Big Data: A Panacea for Optimizing Digital Marketing Strategies.

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Abstract- This paper is aimed at investigating the role of big data in digital marketing. The methodology used in carrying out the research is literature review. Several recent papers on the application of big data for digital marketing was presented, considering their techniques, work done, contribution to knowledge, results and research gap was identified. To fill the knowledge gap, a proposed system was presented using customer segmentation techniques and leveraging data from customers to present a conceptual model capable of improving reliability of digital marketing in real world scenario.

Indexed Terms- Big Data, Customer Segmentation, Challenges, Review, Digital Marketing

I. INTRODUCTION

With the pervasive influence of the internet and digital media, the landscape of business operations has undergone a profound transformation. A staggering 3 billion individuals worldwide engage with the internet for various purposes, including product research, socializing, and networking (Yufeng, 2022). This digital immersion has not only reshaped consumer behavior but also revolutionized marketing methodologies for businesses (Turkmen, 2021). The evolving digital technologies continually reshape the marketing landscape, compelling businesses to adapt swiftly to meet consumer demands and navigate dynamic market conditions. From desktop computers to smart-phones and tablets, consumers now have a plethora of technological platforms at their fingertips, offering them a diverse array of product, service, and pricing options with unparalleled convenience and speed (Yu et al. 2023).
The proliferation of technological tools has facilitated a paradigm shift in online marketing strategies, giving rise to a more user-centric, measurable, and interactive approach (Vafeiadis et al., 2015). This digital marketing evolution has been underscored by the advent of big data and analytical tools, which have become instrumental in enhancing business performance, fostering sustainable value creation, and gaining competitive advantage. With digital transformation, consumers are increasingly embracing digital tools across various aspects of their lives, leaving behind a trail of data generated through their interactions (Selma, 2020). This accumulation of data, stemming from sources such as sensors, the Internet of Things (IoT), websites, social media, and mobile platforms, collectively constitutes the concept of "big data. "The essence of big data lies in its vast volume, encompassing a multitude of data types ranging from traditional operational data to complex unstructured data like images, conversations, and videos sourced from digital and social media (Muneeb, 2018). Harnessing the power of big data, marketers leverage advanced statistical modeling techniques to glean actionable insights into consumer behavior and preferences (Namulia, 2011). Social networking platforms such as Facebook and Twitter wield considerable influence over consumer decision-making processes, prompting businesses to integrate insights derived from these platforms into their marketing strategies (Noura and Amany, 2021). This integration empowers marketing tools to operate with greater efficacy and innovation, enabling businesses to stay attuned to consumer sentiments and market dynamics. Through regular analysis of customer service records and vigilant monitoring of the marketing environment, successful businesses remain agile and responsive, leveraging big data to refine their marketing strategies and drive sustained growth.

II. CONCEPT OF BIG DATA IN DIGITAL MARKETING

In the digital age, businesses are inundated with vast amounts of data generated from various online sources such as social media, websites, mobile apps, and e-commerce platforms. This influx of data, commonly referred to as big data, presents both a challenge and an opportunity for marketers (Fakhri, 2022). Big data analytics has revolutionized the way companies understand and engage with their customers, offering unprecedented insights into consumer behavior and preferences (Chi and Gang, 2022). One of the primary roles of big data in digital marketing is in enhancing customer segmentation and targeting. By analyzing large datasets, marketers can identify distinct customer segments based on demographics, behavior, and interests (Fakhri, 2022). This allows for more personalized and targeted marketing campaigns, resulting in higher conversion rates and ROI. Furthermore, big data enables marketers to track and measure the effectiveness of their campaigns in real-time. Through advanced analytics tools, they can monitor key metrics such as website traffic, engagement levels, and sales conversions. This data-driven approach allows for agile decision-making, as marketers can quickly identify what's working and make adjustments to optimize their strategies (Farooqi and Iqbal, 2019).

Moreover, big data facilitates predictive analytics, enabling marketers to anticipate future trends and customer behavior. By analyzing historical data patterns, marketers can forecast market demand, identify potential opportunities, and proactively tailor their marketing efforts to meet evolving consumer needs. Overall, the role of big data in digital marketing is transformative. It empowers marketers with actionable insights, improves targeting accuracy, enhances campaign performance, and drives innovation. As businesses continue to harness the power of big data, it will undoubtedly remain a cornerstone of digital marketing strategies in the years to come.

III. RELATED WORKS ON BIG DATA FOR DIGITAL MARKETING

In the study conducted by Jae et al. (2022), on predicting the success of bank telemarketing using machine learning, a decision tree model was employed as the sole predictive tool. This model was developed using customer data collected from outbound telemarketing and then implemented through python and evaluated. The study's findings revealed that the entire decision tree model achieved an accuracy rate of 78.4%, indicating an error rate of 21.6%. Further analysis focused on customers who were predicted not to succeed in bank telemarketing. The TNR is 75.63%, TPR is 82.61%. These results underscore the model's ability to distinguish between potential successes and failures in bank telemarketing, offering valuable insights for optimizing marketing strategies and resource allocation. Cedric et al. (2022) examined machine-learning framework for predicting bank telemarketing outcomes. The study introduced a class membership-based (CMB) classifier, a transparent approach particularly suited for data involving nominal variables in decision-making. The CMB approach was applied to data from a bank telemarketing campaign, demonstrating its effectiveness. The results revealed accuracy rate of 97.3% and an Area under Curve (AUC) of 95.9%, underscoring the model's robustness without showing signs of over-fitting. This outcome signifies the model's stability and reliability in predicting bank telemarketing success while maintaining a balance between accuracy and generalization. However, the model was not practically validated. Hassan et al. (2018) presented a novel approach that emphasizes the most crucial features for predicting client classes based on feature types. The dataset utilized pertained to direct marketing campaigns conducted by a Portuguese banking institution, sourced from The UCI Machine Learning Repository. Through the proposed classification technique, the researchers achieved both stability and accuracy in their predictions. The analysis concentrated on attributes like age, instance, job, housing, and education. Notably, the proposed method exhibited impressive performance metrics. It achieved a 60.12% accuracy rate, a recall of 50.00%, and a precision of 67.23%, with the f-measure indicating strong predictive capability which is good, however the model can be improved through practical demonstration of its efficiency. Premkumar et al. (2021), investigated the demand for adopting telemarketing strategies to promote long-term bank deposits among potential customers. The data of out-bound telemarketing was collected from a Portuguese banking institution's direct marketing campaigns involving phone calls and then trained various machine learning algorithms and evaluated. The results reported for Random Forest (RF) is accuracy of 91%, precision of 59.37%, recall of 43.18%, f1-score of 50.0%, and AUC-ROC of 93.53. Support Vector Machine (SVM), achieving an accuracy of 90.53%, precision of 58.62%, recall of 38.63%, f1-score of 46.57%, and AUC of 91.4. Gaussian Naive Bayes (GNB) reported an accuracy of 85.0%, precision of 38.55%, recall of 72.72%, f1-score of 50.39%, and AUC of 93.62. Decision Tree (DT) reported an accuracy of 91.0%, precision of 56.75%, recall of 47.72%, f1-score of 51.85%, and AUC of 71.69. Logistic Regression (LR) was also examined. The findings revealed that the LR model demonstrated the best predictive performance, achieving 92.48% accuracy, 70.58% precision, 54.54% recall, 61.53% f1-score, and an AUC-ROC score of 93.62, thereby highlighting its efficacy in predicting the outcomes of telemarketing efforts. However, the trustworthiness of this model can be enhanced through practical testing. Gu et al., (2020), considered both deep learning and machine learning algorithms for the prediction of telemarketing success. The deep learning models applied are Convolutional Neural Network (CNN), Deep Neural Network (DNN), and proposed multiple-filter Convolutional Neural Network (XmCNN), while machine learning considered for the deep learning validation are Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting Machine (GBM), XGBoost, and LightGBM. The deep learning results when trained and evaluated reported DNN accuracy of 0.8715, False Positive Rate (FPR) of 0.1143, False Negative Rate (FNR) of 0.1870, recall of 0.8493, precision of 0.7918, and an F1-score of 0.8143. CNN configured with 3, 4 and 5 layers respectively were trained and reported for 3-layer CNN; an accuracy of 89.8% FNR of 0.8581, FPR of 0.1941, precision of 0.8177, R of 0.8581, and F1-score of 0.8352 was reported. The 4-layer CNN reported an accuracy of 88.9%, FPR was 0.1902, FNR was 0.8605, recall was recorded 0.8201, precision was 0.8915, and F1-score was reported 0.8376, while 5-layered CNN reported an accuracy of 0.0887, FPR of 0.1889, FNR of 0.8612, recall of 0.8204, precision of 0.8918, and F1-score of 0.8387. The XmCNN, reported an accuracy of 0.9018, FPR of 0.0756, FNR of 0.1916, recall of 0.8664, precision of 0.8366, and F1-score of 0.8502. Overall XmCNN when compared to other deep leaning algorithms reported telemarketing success rate, and when compared with other ML algorithms aforementioned, the deep learning algorithms, generally recorded better success rate. However, the success of this deep leaning algorithms depends on huge volume of data availability, and secondly it s still not the definition of telemarketing success for the study. In Asif's (2018) a study on the predictive success of bank telemarketing was explored through the application of various computational algorithms for classification. The study incorporated four distinct classification algorithms: SVM, Decision Trees, Random Forests, and Artificial Neural Networks. The classification performance of each algorithm was evaluated based on accuracy and the AUC. SVM demonstrated an accuracy of 89.63% and an AUC of 0.7726, while Decision Trees achieved similar results with an accuracy of 89.63% and an AUC of 0.7854. RF emerged as the most accurate classifier, boasting an accuracy of 90.63% and an AUC of 0.9373. Lastly, artificial neural networks reported an accuracy of 89.03% and an AUC of 0.8930. Notably, the results highlighted Random Forests as the algorithm with the highest accuracy at 90.63%, making it the most proficient method for predicting the success of bank telemarketing in this context; however there is no guarantee that this model will replicate similar success in real live as the model was not experimented practically. Fakhri (2022) and Farooqi and Iqbal (2019) presented the focus of predicting the success of bank telemarketing using machine learning techniques. The research evaluated the performance of six distinct models: decision tree, K-Nearest Neighbors (KNN), logistic regression, adaptive boosting (Ad Boost), and gradient boosting (GB) trained with outbound telemarketing data. The decision tree model achieved notable results, with an accuracy of 97.86%, recall of 96.75%, f1-score of 97.83%, and precision of 98.94%. Similarly, KNN displayed an accuracy of 95.28%, recall of 99.12%, f1-score of 95.45%, and precision of 92.05%. Logistic regression reported an accuracy of 74.14%, recall of 63.80%, f1-score of 71.16%, and precision of 80.44%. The random forest model demonstrated impressive performance, recording accuracy of 99.75%, recall of 99.61%, f1-score of 99.75%, and precision of 99.89%. The Adaboost model achieved an accuracy of 95.38%, recall of 92.35%, f1-score of 95.24%, and precision of 98.31%. Lastly, the GB model showcased an accuracy of 94.97%, recall of

91.59%, f1-score of 94.79%, and precision of 98.22%. After thorough analysis, the outcomes indicated that the random forest model outperformed others, emerging as the optimal choice for accurately predicting the success of bank telemarketing campaigns, however the trustworthiness of the model, can be enhanced through experimental validation. Sun et al. (2019) explored the effectiveness of various data mining models for predicting the success of out-bound bank customer telemarketing campaigns. The work considered a dataset consisting of 45211 instances from a Portuguese bank, containing 17 attributes obtained from the UCI Machine Learning Repository (Moro, 2011). Five different algorithms were employed for prediction training which are NB, K-NN, proposed J48 and Multi Layered Perception (MLP). The NB achieved an accuracy of 88.73% while ROC of 0.861 was reported. RF recorded an accuracy of 90.3895% while ROC of 0.927 was reported, and, MLP achieved 89.58% accuracy and a ROC of 0.888, KNN reported accuracy of 89.1531% and ROC of 0.771, and finally, J48 reported an accuracy of 90.5148% and a ROC of 0.875. through comparative analysis it was observed that the RF achieved better classification success, however the study lack clear definition of success, since it was not experimentally validated. Fawaz et al. (2020), proposed a data mining approach, to analyze and predict customer behavior using a telemarketing campaign dataset. The dataset was prepared based on the piece of evidence collected from the customers, during the live call session organized by the bank. Decision tree, Logistic Regression, and multilayer perception were trained to generate the prediction model. The cross-validation processes were employed for measuring and comparing the performance of each of the algorithms. The results demonstrated that the Logistic regression recorded the maximum accuracy of 91.48% while the Decision Tree recorded 89.91% and multilayer perception was 90.10%. Furthermore, the result shows that logistic regression provides the best accuracy among the three models, recorded as 91.48%, while in Jinmo et al., (2021), the use of deep learning model to predict the success of outbound telemarketing for insurance policy loan was applied. The study presented an interpretable multiple-filter Convolutional Neural Network (XmCNN) model designed to mitigate over-fitting and capture diverse high-level features from a vast array of input variables. The dataset of 171,424 customers was extracted and refined from the outbound telemarketing raw data of a Korean life insurance company. After the data was preprocessed and analyzed, dataset containing 44,412 observations were obtained and then imported to train XmCNN. The result reported false positive rate of (4.92%) and F1-score (87.47%). Overall the classification result was good, but the model trustworthiness can be enhanced through practical validation. Masturoh et al. (2021) collected 45211 instances of customer attributed from outbound telemarketing with 17 key attributes and ten trained with MLP. The result when evaluated reported an accuracy of 94,271%, TP Rate of 0.943%, FP Rate of 0.260%, and ROC of 0.899. while these study achieved good classification success with MLP, the model reliability can be enhanced using experimental validation approach; while in Kattareeya and Theera (2021), the same dataset was trained with 100 trees. The result reported an accuracy of 90.06%, and when tested reported 65.24% accuracy. Overall, while these studies contribute to the success of telemarketing, the trustworthiness of the model can be enhanced through practical demonstration. Anas et al. (2019) applied hybrid approach to the success of telemarketing process using MLP and DT. The model was trained wit customer data collected from 2011 to 2016 and containing 1000 samples of 11 customer features. In addition, DT, NB, MLP and SVM were train and analyzed comparatively. The result reported for accuracy of MLP is 90%, SVM is 83%, DT is 79%, NB 75%, while the hybrid model reported 99% and ROC of 9.7%. Similarly Yiyan, (2018) trained logistic regression to predict the success of bank telemarketing considering 21 attributes and comparatively validated using LR, N, DT, SVM and NN. The trained logistic regression reported accuracy of 92.03%, 86.11%, 90.70%, and 90.45% respectively, while other models trained reported AUC result of LR 92.31%, NB 75.90%, SVM 66.31%, NN 90.40% and DT 92.12%. Notably, the LR outperforms other classification models, but despite the success, the reliability of the model can enhanced through practical testing. Youngkeunand (2022) used DT for prediction of the out-bund telemarketing data. Key customer features considered are age, balance, loan, day, duration, campaign. The training results for accuracy reported 78.4% and 2.16% error rate, while testing reported 75.63% for FNR and TPR of 82.61% Similarly, Prince et al. (2022), applied Bayesian and MLP-Neural Networks for prediction of telemarketing success. Outbound telemarketing data was collected from UCI repository and then processed using SMOTE approach to handle unbalanced data. The algorithms were trained and the result reported an accuracy of 83.5% for Bayesian Neural Network, MLP reported 77.7%. Comparing the two model reported 5.8% improvement with Bayesian neural network and 3.13% improvement for AUC. Aliyu et al. (2019) comparative analyzed the performance of the different machine learning algorithms, for the prediction of bank telemarketing success. The dataset of 45,221 instances with 17 attributes was collected from a Portuguese retail bank, in a total of 52,944 phone contacts. The trained machine learning algorithms with the data are Bayesian Neural Network (BNN), NB, Naive Bayes update, LR, MLP, Stochastic Gradient Descent (SGD), Simple Logistics (SL), Sequential Minimal Optimization SMO, Voted Perceptron, Lazy K-star, Random Forest J48, Logistic Model (LM), DT and PART. The accuracy for BNN, NB, and Naive Bayes update reported 88% respectively, while SL, LR, J48, LMT, DT, and Simple Logic recorded 90%. SGD, MP, SMO, PART, lazy K-star reported 89% respectively. TPR was also considered for the evaluation and the results reported for BNN was 0.884, NB, and Naïve Bayes Updated recorded 0.880, LR reported 0.902, MP was 0.900, SGD was 0.894, SL was 0.901, SMO was 0.890, VP was 0.859, Lazy K-star was 0.890, RF was 0.905, J48 was 0.903, LMT was 0.904, DT was 0.899, and PART was 0.891. Overall the RF reported the best accuracy of 95%, while NB reported lowest accuracy of 88%, but the models despite te general success, can be enhanced or reliability through practical experiment. Kattareya and Theera (2021), researched on telemarketing guidance in selling banking services using Machine Learning (ML) algorithm such as RF optimized with Information Gain Ratio and evaluated considering 10-fold Cross-Validation. The model achieved 90.01% accuracy in predicting telemarketing success, which is good, but can be more convincing if tested through practical experiment. Similarly Gu, et. al. (2021) carried out a study to predict the success of outbound telemarketing in insurance policy loans. An Explainable Multiple-Filter Convolutional Neural Network (XmCNN) was used to develop a deep-learning ensemble model to this effect. The XmCNN was used to extract different high-level features using multiple input variables of the dataset before training. The result was evaluated using the FPR, F1-score, Precision, Accuracy, FNR, and Recall. Results reported for FPR is 0.0756, FNR is 01916, Recall is 0.8664, Precision is 0.8366, Accuracy is 0.9018 and F1-Score is 0.8502. In another study by Tékouabou, et. al. (2022), Class Membership-Based (CMB) classifier trained for direct marketing using data of 45,000 customers. The result when tested reported 97.3% accuracy and 95.9% AUC, while Van Erk (2020) considered various ML algorithms such as LR, Group Lasso with Ridge Regularization (GLRR), SVM, DT, NN, and Xtreme Gradient Boost (XGB). Least Absolute Shrinkage and Selection Operator (LASSO) with ridge regularization were used for feature selection, before the ML was trained. The results showed that the XGB-based model reported an AUC score of 0.9. Overall, these studies all contributes positively towards correct prediction of telemarketing success, the reliability of the models in practical application cannot be guaranteed, as none was experimentally validated in real life scenario.

Vongchalerm (2022) carried out an analysis on predicting the success of the banking telemarketing campaigns. LR and DT were trained using customer phone call data collected from 2008 to 2010. The results for LR reported AUC of 0.934, precision of 0.87, and recall o 0.869. DT reported 0.866 on AUC, 0.844 on precision, and 0.844 on recall. Comparism of the study showed that the LR-based model performed better for the analysis than the DT, while in Jin and He (2018) trained the same data using SVM, NN, and DT. The results showed that the DT-based model reported accuracy, precision, recall, and AUC score that is equal to 1. This shows that the DT could predict 100% accurate rate. It is worthy to note from the study that the NN showed better AUC score than the SVM but takes more than 4 times the processing time of the SVM-based model. The study therefore showed that despite a model showing a higher AUC-score, it is important to take into consideration its processing time. Asif (2018) trained SVM, DT, RF and ANN for the classification of telemarketing subscribers. In addition, LASSO, Logistic Regression, Random Forest approaches were utilized for feature selection and processing the data. When comparatively evaluated after training the RF was better with 89.71% accuracy and 0.7720 AUC. In another study Alsolami et. al. (2020), trained DT, Logistic Regression, and MLP were part of this experiment. From the comparative result obtained in the study, logistic regression provided the best accuracy which was recorded as 91.48% across all three models. Similarly, Borugadda, et. al. (2021), researched on the prediction success of bank telemarketing for selling long-term deposit, using RF, Logistic Regression (LR), Gaussian Naïve Bayes (GNB), DT, and SVM trained with telemarketing data with key features such age, job, marital status, education, duration, contact, and date. From the training results, the LR model reported a higher score in all the metrics except in the case of precision which had the GNB-based model yield 72.72% as against 54.54% of the LR-based model. Despite an accuracy of 92.72% reported by the LR-based model, there is still work to be done to increase the precision score of the model.

Research Gap

From the literature review, many researchers have adopted and improved various ML algorithms for the prediction of telemarketing customers; however despite the success, it is not clear the definition of success for the models, as none was tested considering real world scenario. Real world validation of this model is the only yard stick to actually determine the success of the model, and this has remained a critical gap.

IV. PROPOSE CUSTOMER SEGMENTAITON MODEL FOR DIGITAL MARKETING

The proposed system introduces advanced big data analytics and customer segmentation techniques to revolutionize digital marketing within the banking industry. The components for the proposed system development are data collection, big data analysis, and improved machine learning algorithm, training optimization, customer segmentation model, performance evaluation and model deployment. The component interaction diagram was presented in the figure 1. It begins with big data collection of customer information from a selected commercial bank in Nigeria. The data will be analyzed through visual inspection as the first data analytical process, then other data analysis steps such as imputation to remove outliners, and noise, normalization for feature scaling and exploratory data analysis to provide insight on the big data patterns will be applied to make findings which will improve digital marketing. The machine learning algorithm will be developed using artificial neural network and then improved with an adaptive regularization algorithm which is proposed to address issues of over-fitting during training process, and also the Adam optimization algorithm proposed as the new training algorithm to improve speed of training and accuracy of customer segmentation. Thirdly the findings from the big data analysis will be used to develop a contact algorithm and then integrated with the customer segmentation model using python and classification learner software for digital marketing in the Nigerian banking industry. To evaluate the system, real-time experiment will be performed and the results discussed to validate the work.

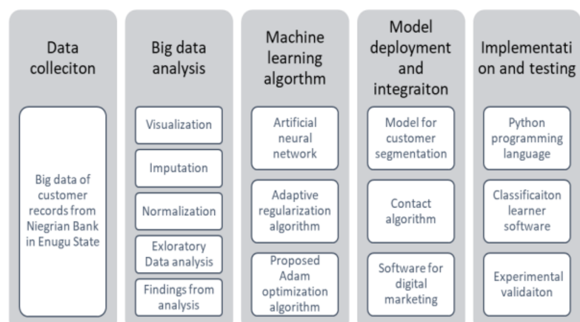

Figure 1: Component interaction diagram of the proposed digital marketing model

CONCLUSION

The study investigates the integration of big data into digital marketing strategies, exploring its concepts, challenges, and potential solutions. Through a comprehensive literature review, it identifies key components of digital marketing and big data, highlighting the significant role big data plays in enhancing marketing efforts. Research gap justified the need for a reliable digital marketing model, which was proposed in this work through customer segmentation and recommended for future digital marketing programs. By implementing these recommendations, businesses can harness the power of big data to improve customer engagement and drive more effective marketing campaigns in the business landscape.

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