MENACIS2021 MENA

11-14-2021

Machine learning in digital marketing.

Youssef Lahbabi
Research Center, EMAA Business School, y.lahbabi@emaa.ma

Samira Raki
Research Center, EMAA Business School, s.raki@emaa.ma

Houda Chakir Lamrani
Research Center, EMAA Business School, h.chakir@emaa.ma

Sara Dehbi
Research Center, EMAA Business School, s.dehbi@emaa.ma

Machine learning in digital marketing

Youssef LAHBABI, y.lahbabi@emaa.ma
Samira RAKI, s.raki@emaa.ma
Houda CHAKIR LAMRANI h.chakir@emaa.ma
and
Sara DEHBI s.dehbi@emaa.ma

Research Center, EMAA Business School, Agadir, Morocco

Abstract

Marketers use machine learning to find patterns in user activities on a website or on a mobile application. This helps them predict the further behavior of users and quickly optimize advertising offers. In this paper, we present a novel algorithm based on Machine Learning used in the Information System for optimizing advertising services, attracting customers, growing sales, adapting the promotional offers that correspond to the hobbies of users, and for setting up a spam filter in the email or the Facebook service. Our framework demonstrates the feasibility of the approach to manage advertising campaigns to produce better results.

Keywords : Artificial Intelligence, Machine Learning, Digital Marketing, Online Advertising, Big Data.

I. Introduction

The number of digital users is increasing on daily basis. It has reached 4.66 billion people as of 2021, which represents 59.5 percent of the world's population (Johnson, 2021). Internet usage generates a massive volume of data with a remarkable influence on diverse fields such as healthcare, business, and weather, sports, and security (Frizzo-Barker et al, 2016; Gahi, Guennoun, & Mouftah, 2016). Consequently, marketing is no exception. Thanks to the ever-advancing Information and Communication Technologies (ICT), marketing is no longer limited to traditional methods uses. In fact, digital marketing has become an essential tool for business in today's digital environment whereby Big Data is a key player. According to Baesens (2014), Big Data has several applications in marketing such as market basket analysis, recommender systems, and customer segmentation.

Liedtke (2016) defines Big Data as "*a relatively large amount of data consisting of multiple types from multiple sources possibly arriving in real-time of varying degrees of accuracy requiring exploratory data analysis and integrative analytical methods*." Big Data is tightly interrelated to Artificial Intelligence (AI) and its advanced technologies. Indeed, Big Data uses "*artificial intelligence techniques to extract value from big datasets*'' (European Data Protection Supervisor 2016, p. 4, as cited in Ishii, 2017). In turn, AI is advanced by technologies such as ''Neural Network'', ''Machine Learning'', ''Deep Learning'', ''Data Mining'', and ''Natural Language Processing'' (Ishii, 2017).

The adoption of AI in digital marketing has the potential to engender consumer insights and market intelligence through AI technologies such as Machine Learning (Davenport et al 2020). Moreover, Machine Learning (ML) impacts digital marketing in predicting consumer behavior, predictive marketing, chatbots, and content marketing (Bayoude et al, 2018). Nevertheless, despite the importance of AI and ML for digital marketing, limited research has addressed this area of study. Ullal et al (2021) pointed out that ML in the field of digital marketing worthy of further research. Besides, the adoption of AI and specifically ML in digital marketing is in its infancy.

Therefore, our objective is to examine the role of ML algorithms in enhancing the targeted online advertising through the use of user-centric approach based on two predefined criteria: User Profiling and Behavioral Targeting. To do so, three types of algorithms were employed to increase the performance and the accuracy of the prediction of ML. The simulation was performed by using the Orange Simulator.

II. Literature Review

1. Digital marketing

With the introduction and advancement of the internet, social media, mobile apps, and other digital communication technologies, marketing trends are shifting from conventional (offline) to digital (online). Digital marketing is a form of marketing through digital channels. It is also referred to as 'internet marketing', 'web marketing', 'online marketing' or 'e-marketing' (Atshaya & Rungta, 2016). However, Yasmin, Tasneem, & Fatema (2015) argue that digital marketing goes beyond internet marketing as it encompasses tools that do not involve the use of the Internet such as SMS and MMS. In the same line, Atshaya & Rungta (2016) emphasize that digital marketing comprises internet marketing and offline digital channels such as television, radio, and game advertising.

In this sense, the internet is a medium of communication rather than a marketing tool through which marketing strategies can be implemented (Olson et al, 2021). In fact, "*digital marketing provides interaction with customers and business partners using digital information and communication technologies and electronic means*" (Novytska et al, 2021, p. 524) to achieve marketing objectives (Chaffey & Ellis-Chadwick, 2012).

Digital marketing is a new place that allows potential consumers to connect to products, to obtain all kinds of product information, to carry out transactions via the Internet once the product has been chosen, to create their requirements, to communicate and interact with companies and brands but also to evaluate them (Mishra, 2020). Also, digital marketing allows companies to achieve their marketing objectives such as distribution and selling of goods, retailing of consumer services, customer relationship management, and influencing consumer behavior at a relatively low cost (Ribeiro & Reis, 2020; Efendioglu, 2016).

The companies are utilizing several digital media channels for the marketing and the promotions of their products as well as for their external communications such as emails, corporate websites, blogs, and social media platforms (e.g. Facebook, Instagram, Twitter, Pinterest, LinkedIn, Snapchat) (Hajarian et al, 2021; Olson et al, 2021). The choice of the platforms for digital marketing depends on target consumers and marketing strategy. However, online consumer behavior engenders large volumes of data which had led to the emergence of consumer analytics. Consumer analytics is *"the junction of Big Data and consumer behavior"* whereby *"Data provide behavioral insights about consumers and marketers translate those insights into market advantage*" (Erevelles, Fukawa, & Swayne, 2016, p. 897).

2. Digital Marketing and Artificial Intelligence

From an academic point of view, digital marketing is viewed as a quickly evolving discipline. According to Dwivedi et al (2020), advances in technology have driven the evolution of consumer behavior through a 'digital metamorphosis' leading to the formation of a 'digital consumer culture', which is a new and largely unexplored area presenting fertile ground for academics, researchers and practitioners interested in understanding this phenomenon.

For decades, computers and AI have been used to help digitalize business processes in companies in the buyerseller relationships as well as to attract and keep customers. AI makes it possible to identify unsuspected patterns in order to increase the chances of success in digital marketing (Wedel & Kannan, 2016). AI has offered an exceptional opportunity for digital marketers to identify, analyze, convert, retain and maintain customers' loyalty by having a better understanding of customers' needs and behavior (Nair & Gupta, 2021). As a result of digitization and the adoption of new technologies, data that was previously collected through channels such as customer satisfaction surveys can now be automatically pulled through social media platforms which increased the volume of information (Miklosik et al, 2019). However, companies tend to lack sufficient knowledge on emerging technologies such as AI and the utilization of ML analytical tools for analyzing and capturing data from social media and multi-channel communication (Dwivedi et al, 2021).

Pedro Domingos, the author of 'Master Algorithm', says that "*AI is the goal; AI is the planet we're headed to. Machine learning is the rocket that's going to get us there. And Big Data is the fuel*" (Conick, 2017). In view of that, online digital marketing is extensively attached to technological advancement (Desai, 2019) and consequently has become a natural candidate for AI (Dargham & Hachimi, 2021) and its components such as ML.

3. Role of Machine Learning in Digital Marketing

Machine Learning technologies are making their way into the field of digital marketing. To automate procedures, technology is poised to change the marketing area. ML is concerned with improving computer programs that can collect data, analyze it, and use it to learn (Hagen et al, 2020). Indeed, ML is a revolutionary technique in digital marketing (a subfield of AI) that uses computer algorithms to learn and improve throughout experiments, processing huge amounts of data (Ribeiro & Reis, 2020), and which has an impact on the daily activities of companies (Youtie, Iacopetta, & Graham, 2007). Furthermore, ML is the process of learning from data. It is used to forecast the future by analyzing data from the past. In fact, predictive analytics and statistics have been around for a long time. We may now utilize ML to do tasks such as speech and facial identification, language translation, recognition, data categorization, and object detection.

Some researchers look to marketing data as the new black gold. In 2016, it was reported that 90 percent of all digital data has been produced in the previous two years (IBM 2016). Marketers are seeking an ultimate objective with ML by exploiting this acquired data to understand consumers better, to provide the greatest possible experience, to create loyalty, and consequently to sell more. Moreover, ML might increase a company's marketing effectiveness by tenfold while lowering financial risks by fivefold by 2030 (Ertz, (2021). Therefore, ML allows to increase the number of conversions, and thus to better control acquisition costs.

Bayoude et al (2018) highlighted that ML has the potential to transform digital marketing in four areas: (1) predicting consumer behavior, (2) predictive marketing, (3) chatbots, and (4) content marketing.

3.1 Predicting consumers' behavior

There is a large data set that is generated from internet usage which needs advanced analytics. The ML algorithm can support managers in taking strategic decisions. For instance, a study undertaken by Giglio et al (2020) demonstrated how ML algorithms help six luxury hotel managers in developing brand management strategies based on big data analytics.

3.2 Predictive marketing

Predictive marketing is a market activity that aims to meet customers' needs (Nazarov, 2019) by tracking users' online activities (Podesta et al, 2014). Indeed, predictive marketing support marketing managers in producing targeted advertising and content (Podesta et al, 2014).

3.3 Chatbots

Chatbot is a conversational assistant agent which interacts with users using natural language (AbuShawar & Atwel, 2015). It improves the service quality by guaranteeing customized service (Chung et al, 2020). It has dominated multiple commercial and private domains (Janssen et al, 2020).

3.4 Content marketing

Content marketing is an inbound marketing strategy that consists of producing and delivering valuable, relevant, and consistent content to attract and retain a well-defined audience to gain profit (Steimle, 2014).

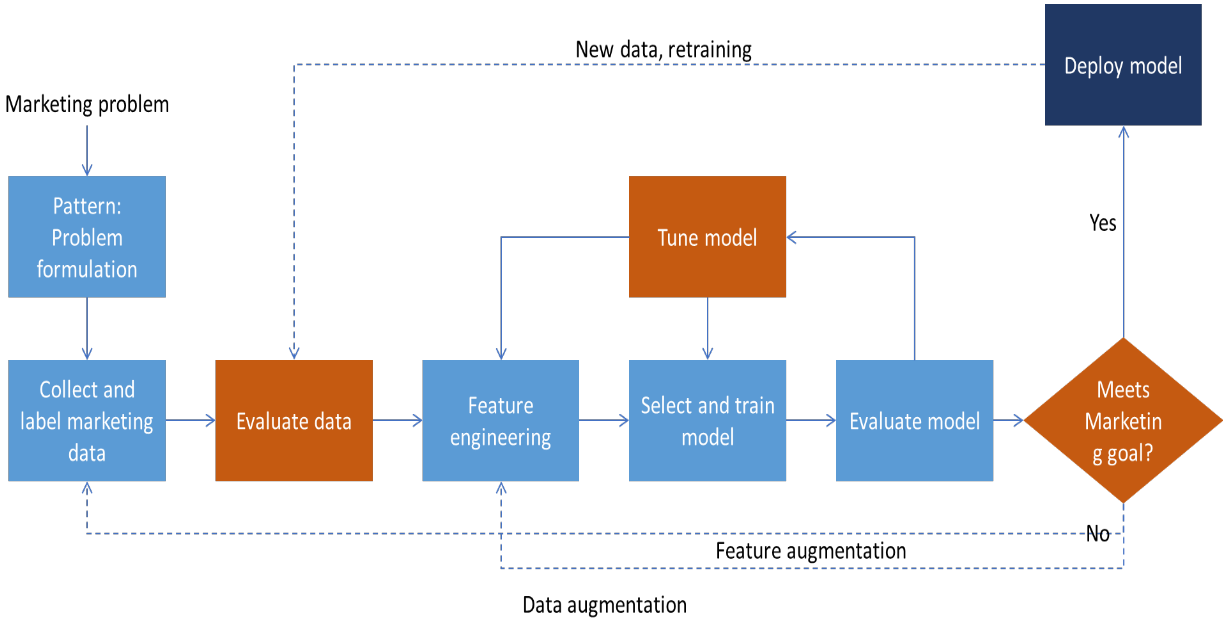

Figure 1: Machine Learning process flowchart

Figure 1 demonstrates the ML process flowchart to meet the marketing goals. The first step of the ML process consists of formulating the marketing problem which needs solid data collection and labeling (see step 2). The third step involves the preprocessing and evaluation of data. The fourth step entails proving new attributes based on feature engineering methods. The fifth and sixth steps consist of modeling / ML algorithms, by training and testing the data based on ML algorithms. These algorithms are automatic because they allow computers to practice inputting data to produce values and to automate decision-making processes. According to Batty et al (2015), the most commonly used algorithms are:

- Neural networks for supervised or unsupervised learning;
- Deep learning and reinforcement learning;
- The KNN method for supervised learning;
- The decision trees;
- Random Forest;
- AdaBoost.

The algorithm determines how the model is interpreted, and models can be assessed to see whether or not the objectives are met. The process focuses on selecting how to use obtained information and findings. The final step is the deployment phase which focuses on organizing, reporting and presenting newly acquired knowledge as needed.

III. Methodology

In this section, various ML techniques that enhance targeted online advertising are investigated and classified into two categories, User-centric and User Profiling **(Figure 2).**

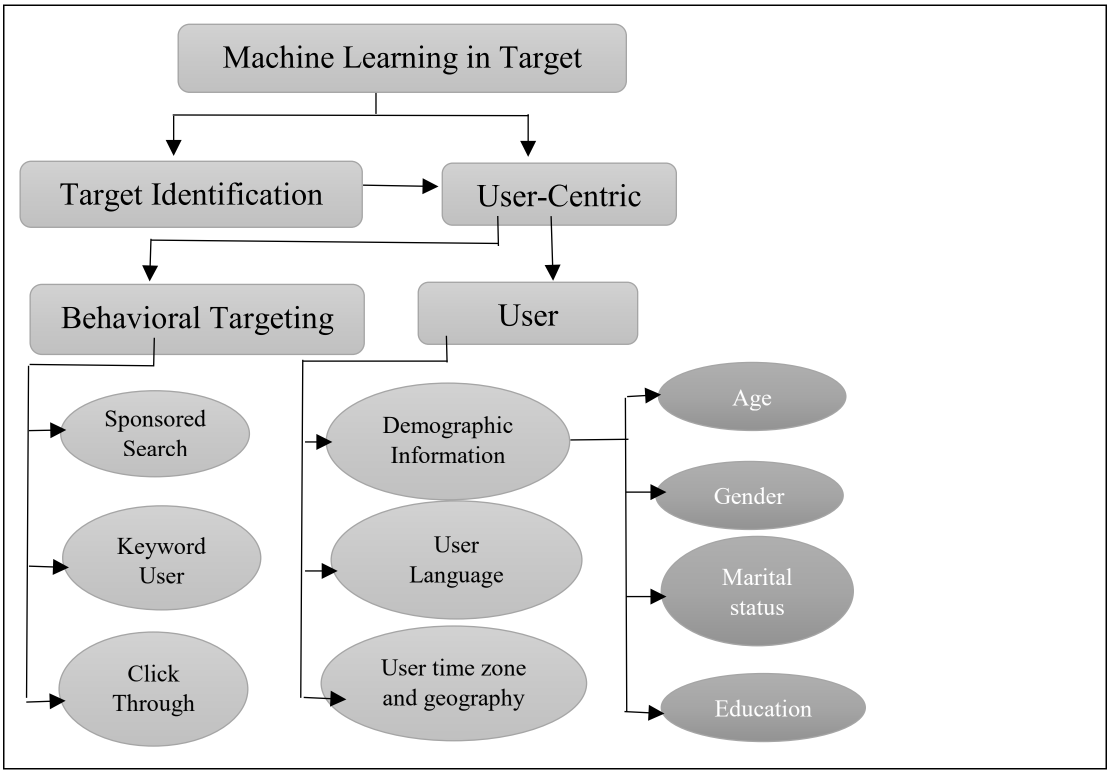

Figure 2. The proposed sequential Model

1. Step 1- Target Identification

The ability to accurately predict specific target audience members in an ever-cluttered digital environment is a challenge that is addressed by ML. Target advertising aims to present the most relevant advertising messages to consumers (Chen et al, 2009), and ML-based approaches allow for the automation and optimization of processes for potential consumer identification, information extraction, and market segmentation. Applications of ML to the user and content-based approaches hold advantages over traditional market segmentation as contents consumed and shared by individuals are more important in predicting target audiences and their purchasing behavior than demographic and geographical data alone (Lo, Cornforth, & Chiong, 2015). For example, textual features of user-generated content on various social media platforms, such as Twitter, can be used to predict and classify target audiences with high accuracy (Lo, Chiong, & Cornforth, 2015). Additionally, improvements in personalization and reduction in intrusiveness of advertising messages help to improve retention of customers, maximize marketing efficiencies, and improve the return on investments (ROI) (Lo, Chiong, & Cornforth, 2015).

2. Step 2- User-Centric

2.1 Behavioral Targeting

One way in which targeted advertisements reach desired consumers is through Behavioral Targeting (BT). In order to select the most relevant advertisements for consumers, BT relies on historical user behavior, such as identifying clicked links, pages visited, searches, and past purchases from the user's browsing history (Chen et al, 2009). With the popularity of search engines, such as Google, online searches and web browsing have become two of the most common online behaviors. Web browsing behavior helps advertisers make inferences regarding users' interests and to define audience segments. Leveraging users' actual online behavior strengthens relevance and personalization of advertising messages to desired consumers (Li et al, 2007). Additionally, the user's search queries also help to determine which advertisements should be displayed to the user by matching them to the advertiser's keywords.

Predicting the click behavior of users is another method to enhance targeted advertising. Cost-per-click (CPC) model, where advertisers pay when users click on an advertisement, is often used as a common pricing method for online advertisements. Therefore, predicting the probability that a user will click on an advertisement, click-through rate (CTR), is unmistakably important (Ta, 2015). CTR predicts the expected revenue for each displayed advertisement as well as ranking, filtering, and the placement of advertisements (Tagami et al, 2013).

Sponsored search (SS) is the placement of textual advertisements based on the match between the user's search query and keywords identified by the advertiser (Wang et al, 2018). For example, when users search for keywords purchased by the advertiser, the corresponding advertisement is then displayed. Optimizing the automated selection of advertisements helps to improve user experience (Addis, Armano, & Vargiu, 2009).

1.1 User Profiling

User profiling, a behavior-based approach, is a recommender system that discovers useful patterns in a user's behavior to determine what the user finds interesting and uninteresting (Addis, Armano, & Vargiu, 2009). Identification of user-interests is essential to suggest customized advertisements to users according to their preferences. As the users indicate an assortment of interests, explicitly (user-provided information) or implicitly (past online searches, reviews, browsing), they can be profiled in terms of attributes and predefined categories (Bilenko & Richardson, 2011). The ability to differentiate between users through behavioral targeting is important as the personalization of messages is crucial in enhancing user experience.

Demographic Information: this parameter can be used to assist with the determination of user profiling models. It describes an approach to the generation of annotated training data by combining geo-located social media profiles with geographically linked demographic data (Poulston, Stevenson, & Bontcheva, 2016). Moreover, another characteristic of demographic information is a collection of settings and information associated with a user. It contains critical information that is used to identify an individual, such as their age, gender, material status, and individual characteristics such as knowledge or education.

User Language: A good interface has been designed around the user, or user-centered designed. As a part of this, the dialogue in user profiling should be expressed in words, phrases, and concepts that are familiar to the user.

User Time Zone and Geography: is a client-specific time zone that can be defined for the user time and user date of each user in the user master record.

IV. Modeling The Machine Learning Classification Hybrid Algorithm (MLCHA)

Our algorithm combines three types of Classification Algorithms K-Nearest Neighbours, Naïve Bayes, and Random Forest. So, the aim of switching between the three classification algorithms is to increase the performance and the accuracy of the prediction in ML.

4.1 Naïve Bayes

Naive Bayes algorithm (Islam et al, 2009) is based on Bayes' theorem with the assumption of independence between every pair of features. Naive Bayes classifiers work well in many real-world situations such as document classification and spam filtering. This algorithm requires a small amount of training data to estimate the necessary parameters. Naive Bayes classifiers are extremely fast compared to more sophisticated methods. To calculate the probability that an event will occur, given that another event has already occurred, we use Bayes's Theorem. To calculate the probability of hypothesis (h) being true, given our prior knowledge(d), we use Bayes's Theorem as follows:

$$P(h|d) = (P(d|h)\ P(h)) / P(d)$$

P(h|d) = Posterior probability. The probability of hypothesis h being true, given the data d, where P (h|d) = P $(d_1|h)$ P $(d_2|h)$… P$(d_n|h)$P(d)

P(d|h) = Likelihood. The probability of data d given that hypothesis h was true.

P(h) = Class prior probability. The probability of hypothesis h being true (irrespective of the data)

P(d) = Predictor prior probability. Probability of the data (irrespective of the hypothesis)

4.2 K-Nearest Neighbours

Neighbours-based classification (Cunningham & Delany, 2020) is a type of lazy learning as it does not attempt to construct a general internal model but simply stores instances of the training data. Classification is computed from a simple majority vote of the k nearest neighbours of each point. This algorithm is simple to implement, robust to noisy training data, and effective if training data is large.

4.3 Random Forest

Random forest classifier (Biau, 2012) is a meta-estimator that fits a number of decision trees on various sub-samples of datasets and uses average to improve the predictive accuracy of the model and controls over-fitting. The sub-sample size is always the same as the original input sample size but the samples are drawn with replacement.

V. Experimental Methodology

This section describes the simulation results of the proposed ML in the digital marketing mechanism. The simulations for the proposed mechanism were performed using the Orange simulator (https://orangedatamining.com). In order to analyze the consumption of a certain brand within seven days, we conducted statistics and analysis on the basic characteristics of the brand's customers within seven days. Data is collected from two aspects: gender and age range of customers. First of all, the proportion of customers according to gender and age interval is shown in **Table 1**.

Table 1: Customer gender and age interval data statistics

	Sex		Age Interval		
	Male (%)	**Female (%)**	**Young adults [18-35] (%)**	**Middle-aged adults [36-55] (%)**	**Older adults [>55] (%)**
Monday	46	56	72	30	10
Tuesday	31	71	64	38	28
Wednesday	51	51	89	13	3
Thursday	53	49	55	47	37
Friday	37	65	54	48	28
Saturday	42	60	46	56	46
Sunday	48	54	51	51	41
Average	44	58	61.6	40.4	27.5

VI. Results and Discussion

Customer Characteristics under the Digital Marketing Model. From the ratio of male to female and the number of age group (young adults, middle-aged adults, older adults) customers of a certain brand in Table 1, it can be seen that the brand's digital marketing model can attract more female customers and young adult customers. These data show that female customers or young people are more interested in marketing activities, and they have more free time.

Predictive Analysis of the Digital Marketing Model under the Classification Hybrid Algorithm (MLCHA).

We analyze and calculate the relevant data of the brand within seven days to predict the total number of customers of the brand under the digital marketing model in the next few days and the number of customers who will purchase the brand and brand revenue. According to the data extracted by the Machine Learning Classification Hybrid Algorithm (MLCHA) and the classification algorithm used to predict and analyze the data set, the final results are shown in **Table 2.**

Table 2: Classification algorithm hybrid prediction data

The next seven days	Total number of customers	Number of purchasers	Brand revenue (%)
Monday	505687	305437	61
Tuesday	524124	375189	64
Wednesday	364186	184396	52
Thursday	529741	274581	51
Friday	206547	106145	36
Saturday	664789	641476	75
Sunday	604397	431467	44

According to the prediction results in **Table 2**, in the next seven days, the number of customers of the brand is very objective. The number of customers will be the largest at weekends. According to the previous analysis of the age groups of customers, it can be seen that the reason for the largest number of customers on holiday at weekends.

In the next week, the number of buyers of the brand will be the highest at the weekend. Therefore, it can be inferred that the brand can get better profits by properly publicizing its products or releasing some activities during the weekend, and the degree of publicity will also become higher.

The results of different methods using Machine Learning Classification Hybrid Algorithm (MLCHA), k-nearest neighbor classification, and random forest. can be seen in **Table 3.**

Table 3: Comparison results of different methods

Method	Forecasted total number of customers	Predicted number of byers	Revenue forecast (%)	Accuracy

Machine Learning Classification Hybrid Algorithm (MLCHA)	604397	431467	43	0.93
k-nearest neighbor classification	604300	431487	47	0.89
Random forest	604360	431427	41	0.90

VII. Conclusion

This paper uses ML methods to analyze brand digital sales in the context of process digital sales related data using classification hybrid algorithms. In this research, the number of customers, customer characteristics, degree of brand publicity, and brand revenue in the digital marketing of a brand within seven days are collected and analyzed. Through the modeling of ML classification hybrid algorithm, the related data of the brand in the next week are predicted. By calculating the experimental data many times, we can get the data forecast of brand digital marketing in the next week.

ML Marketing techniques have certainly helped brands in carrying out advertising campaigns. It is a cost-effective way of carrying out advertisement campaigns. Moreover, these campaigns are more intelligent as they help in reaching out to the target audiences. So, it becomes necessary for businesses to adapt to the new marketing trends and techniques. It not only helps in better advertising but also helps in standing out from the crowd.

References

- AbuShawar, B., & Atwell, E. (2015). ALICE chatbot: Trials and outputs. *Computación y Sistemas*, *19*(4), 625-632.
- Addis, A., Armano, G., & Vargiu, E. (2009, July). Profiling users to perform contextual advertising. In *Proceedings of the 10th Workshop dagli Oggetti agli Agenti (WOA 2009)* (Vol. 73).
- Atshaya, S., & Rungta, S. (2016). Digital Marketing vs. Internet Marketing: A Detailed Study. *International Journal of Novel Research in Marketing Management and Economics*, *3*(1), 29-33.
- Baesens, B. (2014). *Analytics in a big data world: The essential guide to data science and its applications*. John Wiley & Sons.
- Batty, M., Lemberger, P., Morel, M., & Raffaëlli, J. (2015). Big Data et Machine Learning manuel du data scientist.
- Bayoude, K., Ouassit, Y., Ardchir, S., & Azouazi, M. (2018). How machine learning potentials are transforming the practice of digital marketing: state of the art. *Periodicals of Engineering and Natural Sciences (PEN)*, *6*(2), 373-379.
- Biau, G. (2012). Analysis of a random forests model. *The Journal of Machine Learning Research*, *13*, 1063-1095.
- Bilenko, M., & Richardson, M. (2011, August). Predictive client-side profiles for personalized advertising. In *Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining* (pp. 413-421).
- Chaffey, D. and Ellis-Chadwick, F. (2012). Digital Marketing: Strategy, Implementation and Practice, 5th edn. Financial Times Prentice Hall, Harlow.
- Chen, Y., Kapralov, M., Canny, J., & Pavlov, D. (2009). Factor modeling for advertisement targeting. *Advances in Neural Information Processing Systems*, *22*.
- Chung, M., Ko, E., Joung, H., & Kim, S. J. (2020). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research*, *117*, 587-595.
- Conick, H. (2017). The past, present and future of AI in marketing. *Marketing News*, *51*(1), 26-35.
- Cunningham, P., & Delany, S. J. (2020). k-Nearest neighbour classifiers: (with Python examples). *arXiv preprint arXiv:2004.04523*.
- Dargham, M., & Hachimi, H. (2021). Digital marketing in the era of artificial intelligence. *International Journal on Optimization and Applications*, 23.

- Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, *48*(1), 24-42.
- Desai, V. (2019). Digital marketing: A review. *International Journal of Trend in Scientific Research and Development*, *5*(5), 196-200.
- Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., ... & Wang, Y. (2021). Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management*, *59*, 102168.
- Efendioglu, Y. D. (2016). Travel from traditional marketing to digital marketing. *Global Journal of Management and Business Research: E*, *8*.Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big Data consumer analytics and the transformation of marketing. *Journal of business research*, *69*(2), 897-904.
- Ertz, M. (2021). *Marketing responsable*. Editions JFD.
- Frizzo-Barker, J., Chow-White, P. A., Mozafari, M., & Ha, D. (2016). An empirical study of the rise of big data in business scholarship. *International Journal of Information Management*, *36*(3), 403-413.
- Gahi, Y., Guennoun, M., & Mouftah, H. T. (2016, June). Big data analytics: Security and privacy challenges. In *2016 IEEE Symposium on Computers and Communication (ISCC)* (pp. 952-957). IEEE.
- Giglio, S., Pantano, E., Bilotta, E., & Melewar, T. C. (2020). Branding luxury hotels: Evidence from the analysis of consumers'"big" visual data on TripAdvisor. *Journal of Business Research*, *119*, 495-501.
- Hagen, L., Uetake, K., Yang, N., Bollinger, B., Chaney, A. J. B., Dzyabura, D., Etkin, J., Goldfarb, A., Liu, L., Sudhir, K., Wang, Y., Wright, J. R., & Zhu, Y. (2020). How can machine learning aid behavioral marketing research? *Marketing Letters*, *31*(4), 361–370.
- Hajarian, M., Camilleri, M. A., Díaz, P., & Aedo, I. (2021). A taxonomy of online marketing methods. In *Strategic corporate communication in the digital age*. Emerald Publishing Limited.
- IBM. (2016). 10 Key Marketing Trends for 2017 and Ideas for Exceeding Customer Expectations. [Retrieved December 04, 2021], ftp://ftp.www.ibm.com/software/in/pdf/10_Key_Marketing_Trends_for_2017.pdf
- Ishii, K. (2019). Comparative legal study on privacy and personal data protection for robots equipped with artificial intelligence: looking at functional and technological aspects. *AI & SOCIETY*, *34*(3), 509-533.

- Islam, M. S., Khaled, S. M., Farhan, K., Rahman, M. A., & Rahman, J. (2009, December). Modeling spammer behavior: naïve Bayes vs. artificial neural networks. In *2009 International Conference on Information and Multimedia Technology* (pp. 52-55). IEEE.
- Janssen, A., Passlick, J., Cardona, D. R., & Breitner, M. H. (2020). Virtual Assistance in Any Context. *Business & Information Systems Engineering*, *62*(3), 211-225.
- Johnson, J. (Sep 10, 2021). Global digital population as of January 2021. [Retrieved December 04, 2021], https://www.statista.com/statistics/617136/digital-population-worldwide/
- Li, H., Zhang, D., Hu, J., Zeng, H. J., & Chen, Z. (2007, August). Finding keyword from online broadcasting content for targeted advertising. In *Proceedings of the 1st international workshop on Data mining and audience intelligence for advertising* (pp. 55-62).
- Liedtke, C. A. (2016). Quality, analytics, and big data. *Strategic Improvement Systems*, 1-54.
- Lo, S. L., Chiong, R., & Cornforth, D. (2015). Using support vector machine ensembles for target audience classification on Twitter. *PloS one*, *10*(4), e0122855.
- Lo, S. L., Cornforth, D., & Chiong, R. (2015). Effects of training datasets on both the extreme learning machine and support vector machine for target audience identification on twitter. In *Proceedings of ELM-2014 Volume 1* (pp. 417-434). Springer, Cham.
- Miklosik, A., Kuchta, M., Evans, N., & Zak, S. (2019). Towards the adoption of machine learning-based analytical tools in digital marketing. *IEEE Access*, *7*, 85705-85718.
- Mishra, C. K. (2020). Digital Marketing: Scope Opportunities and Challenges. In *Promotion and Marketing Communications*. IntechOpen.
- Nair, K., & Gupta, R. (2021). Application of AI technology in modern digital marketing environment. *World Journal of Entrepreneurship, Management and Sustainable Development*. 17(3), 318-328.
- Nazarov, A. D. (2019, December). Big Data Driven Marketing. In *International Scientific and Practical Conference on Digital Economy (ISCDE 2019)* (pp. 677-680). Atlantis Press.
- Novytska, I., Chychkalo-Kondratska, I., Chyzhevska, M., Sydorenko-Melnyk, H., & TYTARENKO, L. (2021). Digital Marketing in the System of Promotion of Organic Products. *WSEAS Transactions on Business and Economics*, *18*, 524-530.
- Olson, E. M., Olson, K. M., Czaplewski, A. J., & Key, T. M. (2021). Business strategy and the management of digital marketing. *Business Horizons*, *64*(2), 285-293.
- Podesta, J., Pritzker, P., Moniz, E. J., Holdren, J., & Zients, J. (2014). Big data: seizing opportunities, preserving values (Executive Office of the President). *The White House, Washington, DC*.

- Poulston, A., Stevenson, M., & Bontcheva, K. (2016, November). User profiling with geo-located posts and demographic data. In *Proceedings of the First Workshop on NLP and Computational Social Science* (pp. 43-48).
- Ribeiro, T., & Reis, J. L. (2020, April). Artificial Intelligence Applied to Digital Marketing. In *World Conference on Information Systems and Technologies* (pp. 158-169). Springer, Cham.
- Steimle, J. (2014). What is content marketing. Forbes. Dostupno na: http://www. forbes. com/sites/joshsteimle/2014/09/19/what-is-content-marketing.
- Ta, A. P. (2015, October). Factorization machines with follow-the-regularized-leader for CTR prediction in display advertising. In *2015 IEEE International Conference on Big Data (Big Data)* (pp. 2889-2891). IEEE.
- Tagami, Y., Ono, S., Yamamoto, K., Tsukamoto, K., & Tajima, A. (2013, August). Ctr prediction for contextual advertising: Learning-to-rank approach. In *Proceedings of the Seventh International Workshop on Data Mining for Online Advertising* (pp. 1-8).
- Ullal, M. S., Hawaldar, I. T., Soni, R., & Nadeem, M. (2021). The Role of Machine Learning in Digital Marketing. *SAGE Open*, *11*(4), 21582440211050394.Wang, Q., Liu, F. A., Xing, S., & Zhao, X. (2018). A new approach for advertising CTR prediction based on deep neural network via attention mechanism. *Computational and mathematical methods in medicine*, *2018*.
- Wedel, M., & Kannan, P. K. (2016). Marketing analytics for data-rich environments. *Journal of Marketing*, *80*(6), 97-121.
- Yasmin, A., Tasneem, S., & Fatema, K. (2015). Effectiveness of digital marketing in the challenging age: An empirical study. *International Journal of Management Science and Business Administration*, *1*(5), 69-80.
- Youtie, J., Iacopetta, M., & Graham, S. (2008). Assessing the nature of nanotechnology: can we uncover an emerging general purpose technology?. *The Journal of Technology Transfer*, *33*(3), 315-329.