly focuses on customer experience. Sensory marketing addresses the individual customer receiving "sensory" messages, and the premise of sensory marketing is to experience the product with all the senses, this experience should be understood holistically [9].

The first of the senses, mentioned in sensory marketing theory, forces retail establishments to select music appropriately in terms of sound volume and frequency. Properly selected music for the target group can influence the emotions of the viewer especially the positive ones, which help to make a purchase decision more effectively and quickly. Sound art also complements the range of emotional experiences used in sensory marketing [10]. The lowest audible sound intensity level, or the quietest sound a person can hear, is 0 dB. A sound intensity of 50 dB is pleasant for humans, 100 dB is considered the pleasure threshold, and 120 dB is the pain threshold [11]. Therefore, for this study's purposes, the assumption is that sound in a retail establishment for the customer's comfort should be between 50–100 dB. The literature also notes that sound frequency is important for purchasing decisions. [12]. A healthy person can hear sounds between 20 and 20.000 Hz. The 2.000 to 5.000 Hz range causes the cerebral cortex along with the amygdala to interact. When the cortex processes exactly this range, the amygdala body heightens our perception of sound, which is perceived as a danger warning. As a result, sounds become unpleasant for humans [11]. For this reason, these frequencies should be avoided in a commercial establishment.

The temperature has almost no impact on the consumer's purchase intention [13]. Madjid in 2014 explains that the store atmosphere has a significant effect on customer emotions and decisions, there for customer emotions have a significant effect on purchase decisions. Customer emotions act as partial mediating the relationship between the store atmospheres on purchase decisions [14]. Regarding the temperature in the retail establishment, different sources indicate various (although similar) ranges for the ideal temperature. For example, based on recommendations from the Occupational Safety and Health Administration (OSHA), the ideal indoor work environment is between 68 and 76 degrees Fahrenheit [15] which corresponds to 20 to 24.5 degrees Celsius. There are no specific provisions in Polish regulations on the amount of temperature that should be provided in grocery stores, etc. However, considering the Ordinance of the Minister of Labor and Social Policy of September 26, 1997 [16] on general occupational safety and health regulations (as amended), certain limits should not be exceeded. The temperature should not be lower than 18 degrees and should not exceed 24 degrees according to the mentioned Regulation. Furthermore, the work premises should be provided with a temperature appropriate to the type of work being performed. It has been assumed that a temperature too high can fatigue the customer, and for this reason, it has been decided to adopt a temperature range of 18–22 degrees Celsius as desirable in these considerations.

The quality of intangible elements related to the service provision in a retail establishment has already been a research subject, for example, conducted by Pierański in 2011. He considered, among other things, whether the store has a pleasant smell, the store is properly lit, pleasant music is played, and the temperature in the establishment is appropriate [17]. This topic was also addressed in the context of sensory merchandising by Zalewska in 2014. She emphasized that the perception of sensory impressions reaching consumers in the store space has a significant impact on the perception of the establishment in their minds [3]. Research on this topic was also conducted in Canada in 2015. Research findings indicate that atmospheric variables such as cleanliness, scent, lighting, and display/layout have a positive influence on consumers' purchase intention; whereas music and colour have an insignificant impact on consumers' purchase intention [18]. The temperature has almost no impact on the purchase intention of the consumers. These results were questioned by noting that temperature does matter [19]. This was highlighted back in 2022 in research on the role of store atmosphere and product quality in consumer decision-making [20]. However, this topic has not been addressed in the context of the possibility of using machine learning methods. Therefore, the article's authors adopted the goal of demonstrating the applicability of machine learning methods to make management decisions based on the parameters of the atmosphere in a retail establishment.

Machine learning is included in the scope of artificial intelligence (AI) issues. Machine learning (ML) is most often defined as an area of artificial intelligence devoted to algorithms that improve automatically through experience [21]. ML is deeply embedded in applied statistics, but the purpose of the two methods is different. While ML models are designed to make the most accurate predictions, statistical models are used to infer variables and determine relationships between them [22]. Machine learning models have demonstrated great success in learning complex patterns that enable them to make predictions about unobserved data [23]. Therefore, machine learning methods are quite versatile and can be used in many fields, for example, the application of ML tools and data-driven modelling became a standard approach for solving many problems in exploration geology and contributed to the discovery of new reservoirs [24]. It is also helpful in medicine, as described by Chen with co-authors proposing a new convolutional neural network based multimodal disease risk prediction (CNN-MDRP) algorithm using structured and unstructured data from hospital [25]. ML also has applications in solving logistical problems such as blood distribution, as described by Abbasi et al. [26].

In the industrial sector, ML and AI techniques are increasingly used in production systems, particularly for enhancing quality control and optimizing manufacturing processes. For instance, in the production of candle oil cartridges, advanced ML models such as Support Vector Machine and Artificial Neural Networks have been shown to significantly improve quality control by accurately classifying product quality based on critical factors [27]. Similarly, in the burnishing process of shafts, ANN models have been employed to predict surface roughness, leading to optimized process parameters and improved product quality [28]. The domain of logistics and supply chain management (SCM) is not untouched by machine learning and artificial intelligence. These changes are dynamic and advancing at a rapid rate [29].

Artificial intelligence methods can also predict important environmental issues. This was described, among others, by example of prediction of river salinity, where through experimentation, they were able to identify the optimal neural network structure [30]. Moreover, machine learning has been applied in the optimization of material properties in various manufacturing processes. For example, deep neural networks have been developed to detect casting defects in automotive engine production, significantly enhancing the quality and reliability of manufacturing outputs [31]. Additionally, neural models have been used to optimize the properties of ceramic coatings applied via atmospheric plasma spraying, leading to advancements in material science [32, 33]. The impact of ML development on governance, health care and agriculture was described by Pallathadka with co-authors. They concluded that disease prediction, water irrigation optimization, sales growth, profit maximization, sales forecast, inventory management, security, fraud detection, and portfolio management are some of the major uses [34]. For these reasons, the authors of this article also decided to use machine learning to solve management problems.

The main goal of this study is to scientifically justify and explore the feasibility and effectiveness of using machine learning methods to support management decisions based on atmospheric parameters in retail establishments. The research focuses on investigating how various atmospheric factors, such as temperature, sound level, and sound frequency, influence customer behavior, particularly in terms of dwell time and purchase decisions. To accomplish this, the study will develop and validate predictive models using machine learning techniques, including decision trees, support vector machines (SVM), and neural networks. These models are designed to predict and categorize customer dwell time based on analyzed atmospheric parameters. The ultimate goal is to provide actionable insights that can optimize retail management strategies to improve customer satisfaction, increase dwell time, and improve sales performance.

This paper is organized as follows: The introduction section highlights the importance of optimizing the store atmosphere in retail stores and explores the potential of machine learning methods in this context. The materials and methods section details the methods used, including the machine learning techniques and the data collection process. The results and discussion section presents the results of the regression and classification models used to predict customer dwell time based on atmospheric parameters, along with an analysis of the results and their practical applications in retail management. Finally, the conclusion summarizes the main findings and suggests possible directions for future research.

MATERIALS AND METHODS

For the conducted research, the authors proposed the use of machine learning methods including neural networks, support vector machines and decision trees, which were implemented in the Matlab environment, version 2023a. The authors considered two types of models - regression and classification models. Regression models were created to predict the time spent in a retail establishment (in minutes) and classification models to determine the average time spent in an establishment considering three ranges (short, medium and long).

The data collected came from 200 observations by the authors, who studied how long customers spent in the establishment under certain parameters of the store's atmosphere (temperature, volume and sound intensity). Observations were made on how the time for customers to spend in the establishment changed with different parameters creating the atmosphere in the store. The temperature in degrees Celsius, sound intensity in kHz and sound volumes in dB were considered. The observations concerned a large-scale shopping mall containing clothing stores and a discount grocery store. The observations describe all customers, not just those who made a purchase, as some left the mall very quickly, discouraged by the poor environmental conditions.

Temperature, sound (volume) and sound (frequency) were used as input parameters for both types of models. The initial parameter for the regression model was the shopping time, estimated based on these environmental parameters and measured in minutes. For the classification models, the average time spent in the facility was considered, categorized into three ranges: short, medium, and long. The research methodology is presented in two diagrams. The first diagram (Figure 1) is a flowchart that illustrates the steps taken in the study, starting from the definition of the research objectives and problem statement, through data collection and preprocessing, selection of machine learning models, to model training, validation, and performance evaluation. The second diagram (Figure 2) focuses on a key stage of the study, where machine learning methods

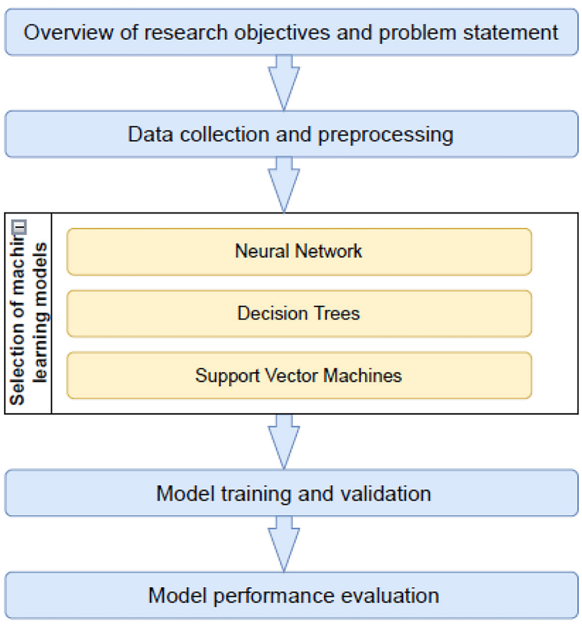


Figure 1. Flowchart of the research methodology

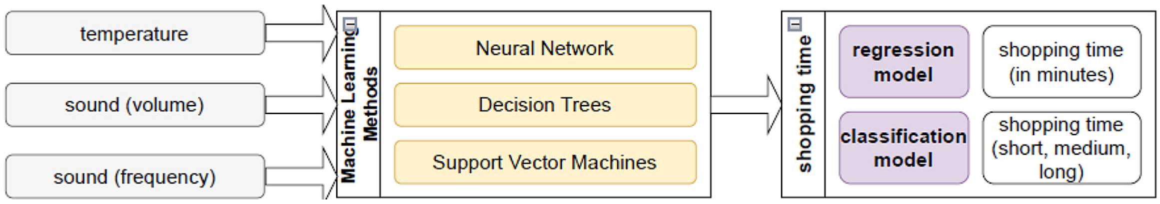


Figure 2. Flowchart of the process of analyzing environmental parameters using machine learning methods

(neural networks, decision trees, and support vector machines) are applied to process atmospheric parameters of the store, such as temperature, sound volume, and sound frequency.

The first method analyzed is decision trees, which are employed in data analysis for classification and regression tasks. They create a tree-like structure of decisions based on "if-then" rules to predict outcomes. In data mining, decision trees are valued for their simplicity and interpretability. They partition data into branches, assigning categories in classification trees and predicting numeric values in regression trees. Model building involves selecting the optimal splits for variables to enhance performance. The Gini coefficient is commonly used to measure dispersion within nodes, aiding in splitting data across dimensions into distinct sectors. This coefficient is calculated based on the conditional probability of each class within a node. The construction of decision tree models focuses on minimizing the mean squared error (MSE) to improve predictions. Critical parameters include setting the maximum tree depth and the minimum number of samples required at each node and leaf to prevent overfitting.

Optimal model settings are determined by experimenting with different configurations, varying the number of trees from 50 to 300 in increments of five. This systematic approach is applied to both regression and classification models. For regression models, the objective is to estimate the shopping time based on environmental parameters. The performance of each configuration is evaluated using MSE to ensure accurate predictions. For classification models, the goal is to categorize the average time spent in the facility into three ranges: short, medium, and long. The performance is assessed using accuracy as the primary metric, along with precision, recall, and F1 score for a comprehensive evaluation.

The second method analyzed is SVM, which are used for both regression and classification tasks in data analysis. SVM models are valued for their robustness and capability to handle high-dimensional data. This approach begins with loading and appropriately transforming the data. Care was taken to maintain the class proportions within each dataset, ensuring that the model training process was not biased towards any particular class. The method involves experimenting with different configurations of hyperparameters, specifically the regularization parameter and the kernel scale, to optimize model performance. These parameters are varied within a logarithmic range from 0.01 to 100 to ensure a comprehensive exploration of the parameter space.

For both regression and classification models, a systematic methodology is employed to determine the optimal hyperparameter settings. The regularization parameter, which controls the trade-off between achieving a low error on the training data and minimizing model complexity, is varied along with the kernel scale, which defines the influence of a single training example. These variations allow the model to adapt to different scales and complexities of the data. A 3-fold cross-validation is used to evaluate the performance of each configuration. This involves partitioning the data into three subsets, training the model on two subsets, and validating it on the remaining subset. This process is repeated three times, with each subset being used as the validation set once. Cross-validation provides a robust estimate of model performance and helps prevent overfitting. By systematically varying the regularization parameter and kernel scale, and using cross-validation to evaluate each configuration, the methodology ensures that the best possible SVM configuration is selected for both regression and classification tasks. This approach balances model complexity with performance, ensuring that the final model is both accurate and generalizable.

The last method analyzed was neural networks with a single hidden layer, where the number of neurons was varied from 6 to 20 to find the optimal balance between model complexity and performance. The dataset consisted of 200 observations, with 75% used for training and the remaining 25% for validation. Three learning algorithms were evaluated for their effectiveness: Levenberg-Marquardt (LM), Bayesian regularization (BR), and scaled conjugate gradient (SCG). SCG is memory-efficient and stops training when improvements cease. LM is fast but requires a significant amount of memory and halts training when no further improvement is observed. BR, although slower, offers superior generalization by adjusting to prevent overfitting. To avoid overfitting, which occurs when a model performs excellently on training data but poorly on new data, the training process was closely monitored. Training was stopped if there were six consecutive increases in validation error or if error rates stopped improving. This approach, known as "early stopping," is designed to halt training when the model's performance on validation data starts to decline.

The neural network models employed the same number of neurons for both regression and classification tasks. A 3-fold cross-validation was used to robustly assess model performance and prevent overfitting. The neural networks were trained using the Adam optimization algorithm, which is efficient and adaptive for such tasks. For each configuration, the performance was evaluated based on accuracy, and the configuration that resulted in the highest average accuracy across all folds was selected as the best model. This approach ensured that the final model achieved a balance between complexity and performance, providing accurate and generalizable results for both regression and classification tasks. The quality of the regression models was evaluated based on specific metrics listed in Table 1. The selection of quality indicators such as regression value (R), MSE, root mean squared error (RMSE), relative information entropy (RIE), mean absolute percentage error (MAPE), and mean absolute error (MAE) is crucial for assessing the performance of machine learning models. These metrics help quantify the accuracy and reliability of the models by measuring how close the predicted values are to the actual data points.

Regression value provides insight into the correlation between outputs and targets, offering a measure of how well the predicted values align with the actual values. Mean squared error evaluates the average squared difference between estimated and actual values, providing a measure of the overall prediction accuracy. Root mean squared error is the square root of MSE, which normalizes the error to the same units as the data, making it easier to interpret. Relative Information Entropy assesses the relative error in predictions, giving an idea of the model's consistency. Mean absolute percentage error measures the average magnitude of errors in predictions as a percentage, offering a normalized view of model precision. Mean absolute error measures the average magnitude of errors in predictions, offering a clear view of model precision.

These metrics were specifically chosen to predict shopping time, estimated based on environmental parameters in minutes. Evaluating shopping time requires a precise and reliable

Table 1. Quality indicators for evaluating the received regression models

Quality Indicator	Formula	Meaning of symbols
Regression value (R)	$R(y,y') = \frac{\operatorname{cov}(y,y')}{\sigma_y \sigma_{y'}}, \qquad R\epsilon < 0,1 >$	σ_y—standard deviation of reference values of the shopping time, $\sigma_{y'}$—standard deviation of predicted values the shopping time, y_i is the actual value of the shopping time, y'_i denotes the value of the shopping time for the i-th observation obtained from the model
Mean squared error (MSE)	$MSE = \frac{1}{n}\sum_{n=1}^{n}(y'_i - y_i)^2$	
Root mean squared error (RMSE)	$RMSE = \sqrt{\frac{1}{n}\sum_{n=1}^{n}(y'_i - y_i)^2}$	
Relative information entropy (RIE)	$RIE = \frac{\lVert y' - y \rVert}{\lVert y \rVert}$	
Mean absolute percentage error (MAPE)	$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{y_i - y'_i}{y_i}\right\rvert$	
Mean absolute error (MAE)	$MAE = = \frac{1}{N}\sum_{i=1}^{N}(\lvert y_i - y'_i\rvert)$	

model since the time customers spend shopping is influenced by various environmental factors. The use of these comprehensive metrics ensures that the model not only predicts accurately but also reliably under different conditions, providing valuable insights for optimizing shopping experiences and managing resources effectively. By analyzing these indicators, we can better understand the strengths and weaknesses of the model, ensuring that it provides meaningful and actionable predictions for shopping time.

The quality of the classification models was evaluated based on specific metrics that are crucial for assessing the performance of machine learning models. These metrics help quantify the accuracy and reliability of the models by measuring how well the predicted classes align with the actual data points. The selected quality indicators include Accuracy, Precision, Recall, F1 Score, and the Confusion Matrix (Table 2). The classification models were calibrated using a default threshold point of 0.5 for binary decisions within each class, which determined the assignment of observations to specific categories. This threshold was applied consistently across all models.

Accuracy measures the proportion of correct predictions out of the total number of predictions, providing a straightforward measure of the model's overall performance. Precision evaluates the number of true positive predictions made by the model relative to the total number of positive predictions, giving insight into the model's ability to avoid false positives. Recall assesses the number of true positive predictions relative to the actual number of positive instances in the dataset, indicating the model's effectiveness in identifying positive cases. The F1 Score, which is the harmonic mean of Precision and Recall, offers a balanced measure that accounts for both false positives and false negatives. The Confusion Matrix provides a detailed breakdown of the model's performance by showing the counts of true positive, true negative, false positive, and false negative predictions, enabling a deeper understanding of the model's strengths and weaknesses.

RESULTS AND DISCUSSION

Shopping time modelling - regression models

The first modelling method tested for predicting shopping time (estimated based on environmental parameters in minutes) employed decision trees. The number of trees varied from 50 to 300, increasing in increments of 5 trees. The optimal results for the decision tree model were achieved with 65 trees. Figure 3 illustrates the mean squared error (MSE) for different numbers of trees in the decision tree models.

The second modelling method tested for predicting shopping time utilized SVM. The optimal results for the SVM model were obtained with a Box Constraint of 100 and a Kernel Scale of 10 (Figure 4). The final method employed was neural networks. The most effective results in neural network modelling were achieved with a hidden layer comprising 16 neurons, as illustrated in Figure 5. Optimal outcomes were obtained using the Levenberg-Marquardt learning algorithm. The network's structure is depicted in Figure 6. The model reached its peak performance during the training phase at epoch 13, recording a performance metric of 290.7167, as detailed in Figure 7.

Figure 8 presents a comparison of three different predictive models used for estimating shopping time based on environmental parameters, measured in minutes. These results represent the performance of each model across the entire dataset. The models evaluated include a neural network model, decision trees, and SVM. Each subplot illustrates the correlation between the predicted and actual shopping times, alongside key performance metrics. In subplot (a), the neural

Table 2. Quality indicators for evaluating the received classification models

Quality indicator	Formula	Meaning of symbols
Accuracy	$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$	TP (true positives) – correctly predicted positive instances, TN (true negatives) – correctly predicted negative instances, FP (false positives) – incorrectly predicted positive instances (actual negatives), FN (false negatives) – incorrectly predicted negative instances (actual positives)
Precision	$Precision = \frac{TP}{TP + FP}$	
Recall	$Recall = \frac{TP}{TP + FN}$	
F1 Score	$F1\ Score = 2\frac{Precision \times Sensitivity}{Precision + Sensitivity}$	

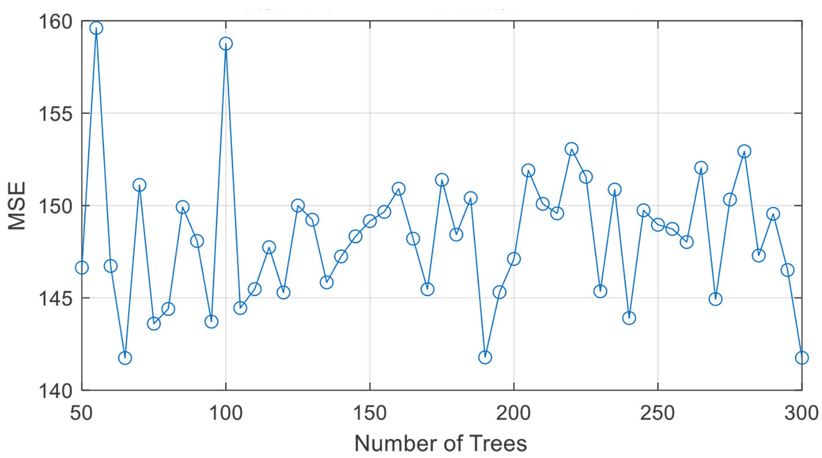


Figure 3. MSE as a function of the number of trees in a decision trees models for the regression model

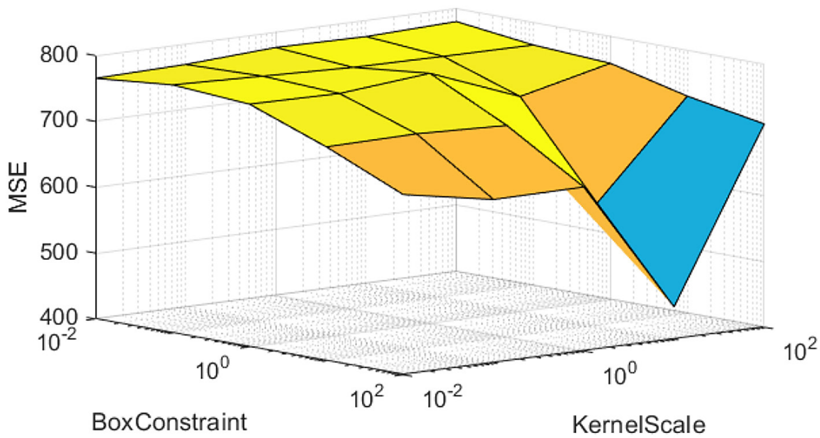


Figure 4. MSE as a function of the box constraint and kernel scale in a SVM models for the regression model

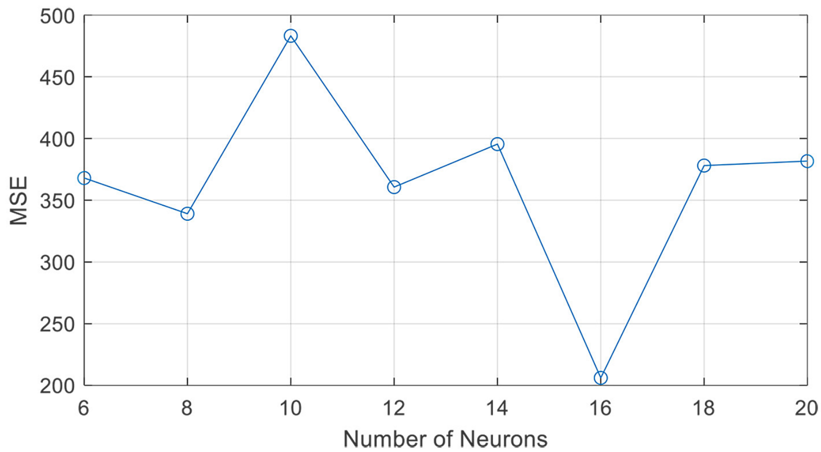


Figure 5. MSE as a function of the number of neurons in a neural network models for the regression model

network model shows a correlation coefficient (R) of 0.83122. The scatter plot depicts the actual shopping time (Target) against the predicted values (Output), with the blue line representing the best fit, indicating a strong relationship between predictions and actual values. Subplot (b) displays the performance of the decision tree model, which achieved the highest correlation coefficient (R) of 0.88171 among the three models. Subplot (c) illustrates the results from the SVM model, with a

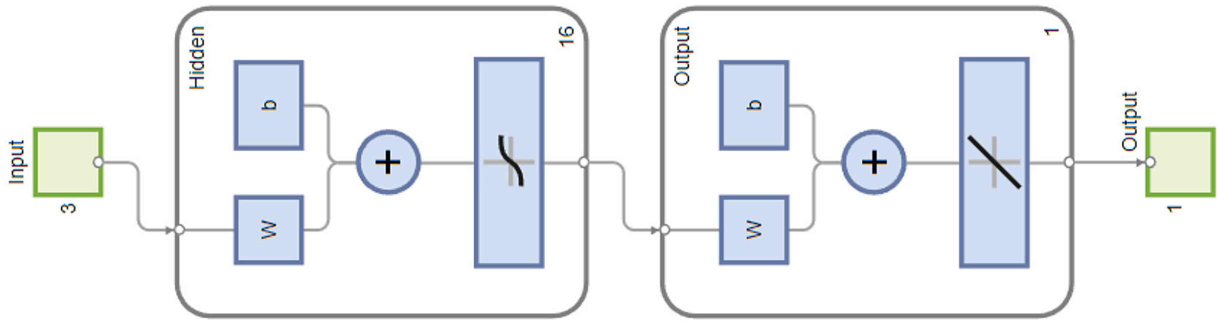


Figure 6. The structure of the best neural network with 16 neurons in hidden layer for the regression model

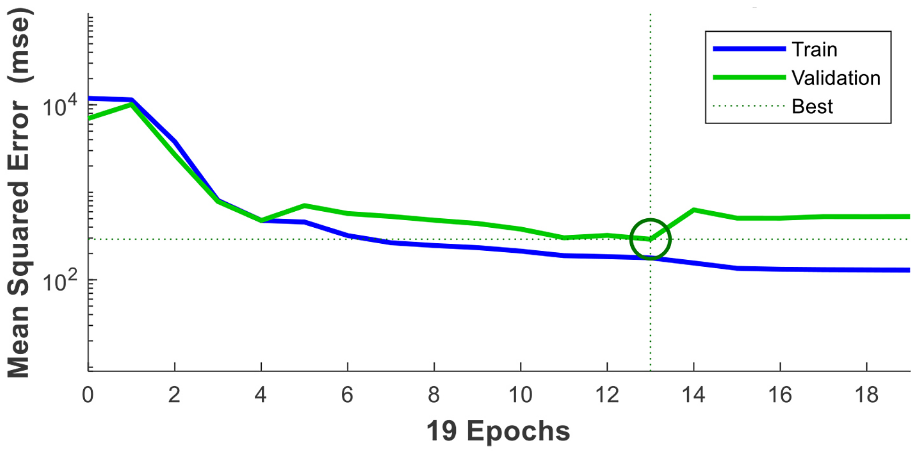


Figure 7. Best validation performance of the best neural network model for the regression model

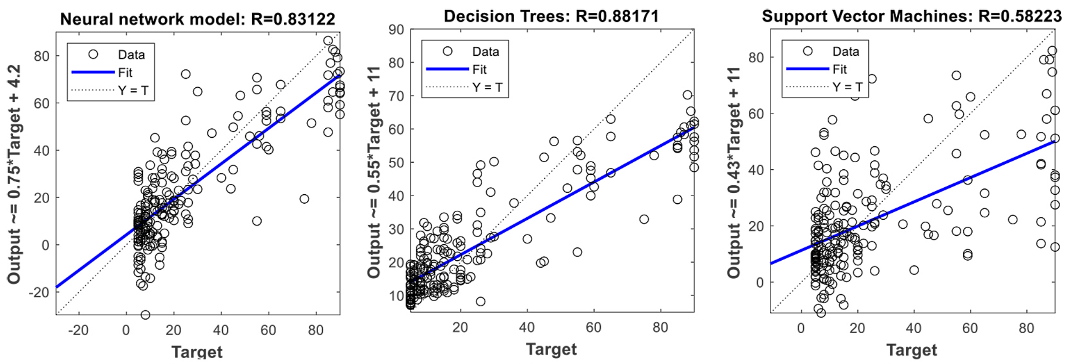


Figure 8. Comparison of the correlation coefficient and the strength of predictive models for shopping time for the regression model

correlation coefficient (R) of 0.58223. The scatter plot shows a weaker correlation between actual and predicted values compared to the other models, with the blue line representing the best fit.

Table 3 provides a comparative analysis of three predictive models – decision trees, SVM, and neural networks – based on their performance in estimating shopping time, measured in minutes. The performance metrics used for this comparison include the R, MSE, RMSE, RIE, MAPE, and MAE. The Decision Trees model demonstrates the highest correlation with actual values, indicated by an R value of 0.88171. It also achieves the lowest MSE (141.7459), RMSE (11.9057), RIE (0.3422), MAPE (0.5698), and MAE (8.6084), highlighting its superior performance in terms of both accuracy and precision. The Neural Network model shows a strong

Table 3. Comparative analysis of predictive model performance for shopping time

Quality Indicator	Decision trees	Support vector machines	Neural network
R	0.88171	0.58223	0.83122
MSE	141.7459	448.8921	206.1932
RMSE	11.9057	21.1871	14.3594
RIE	0.3422	0.6091	0.4128
MAPE	0.5698	0.9731	0.8208
MAE	8.6084	14.6572	10.7091

correlation as well, with an R value of 0.83122. However, it has higher MSE (206.1932) and RMSE (14.3594) compared to Decision Trees. Its RIE (0.4128) and MAPE (0.8208) are also higher, indicating slightly less consistency and precision. The MAE for the Neural Network is 10.7091, which is better than SVM but not as good as Decision Trees. The SVM model has the lowest correlation, with an R value of 0.58223. It also has the highest MSE (448.8921), RMSE (21.1871), RIE (0.6091), MAPE (0.9731), and MAE (14.6572), indicating that it is the least accurate and precise model among the three.

In conclusion, the Decision Trees model is identified as the best performing model for predicting shopping time based on the given environmental parameters. It provides the most accurate and reliable predictions, making it the preferred choice for this task.

Shopping time modelling – classification models

For the classification models, the average time spent in the facility was considered, categorized into three ranges: short, medium, and long. Using decision trees, the best results were obtained with 255 trees. This optimal configuration is evident in Figure 9, which shows the accuracy in relation to the number of trees. As seen in the figure, the accuracy fluctuates with different numbers of trees, but peaks around 255, indicating the best model performance at this point. The graph provides a visual representation of how the model accuracy varies with the number of trees used, highlighting the optimal configuration.

The second modelling method tested for predicting the average time spent in the facility, categorized into three ranges (short, medium, and long), utilized SVM. The optimal results for the SVM classification model were obtained with a Box Constraint of 1 and a Kernel Scale of 10. This configuration provided the best accuracy, as shown in Figure 10. The final method employed was neural networks. The most effective results in neural network modelling for the classification task were achieved with a hidden layer comprising 6 neurons, as illustrated in Figure 11.

Figure 12 presents confusion matrices for three different classification models: decision

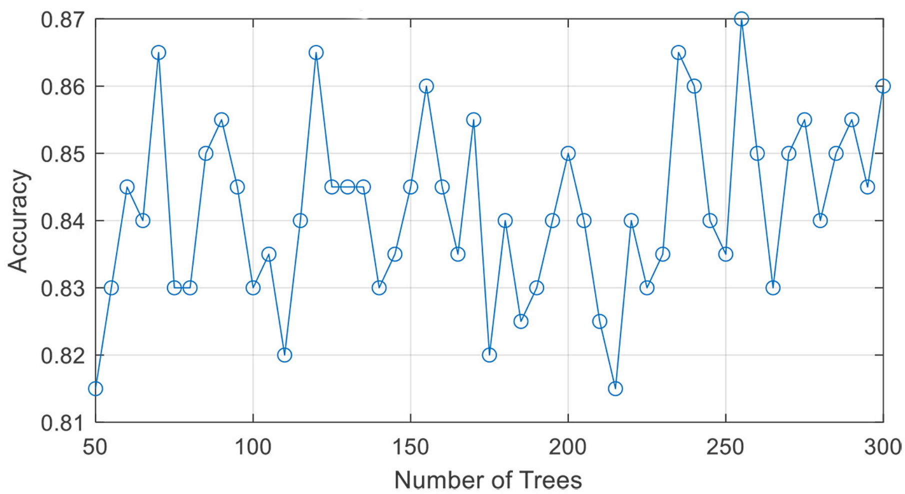


Figure 9. Accuracy as a function of the number of trees in a decision trees models for the classification models

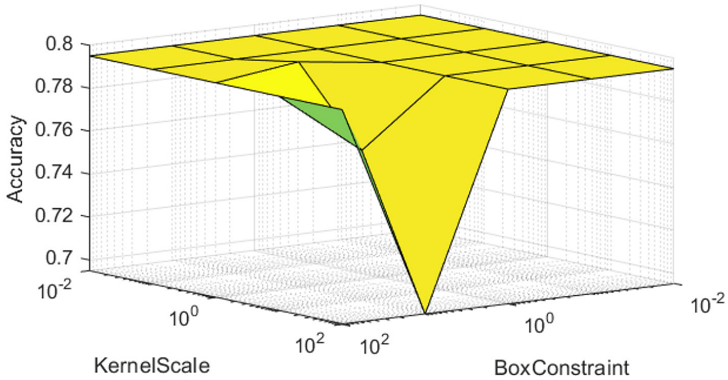


Figure 10. Accuracy as a function of the box constraint and kernel scale in a SVM models for the classification models

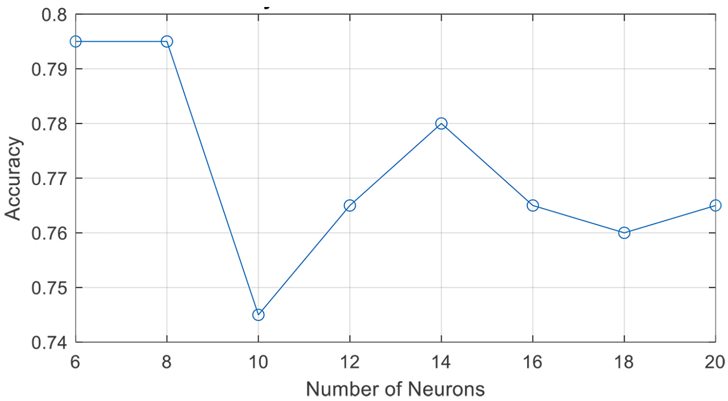
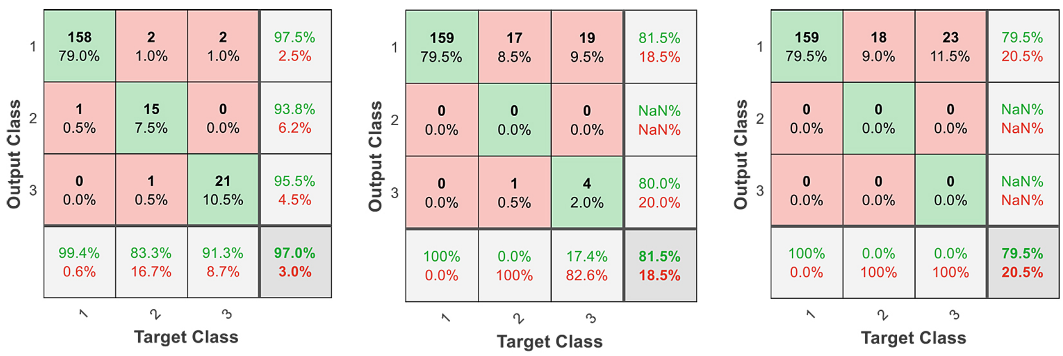


Figure 11. Accuracy as a function of the number of neurons in a neural network models for the classification models



a) b) c)

Figure 12. Confusion matrices for three different classification models: (a) decision trees, (b) SVM, and (c) neural networks

trees, SVM, and neural networks, labeled as a), b), and c), respectively. Each confusion matrix provides a detailed breakdown of the classification performance across three target classes. In the decision trees model, Class 1 (short) had 158 correct predictions (79.0%), with 2 misclassifications as Class 2 (medium) and 2 as Class 3 (long). Class 2 had 15 correct predictions (7.5%) with 1 misclassification as Class 1. Class 3 had 21 correct predictions (10.5%) with 1 misclassification as Class 2. The SVM model showed 159 correct predictions for Class 1 (79.5%) with 17 misclassifications as Class 2 and 19 as Class 3. Class 2 had no correct predictions but 1 misclassification as Class 2 and 4 as Class 3. For the neural network model, Class 1 had 159 correct predictions (79.5%) with 18 misclassifications as Class 2 and 23 as Class 3. Class 2 and Class 3 had no correct predictions and a higher rate of misclassifications. Overall, these matrices highlight the varying performance of each model in accurately predicting the target classes, with Decision Trees showing the highest accuracy for all classes.

Table 4 summarizes the performance metrics for the three classification models: decision tree, SVM, and neural network. The metrics include accuracy, precision, recall, and F1 score. The decision tree model achieved the highest accuracy (0.980), with strong precision (0.913), recall (0.956), and F1 score (0.933). The SVM model showed an accuracy of 0.874, with lower precision (0.389) and recall (0.538). The F1 score for the SVM could not be calculated due to insufficient true positive predictions for one of the classes. The neural network model had an accuracy of 0.863 and a precision of 0.333. The recall and F1 score for the Neural Network could not be calculated due to the absence of true positive predictions for some classes. Based on the above analysis, the Decision Tree model is the best-performing classifier, exhibiting the highest accuracy, precision, recall, and F1 score.

DISCUSSION

The results obtained indicate that ML can be used to solve management problems concerning the optimization of store atmosphere in a retail establishment. Throughout the literature, the versatility and usefulness of machine learning in various domains is emphasized. In the context of using machine learning methods for managerial decision making based on store atmosphere parameters, the summarized studies provide insights into the application of ML in retail environments, with a particular focus on store atmosphere and its impact on consumer behaviour. Store atmosphere is a critical factor in influencing consumer purchasing decisions, as highlighted in several studies. For example, research conducted at the XYZ Cooperative shows that store atmosphere, including elements such as exterior appearance, store layout, and interior design, significantly influences purchase decisions [35]. Similarly, a study of restaurants in Hawaii shows a strong correlation between store ambience and consumer interest, accounting for 92.5% of the variance in purchase rates [36]. These findings underscore the importance of optimizing the store environment to increase customer engagement and sales.

The fact that machine learning is universal and useful in many fields is repeatedly emphasized in the literature. The interplay between learning-driven techniques and optimization theory is expected to cope with the ever-complex nature of smart system design, including smart cities, the Internet of Everything, the Internet of Space Things, autonomous systems, etc [37]. Chun, for example, has already written about the weather dependence of customer purchases, having studied the phenomenon in Japan and noted among customers different psychological evaluations of places to make purchases under varying temperatures [38]. However, he did not use artificial intelligence methods to analyze his results, as this was not yet possible. Artificial intelligence, and in this case machine learning in particular, enables more accurate management decisions, translating into organizational management quality. This was written, for example, by the authors of the article "Machine learning applied to quality management—A study in ship repair domain". The paper demonstrates by example of delivery time estimates how for that purpose the deep quality concept (DQC)—a novel knowledge-focused quality management framework, and machine learning methodology could be effectively used [39]. The classification models used in the article are widely described in the literature as one of the most common tasks of machine learning [40]. Supervised classification is one of the tasks most frequently carried out by so-called Intelligent Systems. Thus, a large number of techniques have been developed based on Artificial Intelligence (logic-based techniques, perceptron-based techniques) and Statistics (Bayesian

Table 4. The performance metrics for the three classification models

Model	Accuracy	Precision	Recall	F1 Score
Decision trees	0.98	0.913	0.956	0.933
SVM	0.874	0.389	0.538	NaN
Neural network	0.863	0.333	NaN	NaN

Networks, Instance-based techniques) [41]. The solution proposed in the article can be used by learning management systems (LMS), which are successfully implemented in enterprises, educational and commercial institutions [42].

Research conducted by the authors suggests that machine learning techniques, such as regression and classification models, can be applied to predict customer dwell time in the store and categorize this dwell time into intervals such as short, medium, and long stay. For regression, the decision tree model's high R value of 0.88171 and its consistently low error metrics make it the most accurate and reliable choice for predicting customer dwell time in the store. For classification, the decision tree model's exceptional accuracy of 0.98, combined with strong precision, recall, and F1 score, highlights its superior ability to correctly categorize the duration of customers' stay in the store. This approach aligns with the broader use of machine learning in retail, where it is employed for sales forecasting, inventory management, and customer segmentation [43, 44].

CONCLUSIONS

The article's purpose was to demonstrate the applicability of machine learning methods to make management decisions based on atmospheric parameters in a retail establishment, to optimize customer dwell time and increase the value of the shopping cart. Management decisions about store atmosphere, such as temperature or sound intensity in retail establishments, can be made based on machine learning methods. These conditions influence whether a customer will stay in the store longer, which in turn can increase the value of their shopping cart. This article presents machine learning models utilizing three main methods: decision trees, SVM, and neural networks. These models were applied to both regression and classification tasks to predict customer dwell time and categorize it into short, medium, and long durations.

The analysis of the results showed that the best outcomes for classification models were achieved using decision trees with 255 trees. The SVM models achieved optimal results with a Box Constraint of 1 and a Kernel Scale of 10. For neural networks, the most effective results were obtained with a hidden layer comprising 6 neurons. A comparison of the three classification models using confusion matrices and metrics such as accuracy, precision, recall, and F1 score indicates that the decision tree model achieved the highest values across all analyzed categories. This makes it the best choice for predicting customer dwell time in a retail facility based on environmental parameters.

The analysis for regression models showed that the best outcomes were achieved using decision trees with 65 trees. SVM models yielded optimal results with a Box Constraint of 100 and a Kernel Scale of 10 and for neural networks, the most effective results were obtained with a hidden layer comprising 16 neurons and using the Levenberg-Marquardt algorithm. A comparison of the three regression models using metrics such as regression value (R), MSE, RMSE, RIE, MAPE, and MAE indicates that the decision tree model achieved the best performance across all categories. This makes it the preferred choice for predicting customer dwell time in retail facilities based on environmental parameters.

The application of machine learning methods to management decision-making has both practical and theoretical implications. The practical application relies on the ability to optimize store atmosphere to increase customer dwell time and customer satisfaction, which can lead to increased sales. Theoretical implications include the development and improvement of modelling methodologies and data analysis in the context of retail establishment management.

Like any research, this also has its limitations. Limitations may result from the quality of input data, variability in store atmosphere, and specific settings of machine learning models. Despite these limitations, the results indicate that machine learning methods can be effectively used to support management decisions in retail establishments, offering a valuable tool for optimizing weather conditions and maximizing the value of customers' shopping carts. In the future, similar studies can be conducted taking into account more factors influencing the time a customer stays in a retail outlet. It is likely that developing artificial intelligence will allow for a more detailed look at this topic.

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