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Research Article

Evolution of digital marketing campaigns with artificial intelligence and machine learning: Analysing success prediction capabilities

Dijital pazarlama kampanyalarının yapay zekâ ve makine öğrenmesi ile evrimi: Başarı tahmin yeteneklerinin analizi

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Abstract

This study aims to investigate the predictive capabilities of machine learning algorithms in forecasting the success of digital marketing campaigns. In addition, the study aims to evaluate the performance of machine learning algorithm classification models and to determine which classification model is more effective in making this prediction. In this direction, a classification analysis was performed with machine learning algorithms using a dataset of 10,001 digital marketing campaigns obtained from the Kaggle platform. The study's theoretical background is based on Attribution Modelling, the Technology Acceptance Model, Incremental Response Modelling, and the Diffusion of Innovations Theory. As a result of the analysis, it was revealed that the success prediction capabilities of machine learning algorithms for marketing campaigns are pretty high. In the study comparing the success prediction abilities of machine learning models, the Gradient Boosting model demonstrated the highest success prediction ability (93.31%). In comparison, the Logistic Regression model has the lowest predictive success rate (53.36%). The findings revealed that machine learning algorithms should be more widely incorporated into the marketing literature and that businesses can run more successful and efficient campaigns by utilising machine learning models in their marketing efforts.

Keywords: Digital Marketing, Machine Learning, Marketing Research, Campaign Success Prediction, Classification Models

Jel Codes: M31

Öz

Bu çalışmanın amacı, dijital pazarlama kampanyalarında makine öğrenmesi algoritmalarının söz konusu kampanyaların başarısını tahmin etme yeteneğini ortaya çıkarmaktır. Ayrıca çalışma, makine öğrenme algoritması sınıflandırma modellerinin performansını ölçerek hangi sınıflandırma modelinin bu tahmini gerçekleştirmede daha başarılı olduğunu ortaya koymayı amaçlamaktadır. Bu amaç doğrultusunda çalışmada Kaggle platformundan elde edilen 10.001 adet dijital pazarlama kampanyasının yer aldığı bir veri seti kullanılarak makine öğrenmesi algoritmaları ile bir sınıflandırma analizi gerçekleştirilmiştir. Çalışmanın teorik altyapısı Atıf Modellemesi, Teknoloji Kabul Modeli, Artımsal Tepki Modellemesi ve Yeniliklerin Yayılımı Teorisine dayanmaktadır. Analizler sonucunda, makine öğrenme algoritmalarının pazarlama kampanyalarının başarı tahmin yeteneklerinin oldukça yüksek olduğu ortaya çıkmıştır. Makine öğrenme modellerinin başarı tahmin yeteneklerinin karşılaştırıldığı çalışmada en yüksek başarı tahmin yeteneğinin Gradient Boosting modeline ait olduğu (%93,31), en düşük başarı tahmin yeteneğinin ise Logistic Regression modeline (%53,36 doğruluk) ait olduğu ortaya çıkmıştır. Çalışma bulguları, makine öğrenme algoritmalarının pazarlama literatüründe daha fazla yer alması gerekliliğini ortaya koymuştur. Ayrıca işletmelerin de pazarlama kampanyalarında makine öğrenme modellerini kullanarak daha başarılı ve verimli kampanyalar yürütebilecekleri bu çalışma sonuçlarında ortaya çıkmıştır.

Anahtar Kelimeler: Dijital Pazarlama, Makine Öğrenme, Pazarlama Araştırmaları, Kampanya Başarı Tahmini, Sınıflandırma Modelleri

Jel Kodları: M31

Introduction

Many essential tangible and intangible strategies have been developed to reveal consumers' behaviour, and the interrelationships of various important marketing concepts have been discussed. The primary purpose of businesses is to create customer value, ensure the sustainable purchase of their products and brands, and increase their value in this direction. In this direction, various methods are employed in marketing to establish relationships between concepts, develop new marketing strategies, and assess the success of these strategies and campaigns. Significant technological developments offer valuable new methods to marketing science in this context. With the daily advancement of artificial intelligence technologies, important classifications can be made by processing large datasets obtained from businesses, and future predictions can be made by revealing consumer behaviour patterns (Zhao, Yu, Li, Han, and Du, 2019, p. 450). In addition, marketing strategies applied with machine learning technology to the data obtained will enable the prediction of campaign success and the creation of the right plan for future marketing campaigns.

Machine learning algorithms enable significant gains in many disciplines by analysing datasets. From heavy industrial technologies to chemical science (Artrith, Butler, Coudert, Han, Isayev, Jain, & Walsh, 2021, p. 505) and from medicine to agriculture, machine learning technology is widely applied across various scientific disciplines. It significantly contributes to these sciences (Liakos, Busato, Moshou, Pearson, and Bochtis, 2018, p. 2). The effects of digital transformation in business science have also become evident in recent years (Türk, 2023, p. 2). Machine learning identifies meaningful data communities by making classifications from dense datasets, yields significant findings with these datasets, suggests future solutions and predictions, and adds considerable value to marketing science (Huang and Rust, 2021, p. 32). Customer segmentation, understanding consumer behaviour, transforming complex data into understandable and actionable insights, and making essential predictions through data analysis are some of the critical contributions of machine learning to marketing science (Hagen et al., 2020, p. 365). Businesses achieve significant time and cost savings using machine learning methods, providing a sustainable competitive advantage. In light of this information, several important research questions have arisen. Can a digital marketing campaign be predicted to be successful by using machine learning, which is assumed to make significant contributions to marketing science? If the answer to the first question is yes, which classification techniques using machine learning algorithms can obtain the most accurate prediction? These research questions reveal the unique value of this study. Moreover, the study's theoretical background is based on Attribution Modelling, the Technology Acceptance Model, Incremental Response Modelling, and the Diffusion of Innovations Theory.

This study aims to demonstrate the effectiveness of machine learning algorithms in forecasting the outcomes of digital marketing initiatives. The study also intends to assess the effectiveness of machine learning algorithm classification models and identify the most successful model in achieving this prediction. In line with these objectives, a classification analysis was performed using machine learning algorithms on a dataset obtained from the Kaggle platform, which contains digital marketing data. The dataset consists of data on 10,001 digital marketing campaigns in various sectors (e-commerce, finance, healthcare, manufacturing, retail, services, technology). The variables in the data set are **as follows: Ad Spend, which represents the t**otal budget allocated for the campaign. **Duration:** The length of the campaign is in days. **Engagement Metric:** A measure of campaign engagement (e.g., clicks, views). **Conversion Rate:** The percentage of conversions achieved. **Success:** Campaign success status (0 = failed, 1 = successful). **Budget Allocation:** Budget allocated to each campaign. **Audience Reach:** The number of people reached by the campaign. **Device Conversion Rate:** Conversion rate by device. **Operating System Conversion Rate:** Conversion rate by operating system. **Browser Conversion Rate**: Conversion rate by browser. These variables represent various characteristics that affect the success of a digital marketing campaign.

The methodological choice in the study was made by considering the data structure, relevance to the research question, relationships between variables, and relevant marketing theories. The study's data set, whose variables are explained in detail above, was first preprocessed. In this process, missing values were removed entirely from the dataset to prevent them from affecting the analysis results. Then, unnecessary variables for the analysis were removed from the data set. Subsequently, categorical data were converted into numerical forms. After normalising the data, the dataset was prepared for analysis. **Random Forest, Gradient Boosting, AdaBoost, Logistic Regression, Support Vector Classifier (SVC), K-Nearest Neighbors, K-Nearest Neighbors**, and **Decision Tree** machine learning models were used in the analyses where **"Success"** was considered as the target variable and other variables as independent variables. Hyperparameter optimisation was performed using GridSearchCV to improve the performance of these models and find the optimal parameters. In the optimisation process, 5-layer cross-validation with **StratifiedKFold** was applied. The models were retrained using the optimal hyperparameters and then evaluated on the test dataset. For each model, metrics such as **accuracy, precision, recall,** and **f1-score** were calculated, and a detailed analysis was performed with a **confusion matrix**. The analysis revealed the models' ability to predict the success of a digital marketing campaign.

The first part of the study presents the conceptual framework by conducting a comprehensive literature review. In the Methodology section, the data set and methodology of the study are discussed in detail, and the findings are presented in the Findings section. In the Discussion section, the study's results are analysed in detail, and comparisons are made with other studies in the literature. The final section presents the study's conclusions, limitations, and significant recommendations for future research and practitioners. Especially for the Gradient Boosting algorithm, the hyperparameter optimisation process was carried out in more detail. In this context, parameters such as n_estimators, learning_rate, max_depth, subsample, min_samples_split, min_samples_leaf, max_features and loss were determined, and a systematic search was performed with the GridSearchCV method by defining appropriate value ranges for each of them. The model performance was evaluated with a 5-layer StratifiedKFold cross-validation structure, and the model was retrained by selecting the best parameter combinations. In this way, the accuracy and overall performance of the Gradient Boosting model is maximised.

Literature review and conceptual framework

Machine learning in marketing

In recent years, machine learning methods have been increasingly used in marketing research (Herhausen, Bernritter, Ngai, Kumar, and Delen, 2024, p. 2). Although the use of machine learning in marketing is discussed from different perspectives in literature, it can be broadly categorised in terms of data, methods, and usage. Huang and Luo (2016) and Malik, Singh, and Srinivasan (2019) conducted marketing research using a support vector machine (SVM), a machine learning method. Ansari et al. (2018), Liu and Toubia (2018) examine "topic models," Chakraborty, Kim, and Sudhir (2019), and Zhang and Luo (2019) discuss "deep learning" methods in marketing. The "Tree ensembles" method is investigated by Rafienian and Yoganarasimhan (2018); the 'Causal Forest' method is investigated by Zhang and Luo (2023). "Network embedding" (Ma et al., 2019), "active learning" (Huang and Luo, 2016), and "reinforcement learning" (Misra, Yadav, and Kaur, 2018) are other methods.

The use of machine learning on data in marketing research is examined by text Liu, Lee, and Srinivasan (2019), Zhang and Luo (2023), image Hartmann, Heitmann, Schamp, and Netzer (2019), video Kawaf (2019), Li et al. (2019), consumer tracking Kakatkar and Spann (2019), and network by Yang, Zhang and Kannan (2019). In terms of usage, the study of machine learning in marketing is examined in the context of prediction, as pioneered by Cui and Curry (2005). Liu et al. (2018) and Hartman et al. (2019) focus on feature extraction. Causal interpretation is studied by Guo, Sriram, and Manchanda (2018), Prescriptive analysis by Misra et al. (2018), and optimisation or estimation by Chiong and Shum (2019).

Boddu, Santoki, Khurana, Koli, Rai, and Agrawal (2022) try to explain the relationship between digital marketing and artificial intelligence by examining machine learning-oriented analytical tools in digital marketing. Pointing out that robots and marketers work well together, he states that this relationship will continue to increase in the future. Miklosik, Kuchta, Evans, and Zak (2019) draw attention to the importance and underutilisation of machine learning in digital marketing for marketing agencies, media companies, and advertisers. Sharma, Poojitha, Saxena, Bhanushali, and Rawal (2022) also emphasise the lack of information about the use of machine learning in digital marketing, its low level of adoption, and the potential for its increased use in advertising in the future. Modak, Ghosh, Sarkar, Sharif, Arif, Bhuiyan and Devi (2024) draw attention to the effects of digital marketing campaigns utilising machine learning models on consumer behaviour, particularly in terms of customer segmentation and personal experiences. Lahbabi, Raki, Chakir Lamrani, and Dehbi (2021) develop an algorithm based on machine learning and demonstrate its importance in identifying consumers' behavioural patterns and developing targeted marketing strategies for these behaviours.

When the research on machine learning algorithms and marketing data is analysed, Abd, Atiyah, Ahmed, and Bakhit (2024) accurately predicted whether customers would buy a product by using machine learning algorithms with customer data. Chen, Cai, and Gu (2021) created a personalised marketing strategy with machine learning algorithms in their study. They predicted consumers' purchasing habits and purchase demands based on the attribute data of luxury goods and predicted which luxury goods customers are likely to purchase. Liu and Yang (2022) examined the decision-making situations of people in content marketing with decision tree-based methods. The researchers determined that the decision tree methodology possesses significant potential for analysing content marketing data and can yield reliable and precise recommendations for content marketing strategies. Kumar and Reddy (2021) examined the digitalisation cycle of bank customers with a machine-learning method. They predicted customers' preferences and usage of online banking services based on banks' marketing data. Lin (2024) draws attention to the impact of machine learning on a brand's digital marketing strategies by concluding that it can improve the effectiveness and conversion rate of the strategy. Machine learning can offer significant advantages in digital brand marketing compared to traditional marketing models.

The use of artificial intelligence technologies in marketing is increasing daily. Machine learning also provides a great advantage to marketers by analysing consumer data. However, data quality issues, the use of modern information extraction and analysis methods, and the handling of unstructured data are seen as key areas that marketers should focus on in this field. It is also recommended that marketing researchers should not immediately abandon the cognitive and methodological procedures they have acquired through philosophical and scientific thinking.

Pan, Gao, and Luo (2018) compared two models from their previous studies using a single model to predict what makes companies successful; Afolabi, Ifunaya, Ojo, and Moses (2019) used a limited number of models for a similar purpose, Dhir and Raj (2018) and Lee, Park, Kim, and Choi (2018) used a limited number of models with machine learning techniques. Customer segmentation, purchase intentions, and customer conversion rates are key areas of focus in marketing. However, digital marketing campaigns have not been analysed, especially considering the effectiveness of digital marketing in reaching customers today. Other studies, examined in detail in the discussion section, reveal the differences between this study and indicate the reasons that led to the current research. In addition, considering that there are minimal studies in digital marketing with machine learning-based approaches, and since the current study compares more than one algorithm and proposes a model, this situation is emphasised.

Conceptual framework and theoretical background

Machine learning is an artificial intelligence tool that processes large datasets using computer programs developed through experimentation and iterative refinement. Although it is faster than other artificial intelligence applications, it is also considered the primary source of communication and interaction with consumers in marketing (Cambria, Grassi, Hussain, and Havasi, 2012, p. 559; Salminen, Yoganathan, Corporan, Jansen, and Jung, 2019, p. 206). Machine learning is an artificial intelligence tool that can create analytical models using data analysis and process large datasets, providing marketers with predictions about consumer behaviour and enhancing performance in marketing operations (Cui, Wong, and Lui, 2006, p. 599).

Digital marketing has experienced a significant boom in recent years, driven by the emergence of machine learning models and algorithms. With the big data obtained from consumers through machine learning, marketers have gained great power in making informed decisions and creating personalised consumer experiences. Machine learning algorithms are an innovative technique for developing digital marketing communications with consumers, discovering consumers' behaviour patterns, and predicting them based on big data (Saba, Gandhi, Rajendran, and Abraham, 2023, p. 2). It reveals great potential for marketing science in making effective marketing decisions, interacting with consumers, and using it in strategic planning (Miklosik et al., 2019, p. 85705).

The fact that machine learning undertakes various tasks using multiple methods in marketing has triggered its rapid development and widespread adoption (Ma and Sun, 2020: pp. 483-484). Although machine learning in marketing is applied in many ways, it can be broadly summarised in four steps by Herhausen et al. (2024), inspired by Van Giffen, Herhausen, and Fahse (2022), as illustrated in Figure 1. Pertinent marketing phenomena generate data, which undergoes preprocessing to incorporate descriptions and extract features. The enriched data are subsequently used to train and validate a machine learning (ML) model. Ultimately, the classifications and predictions derived from the ML model inform marketing decisions.

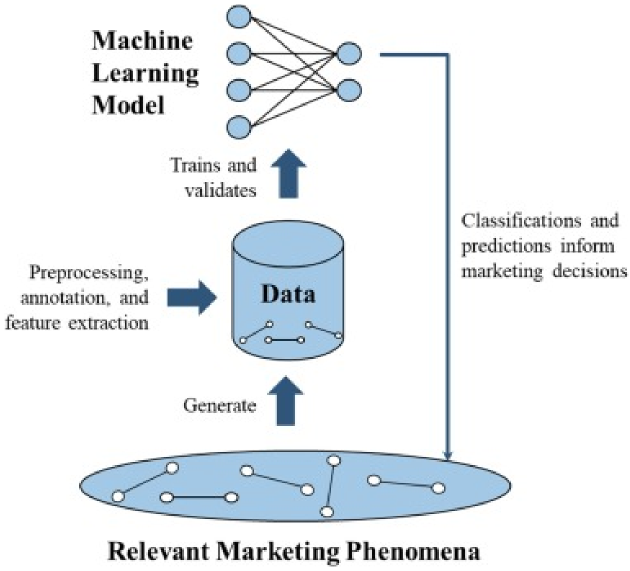

Figure 1: A Streamlined Framework for Machine Learning in Marketing

Source: Van Giffen et al. (2022); Herhausen et al. (2024)

A conceptual framework for marketing machine learning applications is proposed by Ngai and Wu (2022). They try to explain machine learning through machine learning applications based on the 7P marketing mix. Figure 2 depicts the use of machine learning in marketing.

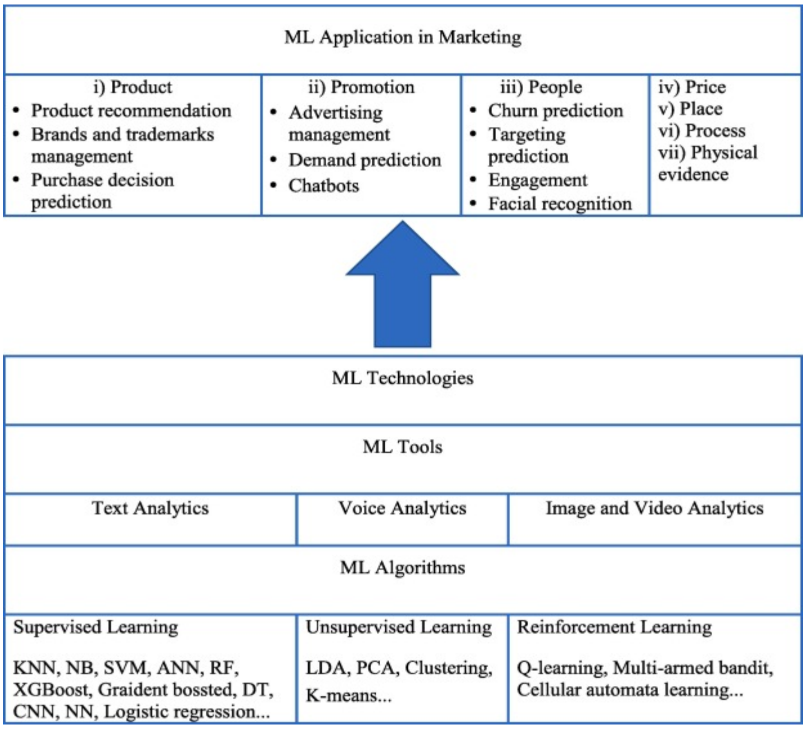

Figure 2: Machine Learning Application in Marketing

Source: Ngai and Wu (2022)

As seen in the figure, machine learning is examined in terms of the 7P marketing mix elements, and the essential tools and algorithms that contribute to these elements are expressed. Ngai and Wu (2022: p. 38) then show the methods and tools utilised in machine learning and ML, including text, voice, images, and videos, as well as supervised, unsupervised, and reinforcement learning.

When measuring the effectiveness of digital marketing advertising campaigns, it is essential to understand which channels contribute to consumers' purchase conversions. This process is known as attribution (Nisar and Young, 2018). The current study uses attribute modelling to analyse the factors that affect the success of digital marketing campaigns. On the other hand, users' communication styles towards the campaign, their reactions towards the campaign, and their attitudes towards a new technology can be based on Davis's (1989) Technology Acceptance Model. This situation can be associated with the study's Engagement Metric and Conversion Rate variables. Incremental Response

Modelling can also be associated with Incremental Response Modelling, which is used to model the incremental responses of consumers to the campaign and to analyse the differences between those who are exposed to the digital marketing campaign and those who are not (Sanisoglu, Burnaz, and Kaya, 2024). Finally, which groups adopt the campaign and the adoption rate can be analysed within the scope of the Diffusion of Innovations Theory. This theory contributes to analysing consumers according to the speed of innovation adoption and creating strategies accordingly (Min, So, and Jeong, 2021). The study's audience reach, conversion rate, and browser conversion rate variables can be related to this context.

Method

This research aims to evaluate the effectiveness of digital marketing campaigns utilising machine learning algorithms. The analysis was performed using Python 3.11. During the study, various libraries were used for data processing, model development, and evaluation. The libraries used are Pandas (data processing), Scikit-learn (machine learning algorithms and cross-validation), Imbalanced-learn (data balancing), Matplotlib (visualisation), Openpyxl (saving results to Excel), and Numpy (mathematical operations).

The study's data set consists of data on 10,001 digital marketing campaigns in various sectors (e-commerce, finance, health, manufacturing, retail, services, technology). Information about the variables in the data set is as follows: **Advertising Spend:** Total budget allocated for the campaign. **Duration:** The length of the campaign is in days. **Engagement Metric:** A measure of campaign engagement (e.g., clicks, views). **Conversion Rate:** The percentage of conversions achieved. **Success:** Campaign success status (0=failed, 1=successful). **Budget Allocation:** Budget allocated to each campaign. **Audience Reach:** Number of people reached by the campaign. **Device Conversion Rate:** Conversion rate by device. **OS Conversion Rate**: Conversion rate by operating system. **Browser Conversion Rate:** Conversion rate by browser. These variables are significant in determining the success of digital marketing campaigns.

The data preparation process started with cleaning the missing data. Variables that were unnecessary for the analysis, such as campaign ID, were removed from the data set. Categorical variables were transformed with the One-Hot Encoding method for digitisation. All features were normalised with the StandardScaler method. It was found that there was an imbalance in the classes of the target variable in the dataset. This imbalance was eliminated with the ADASYN method.

In the dataset, the variable "success" was designated as the target variable (dependent variable). All other variables were used as independent variables in the analysis. It was determined that there was an imbalance between the classes of the "success" variable, representing the success rate in the dataset. To address this issue, the ADASYN (Adaptive Synthetic Sampling) algorithm was employed, and new samples were generated for the minority class. This method aims to improve the performance of the models by ensuring the balance between the classes.

We used a variety of machine learning algorithms during the model generation process. **Gradient Boosting, Random Forest, Logistic Regression, Support Vector Classifier (SVC), K-Nearest Neighbors (KNN), AdaBoost,** and **Decision Tree** algorithms were applied in the study. Logistic regression was used for linear relationships, while decision trees and random forests were used to rank the importance of variables. Gradient boosting and AdaBoost were employed to achieve high accuracy. A comparison of the models was carried out using metrics such as Accuracy, F1-Score, ROC-AUC, and cross-validation to evaluate their performance. Finally, feature importance ranking and hyperparameter optimisation were used to enhance the methods' explainability. Improving the models' performance is the current goal, and the GridSearchCV approach is used for hyperparameter optimisation. To achieve this goal, the 5-layer StratifiedKFold method was employed for cross-validation. Each of the five equal halves of the dataset served as a separate training and testing dataset. The layered structure preserved class proportions for the objective variable and guaranteed a balanced distribution inside each fold.

The machine learning models selected in the study were analysed according to their ability to predict the success of a digital marketing campaign, considering linear and non-linear relationships. To demonstrate the validity and reliability of the research tools, feature importance rankings and model comparisons were conducted. In addition, data collection, examination, verification, models used, study variables, model development stages, and visualisation of modelling results are explained in detail.

Using the test dataset, the models were retrained using optimal hyperparameters. For each model, measures including **accuracy, precision, recall**, and F**1-score** were computed, accompanied by a comprehensive analysis utilising a confusion matrix. While the performance of each model is recorded in an Excel file, essential indicators are visualised and presented. Confusion matrix images and feature important scores are shown. Model performances and outputs are systematically reported to facilitate practical interpretation of the study.

The results obtained were saved in Excel files. These files presented the accuracy rates, classification metrics, and hyperparameter optimisation results for each model in detail. GridSearchCV was used to determine the best parameters for each model in the study. Hyperparameter optimisation selected the best performance parameters by testing different combinations. At the end of the study, the most suitable machine learning model for predicting the success of digital marketing campaigns was determined.

Findings

Interpretation of model performances

The outcomes for the models are displayed in Table 1.

Table 1: Model Performances

Model	**Accuracy**	**Precision** (Class 0)	**Recall** (Class 0)	**F1-Score** (Class 0)	**Precision** (Class 1)	**Recall** (Class 1)	**F1-Score** (Class 1)
Random Forest	0.929887	0.931432	0.928884	0.930156	0.928335	0.930901	0.929616
Gradient Boosting	0.933187	0.964265	0.900438	0.931259	0.905699	0.96628	0.935009
AdaBoost	0.728073	0.877588	0.53337	0.663491	0.662312	0.92482	0.771857
Logistic Regression	0.533682	0.534021	0.56674	0.549894	0.533294	0.500276	0.516258
SVC	0.739896	0.702852	0.835886	0.763618	0.794942	0.642897	0.71088
K-Nearest Neighbors	0.85675	0.782046	0.991247	0.874306	0.987879	0.72084	0.833493
Decision Tree	0.828705	0.805993	0.868162	0.835923	0.855516	0.788834	0.820823

The results were used to compare the performance of various models. The Random Forest model performed well with 92.99% accuracy and high precision, recall, and f1-score values. Gradient Boosting performed the best in this study, reaching the highest accuracy (93.31%). On the other hand, the AdaBoost model performed less well, with 72.8% accuracy and low recall and f1-score values, especially for class 0.

The Logistic Regression model performed below expectations, achieving 53.36% accuracy and failing to provide balanced class performance. The SVC model showed a moderate performance with 73.98% accuracy, while the K-Nearest Neighbors and Decision Tree models provided better results with 85.68% and 82.87% accuracy, respectively.

The Gradient Boosting model outperformed the other models in terms of score metrics (precision, recall, and F1-score) for both classes 0 and 1. The merits and drawbacks of alternative models may vary depending on the specific application domain.

This study investigates the ability to predict the success of digital marketing campaigns, measuring the performance scores of the employed models using various metrics. The measurements are elaborated upon with a confusion matrix illustrated in Figure 3, accompanied by visuals.

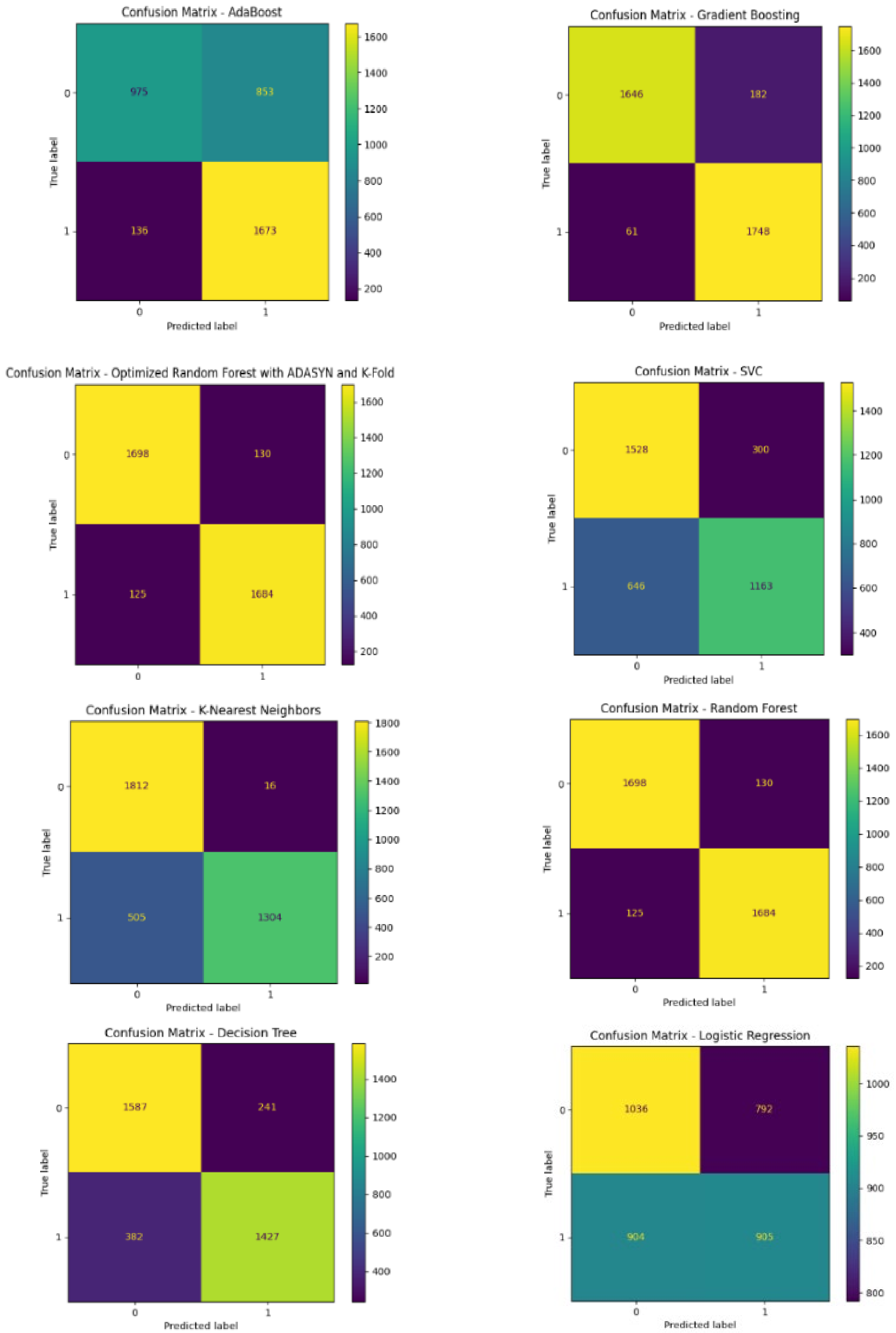

Figure 3: Confusion Matrix

Among all the models developed, the highest accuracy was with Gradient Boosting at 93.31%. This model's performance was relatively balanced, yielding very high precision and recall values for classes 0 and 1, thereby demonstrating its ability to separate both positive and negative classes in predictions reliably. During the confusion matrix analysis, the low levels of false positives and false negatives are significant findings supporting stability and accuracy. The Random Forest model achieved a high performance rate of 92.99%. Precision and recall values also support this performance. This model yields effective results even on imbalanced datasets by offering balanced prediction capabilities for classes 0 and 1. By analysing the confusion matrix, the model demonstrates a low rate of false predictions, achieving high success rates for both classes, thereby increasing the overall success and reliability of the model. KNN brings to attention its performance with the best rate, 85.68%, in class 0. The very low values of the false negative rate for class 0 show that this model is highly successful in classifying this class. However, the relatively high number of false negatives for class 1 limits the model's ability to discriminate class 1. This could mean the model performs well in one class but worse in another. The Decision Tree demonstrated a commendable performance, achieving an accuracy of 82.87%. The confusion matrix analysis indicates a satisfactory correct prediction rate for class 0, although a higher number of false negatives were observed in class 1. While this model provides straightforward and rapid outcomes, it may experience some performance declines when handling intricate datasets. The SVC model exhibited a moderate performance, achieving an accuracy of 73.98%. Although the actual negative rate for class 0 is considerable, the false negative rate for class 1 is even greater; this indicates that the model struggles to differentiate class 1. This outcome suggests that the model requires optimisation using more balanced datasets or alternative kernel functions. The AdaBoost model achieved an accuracy of 72.8%, exhibiting low recall and f1-score values, particularly for class 0. The results from the confusion matrix indicate that the model showed a higher number of false-positive and false-negative predictions in class 0. This suggests that the model exhibits sensitivity to data imbalances and can be enhanced through various data augmentation techniques. The Logistic Regression model exhibited the least favourable performance, achieving an accuracy of 53.36%. Significant prediction errors between class 0 and class 1 indicate that the model is not well-suited for imbalanced data sets. The confusion matrix analysis reveals that false negatives and overly optimistic predictions indicate potential effectiveness on more straightforward datasets or less complex issues.

The data and models revealed in the study can form the basis for a successful digital marketing campaign. In a digital marketing campaign, the impact factors (variables) proposed in the study can serve as an example for other studies. In addition, the model proposed in terms of the correlation between these data and the modelling with which they will be analysed can facilitate marketers' strategies. The importance of data-driven work in the planning and evaluation phases of digital marketing campaigns draws attention. Models such as Gradient Boosting and Random Forest can provide valuable insights into customer segmentation and conversion potential within the campaign. Engagement Metric and Conversion Rate stand out among the factors affecting the campaign's success according to the order of importance of the features. While variables such as Ad Spending and Budget Allocation provide information about the financial efficiency of the campaign, they not only contribute to the model but also offer clues about the factors that may affect success. Finally, as stated by Blomster and Koivumäki (2022), the application of machine learning models may also differ according to businesses' specific resources, competencies, and capabilities. The results of technical analyses of machine learning models indicate that when marketers accurately perceive the results and process the data effectively, they can achieve the success factors in campaigns more efficiently. Kim, Kim, and Geum (2023) also support the idea that the factors highlighted in the feature importance ranking can impact marketing campaigns in the current study.

In conclusion, among the models used in this study, Gradient Boosting yielded the best results, achieving the highest accuracy and balanced prediction performance. Random Forest was also a strong alternative with excellent results. On the other hand, models such as AdaBoost and Logistic Regression did not perform adequately on unbalanced datasets and required improvement. It is recommended that a model be chosen based on the characteristics of the data set and the analysis requirements.

Discussion

Changes and developments in technology impact the science of marketing and many other fields of study. In the early years of internet technology, it is seen that issues such as "e-commerce" and "online shopping," which reveal the Web 2.0 aspect of marketing, and the concept of "social media marketing" with the emergence of social media constitute the scope of digital marketing and are discussed in detail in many studies. Today, the technological revolution that has emerged, especially with the aid of artificial intelligence-supported technologies, is leading marketing science to be handled through these technologies in this context. Studies using machine learning models stand out in this regard. Hair and Sarstedt (2021) examine data, measurement, and causal inference in machine learning from a marketing perspective. With a comprehensive literature review, Miklosik and Evans (2020) explain big data and machine learning in digital transformation in the marketing sector. Ngai and Wu (2022) present the conceptual framework for using ML-based applications in marketing. They provide a detailed description of the processing, classification, and prediction of consumer data using machine learning algorithms. Similarly, this study aims to reveal the predictive capabilities of machine learning models for success using data on digital marketing communication campaigns, presenting the conceptual framework.

Sharma et al. (2021) apply machine learning models to digital marketing campaigns using a dataset of sales from the Kaggle platform, which encompasses various advertising media, including television, radio, and print media, such as newspapers. They also investigate predicting the impact of online promotional techniques to increase web-based advertising and reveal the predictive ability of machine learning models with a rate of 94.50%. In addition to this similarity with the current study, it differs in employing various AI techniques, including neural networks and linear regression. Zhang (2022) demonstrated that machine learning models can create consumer portraits based on a bank's general dataset. He predicted consumers' borrowing status based on the predictive ability of algorithms such as the BP neural network, SVM, and the random forest algorithm. The findings indicate that the random forest algorithm achieves the highest prediction accuracy, averaging 94% across 10 calculations, and can assist banks in identifying potential target customers to a certain degree.

Abd et al. (2024) determined that machine learning effectively predicted purchasing decisions based on consumer data. They examined customer data using analogous machine learning methods to those employed in the present investigation. The study revealed that the Random Forest model, a machine learning algorithm, is the most effective for predicting client purchase status. Chen et al. (2021) utilised machine learning to formulate predictions regarding individualised marketing techniques and customer purchasing behaviours, specifically with luxury goods acquisitions. Liu and Yang (2022) further echoed the importance of machine learning algorithms in data processing for content marketing. Data regarding content marketing was processed using machine learning models to deduce optimal content marketing recommendations. Kumar and Reddy (2021) use a set of computations (arbitrary woodlands, restrictive surmising trees, and causal timberlands) to characterise the features predicting bank customers' digitalisation interaction, outline the succession of buyers' dynamic activities, and investigate the existence of causal links in the digitalisation cycle. The study finds that the Random Forest model works best. They also accurately predict 88.41% of bank customers' online banking purchase and usage preferences. Lin (2024) draws attention to the impact of machine learning on a brand's digital marketing strategies by concluding that through the collection and analysis of digital marketing data, a brand's digital marketing strategies can improve the effectiveness and conversion rate of the strategy.

Das (2015) created a prediction model to identify customers who are most likely to respond to the company's offers based on their past buying tendencies and analysed the model that provides the maximum accuracy for the dataset. Three commonly used algorithms — Naïve Bayes Classification, K-Nearest Neighbour (KNN), and Support Vector Machine (SVM) — were selected to target a pool of customers for direct marketing. Among all classifiers, the experimental results show that the Naïve Bayes Classification achieves the highest accuracy and specificity. Modak et al. (2024) highlight the superior performance of neural network models over traditional models, such as Random Forest and Logistic Regression, achieving up to 89% accuracy and F1 scores of 88%, highlighting their transformative potential in reshaping digital marketing strategies in the banking industry.

The study uses machine learning models to predict bank time deposit subscriptions. Similarly, the Kaggle data was analysed, and the Random Forest Classifier demonstrated the highest accuracy rate (87.8%). In their research, Panarese, Settani, Vitti, and Galiano (2022) employ machine learning algorithms for sales forecasting and demonstrate that the Gradient Boosting model achieves the highest predictive ability, a finding similar to the current study. They stated that the success of machine learning models in predicting the sales of a newly launched product would give marketers a competitive advantage.

In another study examining personalisation, automation, and user behaviour in digital marketing with machine learning, Nikolajeva and Teilans (2021) reveal similarities with the current study's results. The study emphasises the importance of machine learning in successful marketing campaigns and recommends creating website-specific ads separately in all sales funnels.

Cui and Curry (2005) investigate the application of machine learning in marketing to predict outcomes, including automated modelling, mass production models, intelligent software agents, and data mining. Unlike the current study, they only examine the support vector machine (SVM). Hakim et al. (2021) approach the study of machine learning in marketing from a distinct perspective, incorporating neuromarketing into their research. They utilised machine learning algorithms in conjunction with the electroencephalography (EEG) method.

This study is similar to the studies discussed above in that it predicts success in digital marketing using machine learning models and compares the prediction capabilities of these models. Additionally, the ADASYN (Adaptive Synthetic Sampling) method was employed in this study to mitigate dataset imbalances. Stratified K-Fold cross-validation was applied to divide the dataset into five equal parts, and each part was used as both training and test data, thus providing more reliable results for the models. Additionally, hyperparameter optimisation was performed to determine the optimal parameters for each model. These applications (using the ADASYN method, Stratified K-Fold cross-validation, and hyperparameter optimisation) differentiate this study from the above studies and reveal the unique value of the study. Finally, the differences in the machine learning algorithms used in the study also differentiate the study from other studies.

The findings obtained for the research question "Can the success of digital marketing campaigns be predicted using machine learning algorithms?" presented in the study provide a positive answer to this question. The high accuracy rates of the analysed models, especially algorithms such as Gradient Boosting and Random Forest, have shown strong performance in success prediction. Moreover, considering the ADASYN method applied to address class imbalances in the dataset and the importance levels of the variables, it is evident that the main factors affecting the success of the campaigns can be statistically decomposed.

While these results contribute to explaining users' digital interaction behaviours within the framework of the Technology Acceptance Model (TAM), they also provide important clues about the adoption process of digital marketing tools in terms of the Diffusion of Innovations Theory (DOI). In the context of Incremental Response Modeling, data-based measurement and prediction of consumer reactions reveal that marketing strategies can be dynamically reshaped.

Conclusion

The use of machine learning in digital marketing appears to outperform existing practices (Ullal et al., 2021). The use of machine learning in digital marketing strategies has been successful in enhancing the understanding of target consumer behaviour and optimising interactions with consumers (Bayoude, Ouassit, Ardchir, and Azouazi, 2018, pp. 375-377). By predicting consumer behaviour, it is also observed that these models are being developed in combination with new technologies, such as customer segmentation, providing personalised offers, and even blockchain (Kaponis and Maragoudakis, 2022), pp. 2-9).

In recent years, machine learning has enabled companies to become more efficient in their marketing strategies. By processing data and utilising machine learning models, marketers can personalise interactions with consumers, better understand their behaviour, and analyse purchase intentions (Bayoude, Ouassit, Ardchir, and Azouazi, 2018).

Machine learning can predict future trends and facilitate informed decision-making by providing valuable insights from large datasets. This feature dramatically influences and improves an enterprise's strategic decision-making (Miklosik et al., 2019). It can help marketers make strategic decisions more efficiently by providing easy access to accurate consumer information (Ullal et al., 2021). Recently, machine learning has been extensively used in marketing. The primary marketing challenges addressed by machine learning are customer behaviour, recommendation systems, predictive analytics, market segmentation, and textual content analysis (Duarte et al., 2022).

This paper aims to reveal the power of machine learning models utilising artificial intelligence in marketing science. Therefore, the analyses conducted in this study showed that the success of digital marketing campaigns can be predicted using machine learning models. The Gradient Boosting model was the machine learning model that performed the prediction most successfully. The Gradient Boosting model stood out as the model with the highest accuracy (93.31%). The Random Forest model ranked second with 92.99% accuracy and high precision. As a result of the analysis, the Logistic Regression model stands out as the machine learning model with the lowest predictive ability, achieving an accuracy of 53.36%. The SVC model demonstrated moderate performance with 73.98% accuracy, while the K-Nearest Neighbours and Decision Tree models achieved better results with 85.68% and 82.87% accuracy, respectively.

The results of the aforementioned study highlight the significance of machine learning algorithms in marketing science. As in many other disciplines, using new technologies in marketing science is essential. Integrating new technologies, such as machine learning, into strategies and campaigns will create sustainable value for businesses, consumers, and society. With these technologies, businesses can gain a sustainable competitive advantage by predicting the success of their campaigns and strategies.

Consumers will be exposed to more effective campaigns and will receive the right product and brand communication. Efficient communication between businesses and consumers will also contribute to societal value in terms of sustainability. It is anticipated that the findings of the study may be helpful for marketers and managers to understand the multifaceted nature of ML in marketing from the perspectives of both consumers and businesses.

This study assesses the ability to predict the success of machine learning models in digital marketing campaigns. The study's dataset comprises marketing campaigns from the e-commerce, finance, healthcare, manufacturing, retail, services, and technology sectors. This issue emerges as a limitation of this study. A study can utilise different datasets, including campaigns from other sectors. There is also a limitation in terms of analysis. Various marketing analyses, such as customer segmentation, sales forecasting, market analysis, and competitive analysis, can be applied using machine learning models.

Artificial intelligence-based technologies are continually evolving and advancing. This rapid change and development lead to some requirements for future studies and practitioners. Both academics and practitioners should closely monitor current machine learning algorithms and their potential future transformations.

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