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Predictive modeling and decision support using machine learning in business contexts

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ABSTRACT

With the growing emphasis on data-driven decision making, artificial intelligence (AI) methods have become increasingly important in managerial practice. This study aims to develop and evaluate supervised machine learning models for predicting customer brand loyalty and satisfaction based on selected behavioral, attitudinal, and programmatic attributes. This paper presents a lightweight decision support application that leverages machine learning techniques – specifically, artificial neural networks (ANN) and support vector machines (SVM) – to predict key customer-related indicators: brand loyalty and satisfaction. The models were trained on behavioral and attitudinal inputs and achieved excellent predictive performance, with test accuracies reaching 100%. The novelty of this study lies in the deployment of these models within an intuitive graphical user interface (GUI), enabling real-time predictions by non-technical users. Unlike traditional approaches focused solely on algorithm development, this research demonstrates a practical implementation of computational intelligence for operational and tactical business decision-making. The tool supports managers in profiling customers, optimizing loyalty programs, and enhancing customer engagement strategies through accessible AI-powered insights.

Keywords: machine learning, neural networks, support vector machines, decision trees, decision support systems, customer satisfaction, brand loyalty.

INTRODUCTION

Machine learning (ML), a subset of artificial intelligence (AI), focuses on algorithms that improve automatically through experience [1]. ML has its roots in applied statistics, but the goals of the two approaches are different. ML models are designed to make the most accurate predictions possible, while statistical models focus on inferring variables and identifying relationships between them [2]. ML models have shown great success in learning complex patterns that allow them to make predictions about unobserved data [3]. ML is extremely versatile and widely applied across industries. For instance, data-driven models have become a standard approach to solving many problems in exploration geology, contributing to the discovery of new deposits [4]. It is also helpful in medical science, as studied and described, for example, by Chen et al. who propose a new convolutional neural network-based multimodal disease risk prediction (CNN-MDRP) algorithm using structured and unstructured data from hospitals [5].

ML and AI techniques are increasingly being used in manufacturing systems. The field 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 pace [6]. Important climate and environmental issues can also be predicted using AI methods. One example is the study "Using machine learning algorithms to predict climate change impacts on agriculture". In their study, the authors used ML algorithms with meteorological and crop data to accurately predict regional climate change impacts on agricultural yields. The analysis included meteorological data such as temperature, precipitation, and climate variability, as well as crop and yield variables. The ML models were able to provide more accurate predictions of the impact of climate change on crop yields in different regions, which could help develop adaptation strategies in agriculture [7]. The review study "Machine Learning for Environmental Monitoring: A Review of the State-of-the-Art" discusses the use of ML algorithms for environmental monitoring, including air quality, water quality, and biodiversity. Examples of applications include predicting air pollution levels and monitoring changes in ecosystems, allowing for earlier detection of environmental threats [8].

The Industry used a deep ANN to detect defects in silumin castings, achieving high classification performance even with an unbalanced data set [9]. In turn, Klosowski et al. proposed to use LSTM networks to reconstruct moisture images in masonry based on impedance tomography data [10]. In the field of agri-food processing, Falih et al. used convolutional neural networks to classify the hardness of apple slices based on their RGB image, achieving high accuracy and stability of the DenseNet-201 + SVM-Cubic classifier [11].

ML can also be used for customer segmentation, as noted by Monil et al. when they wrote about different clustering approaches for customer segmentation and the appropriate application of different marketing strategies. They also discussed the possibility of a hybrid combination of a clustering algorithm that can outperform a single mode [12]. The use of ML in segmentation was also described by Ozan. His study aimed to solve the problem of segmenting a company's data using its actual customer payment data. He took advantage of the fact that ML methods are useful for solving data management problems. He compared different classification methods used to distinguish between premium and standard customers in the company's database. Two-dimensional customer payment information was used as input variables (features), and the methods are compared according to their separation performance [13].

There are also well-known studies that have used ML to analyze and predict customer behavior. An example is the study by Jing Li et al. where they used ML techniques such as decision tree, cluster analysis, and Naive Bayes algorithm to analyze customer characteristics and attributes with historical purchase records, and analyzed the key factors that influence the purchase behavior of potential customers, selecting high-promotion models using a promotion graph to realize accurate marketing [14]. A comparison of supervised ML techniques for predicting customer churn based on behavioral analysis was also addressed. The results showed significant predictive superiority of boosting versions over simple and bagging models [15]. Similarly, Momin et al. conducted a comparative study using the IBM Telco Customer Attrition dataset, evaluating artificial neural networks alongside traditional classifiers such as K-nearest Neighbours, naive bayes, random forest, decision tree, and logistic regression. Their results highlighted the competitive performance of ANN in predicting churn with high accuracy, further supporting its applicability in customer behavior modeling [16].

Given the ML opportunities identified above, the authors of the article also decided to apply ML to solve management problems, particularly those related to customer loyalty and satisfaction.

Customer loyalty is a key behavioral trait valued across most commercial markets. Various authors, based on numerous studies, show that customer satisfaction and loyalty are the basis for high levels of customer lifetime value, and they support a range of customer behaviors with widely varying values, characterized by loyalty itself (repeat purchases), commitment (willingness to recommend a product or service to others), apostle behavior (willingness to convince others to use a product or service), and ownership (willingness to recommend improvements to a product or service) [17]. It has been studied in detail by Fred Reichheld and others as part of a study of the impact of customer, employee, and investor loyalty on profits and growth [18]. A loyal customer provides stability and security, allowing you to build a sustainable competitive advantage in the marketplace [19]. The complex nature of loyalty, the diversity of its causes, and the multiplicity of ways to measure it make it difficult to define this concept unambiguously and to establish methods for measuring it [20]. In many definitions of loyalty, special attention is paid to the fact that it represents an enduring relationship and emotional attachment of the customer to the company, its employees or the products offered. The essence of this phenomenon is well captured by an approach that views loyalty as a long-term state of the customer's attitude toward a company whose offerings he regularly selects and accepts its terms. Loyal customers exhibit repeat purchasing behavior and strong resistance to competitor actions. Building such loyalty requires strategic and comprehensive marketing efforts [20]. Customer satisfaction, on the other hand, is one of the most important determinants of customer loyalty [21]. Customer satisfaction and loyalty are very often measured by companies that want to maintain a good relationship with their customers and provide them with the highest quality products, services and support.

These measurements take into account factors such as purchase category, brand loyalty, influence of social media on purchase decisions, sensitivity to discounts, and more, loyalty program membership, return rate or purchase intent. The relationship between purchase category and satisfaction and loyalty has been studied by Dong et al, among others. These studies reveal important resource allocation implications based on the functional forms of the impact of satisfaction on repurchase intentions, as well as strategic segmentation implications related to the changing impact of product category characteristics, customer economic and demographic variables, and market characteristics [22]. In turn, brand loyalty has been written about by Zhang et al. The results indicate that consumers' brand loyalty positively affects the retailer's dependence on the supplier, while consumers' store loyalty positively affects the supplier's dependence on the retailer. In addition, the retailer's dependence is higher when consumers' brand loyalty is higher than store loyalty; the supplier's dependence is higher when consumers' store loyalty is higher than brand loyalty; and the retailer's dependence increases with the increase of consumers' brand and store loyalty when consumers' brand and store loyalty are equal [23]. The impact of social media on the purchase decision was explored by Łopacinski and Łysik, who showed how seriously social media and mobile technologies are now influencing the market [24]. On the other hand, the influence of social media on brand loyalty was pointed out by Erdoğmuş and Çiçek. The results of their study showed that customers' brand loyalty is positively affected when the brand offers advantageous campaigns, offers relevant content, offers popular content, appears on different platforms and offers applications on social media [25]. Customers' sensitivity to discounts and their participation in loyalty programs have been studied by Cortiñas et al. They show that loyalty cardholders exhibit certain characteristic behaviors. When differences exist, cardholders are less sensitive to regular prices, but more sensitive to price promotions in certain product categories [26]. In turn, Wieseke et al. showed that the reason for the positive effect of loyalty on discounting is twofold: loyal customers demand a reward for their loyalty, citing their higher perceived bargaining power, and in order to retain loyal customers, sellers are more likely to offer discounts. In addition, these mechanisms are moderated by the basis of customer loyalty (price versus quality) and the length of the seller-customer relationship [27].

Given the above research context, this study aims to develop and evaluate supervised ML models for predicting customer brand loyalty and satisfaction based on selected behavioral, attitudinal, and programmatic attributes. The main goal is not only to evaluate the predictive accuracy of advanced classification algorithms such as ANN and SVM, but also to integrate them into a standalone, user-friendly expert system designed to support business decisions.

The core novelty of this approach lies in the practical fusion of computational intelligence methods with an intuitive graphical user interface (GUI), enabling non-technical users to access AI-driven insights without the need for programming or data pre-processing. Unlike traditional research that focuses solely on model performance or theoretical segmentation frameworks, this study delivers a fully deployable AI solution that bridges the gap between algorithm development and real-world application.

By combining high-performance AI classifiers with interface-level usability and validating the system on real customer data, the research contributes to the field of applied AI and expert systems in the business domain. The developed tool supports personalized marketing, loyalty program optimization, and customer profiling, and exemplifies the practical implementation of lightweight AI-based decision support systems - well aligned with current trends in computer engineering, particularly in AI methods and information technologies.

MATERIALS AND METHODS

The purpose of this study was to develop predictive models capable of estimating two key indicators of customer behavior: brand loyalty and customer satisfaction. Both target variables were defined as ordinal variables with multiple categories. Customer satisfaction was measured on a ten-point scale ranging from 1 (extremely dissatisfied) to 10 (extremely satisfied), while brand loyalty was expressed on a five-point scale ranging from 1 (very low loyalty) to 5 (very high loyalty). The predictive modeling task was thus framed as a multi-class ordinal classification problem, and two separate models were constructed for each response variable. The ultimate goal was to create accurate and deployable models that could generate reliable predictions for these two outcomes based on customer-related input features. As the analysis was conducted on a synthetic dataset, this should be taken into account when assessing the generalizability of the developed models.

The dataset used in the analysis consisted of 1000 labeled observations, each corresponding to a single customer profile [28]. Five independent variables were used as predictors, all representing behavioral, attitudinal or programmatic dimensions of consumer activity. The first variable, Social Media Influence, captured the extent to which the customer is influenced by content on social media platforms. This variable was categorical and included the values: None, Low, Medium, and High. The second variable, Discount Sensitivity, measured customer responsiveness to promotions and discounts and was also a categorical variable with three levels: Not Sensitive, Somewhat Sensitive, and Very Sensitive. The third predictor, Return Rate, was a numeric variable that took discrete integer values: 0, 1, or 2, representing the number of previous returns recorded for the customer. The fourth variable, Customer Loyalty Program Member, was binary and coded the customer's loyalty program membership status: True or False. The fifth input characteristic, Purchase Intent, denoted the type of purchase motivation and was categorized as impulse, need-based, planned, or desire-based, reflecting the underlying behavioral intent behind purchase actions.

All categorical variables were automatically processed by the MATLAB Classification Learner application, which internally handles categorical data encoding for compatibility with ML algorithms. Three ML algorithms were selected for model development: DT, SVM, and ANN. These techniques were chosen for their complementary strengths and proven performance in structured classification tasks. Decision trees provided an interpretable and efficient basis for classification, providing insight into feature importance and decision logic. ANN, configured as multilayer feedforward architectures, were used to capture complex, non-linear interactions between input features, with ReLU activation functions and appropriate regularization techniques to prevent overfitting. SVM, using radial basis function (RBF) kernels as well as polynomial variants, were included for their effectiveness in handling nonlinear decision boundaries and high-dimensional feature spaces.

Decision tree classifiers were constructed with different model capacities by adjusting the maximum number of splits allowed. Three configurations were tested: trees with 4, 20, and 100 maximum splits. The split criterion for all tree models was defined consistently using the Gini diversity index, and surrogate splits were disabled to maintain model interpretability. These configurations allowed examination of underfitting in shallow trees and potential overfitting in deeper models, providing insight into the optimal tree depth for predicting both satisfaction and loyalty.

Support Vector Machine classifiers were evaluated across a range of kernel functions and hyperparameters. Three variants of the gaussian radial basis function (RBF) kernel were tested with kernel scales of 0.43, 1.7, and 6.9, and in all cases a fixed box constraint level of 1 was applied. In addition to RBF, linear, quadratic, and cubic polynomial kernels were also implemented using MATLAB's automatic kernel scaling. The multi-class classification strategy followed the one-vs-one scheme, which is handled internally by the application. Predictor standardization was enabled by default for all SVM configurations except those based on explicit kernel expansions. The range of kernel types tested allowed exploration of the effect of different feature space transformations on class separability and model robustness.

Feedforward neural networks were trained using fully connected architectures with different depths and widths. The number of hidden layers varied from 1 to 3, and for each depth level, the number of neurons per layer was set to 10, 25, or 100. The rectified linear unit (ReLU) activation function was used in all hidden layers to introduce nonlinearity, and the output layer used softmax activation appropriate for multi-class classification. Training was limited to a maximum of 1000 iterations, and no regularization was applied as the regularization parameter λ was set to zero. The input features were automatically standardized by the application prior to training, which improved numerical stability and convergence behavior. This experimental design allowed the evaluation of how both depth (number of layers) and breadth (number of neurons) affect model expressiveness and generalization.

All models were trained using fivefold cross-validation to ensure reliable estimation of the generalization error and to reduce the influence of random data partitioning. After hyperparameter tuning and model selection, the final classifiers were retrained on the full training data and evaluated on a separate hold-out test set. Performance metrics included classification accuracy and confusion matrix analysis. Accuracy was defined as the proportion of correctly predicted labels in the test set. Confusion matrices were computed for each model to visualize the distribution of correct and incorrect predictions across all output classes, allowing analysis of model sensitivity to adjacent class misclassification, which is particularly relevant for ordinal outcomes.

The best-performing models for each prediction task – brand loyalty and customer satisfaction – were integrated into a standalone business decision support application. The application takes the five input characteristics as user-defined parameters and returns predicted loyalty and satisfaction levels, enabling personalized interventions, customer segmentation, and optimization of retention strategies.

RESULTS

Brand loyalty modelling

Three classification models: DT, SVM, and ANN were independently trained and evaluated to predict brand loyalty based on five input features.

The best performing configuration for the Decision Tree classifier was the Fine Tree preset, which allowed up to 100 decision splits. The model used the Gini diversity index as the splitting criterion and had surrogate splits disabled. For the SVM model, the Cubic SVM preset yielded optimal results, using a third-degree polynomial kernel with automatic kernel scaling, a box constraint level of 1, and a one-vs-one multiclass coding strategy. The neural network was configured as a two-layer fully connected architecture with two hidden layers of 10 neurons each, using ReLU activation, and trained for up to 1000 iterations with no regularization ($\lambda = 0$). The comparative performance of these models is summarized in Table 1.

In terms of test accuracy, both SVM and ANN models achieved perfect classification performance (100.0%), while the decision tree model achieved an accuracy of 92.0%. Similar trends were observed in the validation results, with the decision tree achieving 88.9% and both SVM and ANN reaching 99.9%. These results confirm the high predictive power of nonlinear models, especially those capable of capturing complex interactions in the input space.

To further assess the structure of the classification errors, confusion matrices were generated for all three models and are shown in Figure 1 and Figure 2. To further assess the structure of the classification errors, confusion matrices were generated for all three models and are shown in Figure 1 and Figure 2. The decision tree model, while showing good overall performance, showed a clear pattern of misclassifications between adjacent brand loyalty classes. In both the validation and test data sets, the model had difficulty distinguishing between intermediate classes,

Table 1. Training parameters

Model	Decision tree	SVM	Neural Network
Accuracy % (Validation)	88.9	99.9	99.9
Accuracy % (Test)	92.0	100.0	100.0
Prediction speed (obs/sec)	63000	17000	56000
Training time (sec)	4.5388	4.9928	4.9986
Model size (kB)	41	103	9

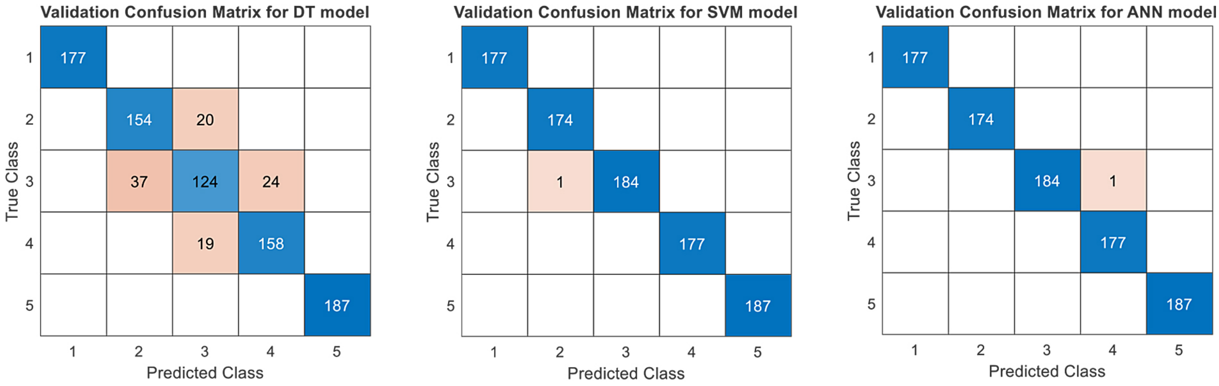

Figure 1. The confusion matrices for developed models for validation data

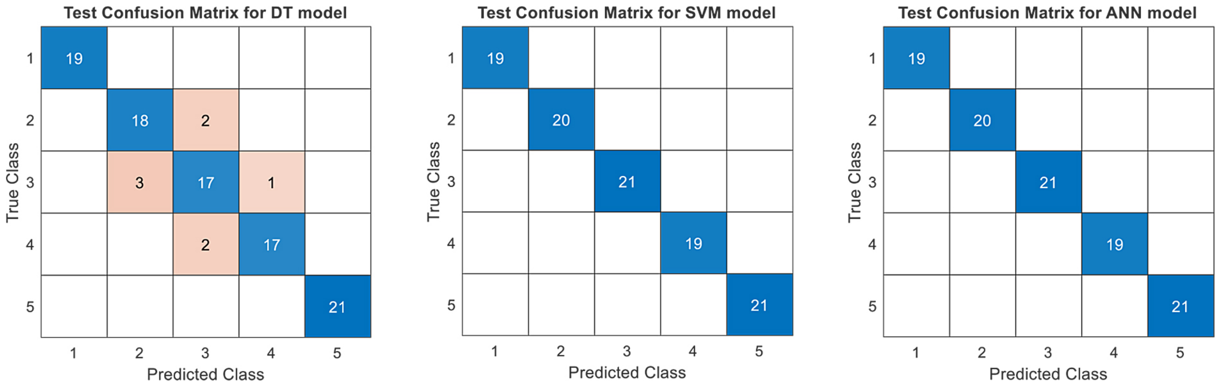

Figure 2. The confusion matrices for developed models for test data

particularly between classes 2, 3, and 4. Some instances were assigned to adjacent categories, which is a common problem with decision tree classifiers when dealing with ordinal multi-class problems. Nevertheless, the model performed reliably on the extreme classes, particularly classes 1 and 5, which were consistently classified with high accuracy. This suggests that the tree-based model was effective in identifying distinct loyalty profiles, although its granularity was limited in distinguishing more subtle distinctions.

In contrast, both the SVM and neural network models achieved near perfect classification results. No errors were observed in the test sets for either model, and only one or two misclassifications occurred during validation. In particular, the neural network showed the highest stability, combining perfect classification accuracy in test conditions with minimal model size and high inference speed.

Although both the SVM and ANN models achieved identical levels of accuracy, computational efficiency was also considered in the final model selection. Between the two, the neural network had a significantly faster prediction speed (56,000 vs. 17,000 observations per second) and a much smaller model size (9 kB vs. 103 kB), making it much more suitable for integration into lightweight, responsive systems. For these reasons, the dual-layer neural network model was selected as the optimal solution for use in the application, which predicts brand loyalty levels based on customer profile data. Its architecture provides the best trade-off between classification accuracy and practical deployability.

Customer satisfaction modelling

The same set of three ML algorithms was used to model customer satisfaction: DT, SVM, and ANN were applied using consistent training configurations and evaluation procedures. Each model was trained on the same input features and validated using both cross-validation and an independent test set, allowing a reliable comparison of their classification capabilities. The configuration details and performance metrics are summarized in Table 2, while the corresponding confusion

Table 2. Training parameters

Model	Decision tree	SVM	Neural Network
Accuracy % (Validation)	53.2	97.7	93.0
Accuracy % (Test)	59.0	100.0	99.0
Prediction speed (obs/sec)	80000	2200	26000
Training time (sec)	3.0885	8.6215	15.663
Model size (kB)	76	614	26

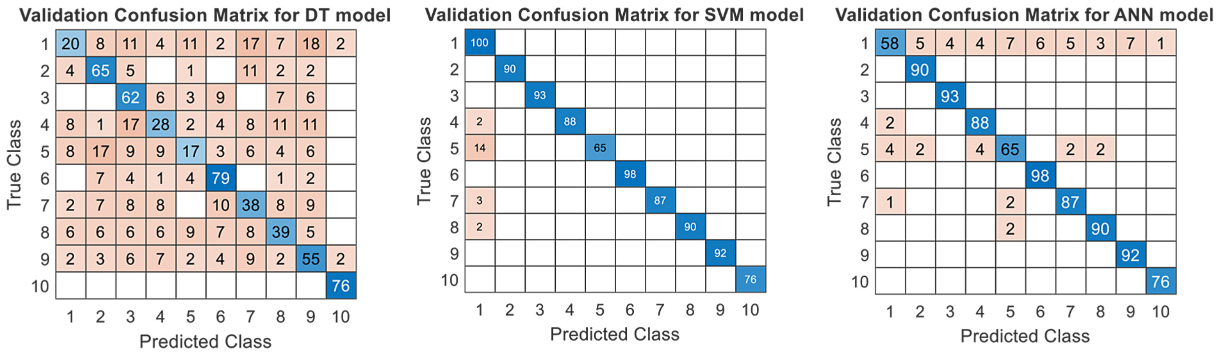

Figure 3. The confusion matrices for developed models for validation data

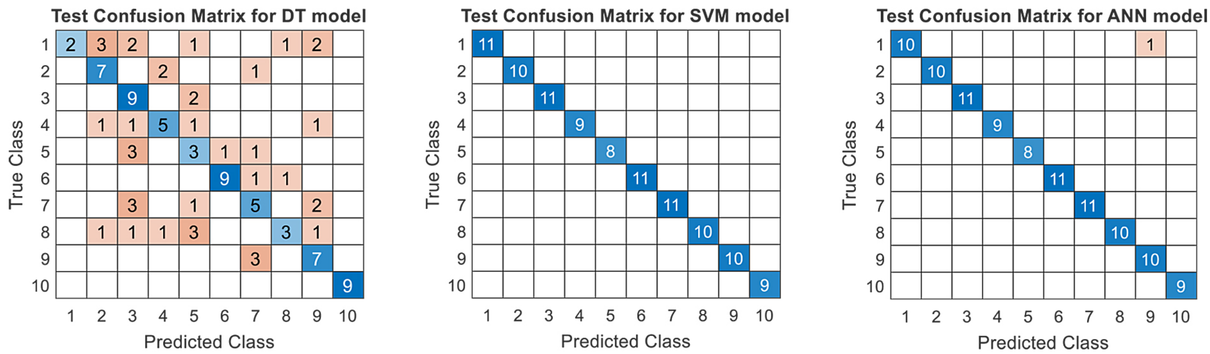

Figure 4. The confusion matrices for developed models for test data

matrices are shown in Figure 3 (validation data) and Figure 4 (test data).

The DT classifier was used with a maximum of 100 allowed splits and the Gini diversity index as the splitting criterion. This configuration was the best performing among all decision tree models tested. Despite this optimization, the model achieved a validation accuracy of 53.2% and a test accuracy of 59.0%, which were significantly lower than the results obtained by the other two algorithms. As shown in the confusion matrices, the decision tree struggled to discriminate between several satisfaction levels, especially those in the middle of the scale. Misclassifications were spread across nearly all classes, reflecting the model's limited ability to capture the complexity and subtlety inherent in the customer satisfaction variable.

In contrast, the SVM classifier, configured as a Fine Gaussian SVM with a kernel scale of 0.56 and multiclass one-vs-one coding, delivered outstanding performance, achieving 97.7% accuracy on the validation set and 100.0% on the test set. The corresponding confusion matrices show strong diagonal dominance with minimal or no misclassifications, confirming the model's high generalization ability and suitability for the nonlinear structure of the input data.

The neural network model optimized with a single wide hidden layer of 100 neurons also performed very well. It achieved 93.0% validation accuracy and 99.0% test accuracy. Although a small number of classification errors occurred

– mostly between adjacent satisfaction levels – the network showed strong consistency across classes and maintained a favorable trade-off between performance and computational efficiency.

While both the SVM and ANN models produced excellent results, the final model selection prioritized predictive performance on unseen data. The SVM model achieved perfect generalization, reaching 100.0% test accuracy with only minor validation errors. Although the neural network demonstrated slightly faster prediction speed and smaller model size, the flawless classification performance of the SVM provided a decisive advantage in terms of model reliability and trustworthiness for decision support. Therefore, the SVM model was selected as the optimal solution for predicting customer satisfaction. Its ability to handle nonlinear relationships and its demonstrated generalization ability make it the most appropriate choice for use in the target application.

Decision support with artificial intelligence models in management applications

The main objective of the developed solution was to create an interactive, lightweight decision support tool based on AI techniques that enables fast and accurate prediction of qualitative indicators relevant to management processes. The system was designed to assist operational-level decision makers by transforming behavioral input data into actionable classifications using pre-trained ML models.

To accomplish this, two ML algorithms-a fully connected neural network and a support vector machine-were integrated into a standalone application built in MATLAB. These models were previously trained to predict two separate but complementary indicators: customer loyalty and customer satisfaction. The application provides an intuitive graphical user interface that allows the user to input a concise set of variables and receive instant predictions without requiring programming skills or data pre-processing.

The application's graphical user interface (GUI) is designed for clarity and intuitive interaction (see Figure 5). The interface image provides a detailed view of the system layout, helping to illustrate how input selection and prediction outputs are presented to the user. At the top of the window, a header labeled "Customer Loyalty & Satisfaction Predictor" clearly communicates the purpose of the tool. The center of the interface contains a series of labels, drop-down menus, and an input field that allow the user to define the values of five input variables required by the predictive models.

The user can select the level of social media influence and discount sensitivity from three predefined categories. The return rate is manually entered as a numeric value ranging from 0 to 5. The user also specifies loyalty program membership status and purchase intent using drop-down lists. This layout allows for quick and easy input

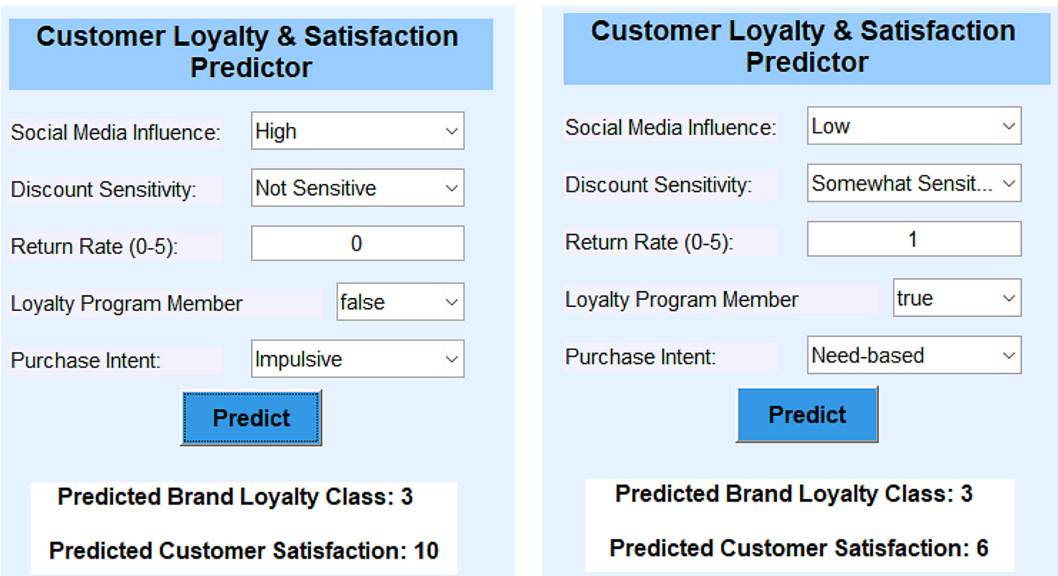

Figure 5. The confusion matrices for developed models for test data

configuration without requiring technical expertise or knowledge of the model structure.

Once the input is provided, clicking the "Predict" button initiates the prediction routine. In the background, two classification models are called: one for predicting customer loyalty and another for estimating customer satisfaction. The input values are automatically formatted and structured into the appropriate tables required by the respective models, which have been pre-trained and stored in separate files.

The prediction results are displayed in the lower part of the interface in the form of two separate lines: one indicating the predicted loyalty class and the other indicating the expected satisfaction level. In case of input errors (e.g. missing or non-numeric data), the system automatically generates a clear message instructing the user to correct the input.

This interface serves as a practical example of how AI techniques can be incorporated into decision support systems. Through its clean layout and embedded classifiers, the application enables real-time inference from qualitative behavioral data. It can be used effectively in real-world scenarios involving customer relationship management, marketing segmentation, or personalized service strategies. The design emphasizes ease of integration and scalability, making it adaptable to other domains where rapid forecasting and decision making are essential.

DISCUSSION

The findings of this study demonstrate that AI techniques, particularly supervised ML models such as SVM and ANN, can be effectively applied to predict key behavioral indicators like customer loyalty and satisfaction. These results are in line with previous studies that emphasized the utility of ML in understanding customer behavior and improving segmentation strategies. For example, Monil et al. [12] highlighted the potential of hybrid clustering algorithms for customer segmentation, while Ozan [13] applied ML techniques to distinguish premium and standard clients based on payment behaviors.

One of the key advantages of the proposed solution is its simplicity and interpretability. While neural networks and SVMs are often viewed as black-box models, their integration into a user-friendly GUI bridges the gap between complex computational models and business users. The interface design allows users without technical expertise to benefit from AI-driven insights, helping to democratize ML technologies in organizational settings. This usability and transparency are particularly important in decision support contexts, where ease of use and trust in system outputs play a decisive role in adoption. These observations align with recent findings by Tanhaei et al., who demonstrated the value of decision support models in forecasting customer value and linking expenditures to behavioral patterns—ultimately enhancing the quality of customer-centric strategic decisions [29].

The decision support tool developed in this study provides a lightweight and accessible interface for non-technical users, allowing for real-time inference from structured qualitative inputs. This contributes to the ongoing trend of democratizing AI tools in business applications, as emphasized in the review by "Machine learning for environmental monitoring: A review of the state-of-the-art" [8], where the importance of interpretable and user-friendly systems was underlined.

Despite these promising results, some limitations must be acknowledged. The models were trained and tested on a synthetic dataset that may not capture all the variability present in real-world customer data. While the feature set used in this study was compact and practical, expanding it with transactional or demographic data could increase model accuracy and generalizability.

In addition, while the current implementation requires manual input, integration with CRM systems or customer data streams could enable real-time batch or streaming predictions in production environments. Future iterations of the application could also include explicable AI mechanisms (e.g., SHAP or LIME) to increase the transparency and interpretability of the predictions.

This study demonstrates that ML models can be effectively trained and deployed to support managerial decision-making processes related to customer satisfaction and loyalty. The developed tool provides a scalable, accessible, and interpretable solution with the potential to improve customer retention, satisfaction, and long-term value creation in various commercial and service-oriented contexts.

CONCLUSSIONS

This study demonstrated the effectiveness of supervised ML models-particularly SVM and ANNs-in predicting two key behavioral attributes in customer relationship management: brand loyalty and customer satisfaction. Among the developed classifiers, both the SVM and ANN models achieved exceptionally high test accuracies, reaching 100.0% for loyalty prediction and 100.0% (SVM) / 99.0% (ANN) for satisfaction prediction. These results confirm the strong predictive capabilities of nonlinear models, especially when dealing with multi-class, ordinal classification tasks involving attitudinal and behavioral data.

In terms of model efficiency, the ANN classifier showed the best trade-off between performance and resources: it required only 9 kB of memory, predicted at a speed of 56,000 observations per second, and still maintained 100% classification accuracy for loyalty. For customer satisfaction, the SVM model was ultimately selected, achieving perfect generalization at the cost of higher model complexity (614 kB) and lower prediction speed (2,200 observations/sec). These results illustrate how performance metrics such as accuracy, latency, and model size should be considered together when selecting models for use in real-world applications.

The developed application successfully integrates these models into an easy-to-use decision support interface that enables non-technical users to make reliable predictions based on behavioral input variables. This tool demonstrates how ML can be made accessible in managerial contexts – enhancing segmentation strategies, supporting customer retention efforts, and enabling customer scoring.

The study confirms the practical feasibility and strategic value of incorporating AI-based systems into business decision processes. Future work should focus on extending the application's capabilities, including real-time data integration (e.g., CRM systems), model interpretability modules (e.g., SHAP, LIME), and testing with broader demographic or transactional datasets to assess model robustness across market segments. Real-time integration could be practically implemented by linking the GUI to live data streams via RESTful APIs or direct database connectors, allowing continuous customer profiling and instant response strategies. Incorporating interpretability methods such as SHAP or LIME would enable users to visualize the influence of each input feature on the prediction outcome, improving transparency and supporting more informed managerial decisions.

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