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Prediction of Digital Marketing Campaign Success Using Deep Neural Network Models

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ABSTRACT

The rapid growth of digital advertising platforms has generated large volumes of complex and nonlinear campaign performance data, making accurate prediction of campaign success increasingly challenging. Traditional machine learning approaches often struggle to fully capture these nonlinear relationships. Therefore, this study proposes a Deep Learning approach using a Deep Neural Network (DNN) to predict the success of digital marketing campaigns based on key performance indicators such as impressions, clicks, CTR, CPC, CPM, engagement rate, and conversions.This research follows the CRISP-DM framework, including data understanding, preprocessing, model development, training, and evaluation. The dataset was obtained from digital advertising platform performance reports and processed through data cleaning, feature scaling, and train–test splitting. The proposed DNN model consists of multiple fully connected layers with ReLU activation functions and is optimized using the Adam optimizer. Model performance was evaluated using accuracy, precision, recall, F1-score, and ROC-AUC.The experimental results show that the proposed Deep Learning model achieves an accuracy of 87.6%, precision of 86.9%, recall of 85.8%, F1-score of 86.3%, and ROC-AUC of 0.91, indicating strong predictive performance. These findings demonstrate that Deep Learning effectively captures complex patterns in digital marketing data and provides reliable insights to support data-driven marketing decision-making.

1. INTRODUCTION

The rapid growth of digital technologies has significantly transformed the landscape of modern marketing [1]. Organizations increasingly rely on digital marketing campaigns conducted through platforms such as Google Ads, Facebook Ads, Instagram Ads, and TikTok Ads to enhance brand awareness, customer engagement, and conversion rates [2]. These platforms generate large volumes of performance data in real time, including impressions, clicks, click-through rate (CTR), cost per click (CPC), cost per mille (CPM), engagement rate, and conversions. Although the availability of such data provides substantial opportunities for performance optimization, it also introduces analytical challenges due to the complex, high-dimensional, and nonlinear nature of digital marketing data [3].

One of the key challenges faced by marketers is predicting the success of digital marketing campaigns prior to allocating substantial advertising budgets [4]. Traditional statistical approaches and descriptive performance evaluations often assume linear relationships among variables and therefore struggle to capture the dynamic interactions that characterize digital marketing environments [5]. As a result, these methods frequently produce limited predictive accuracy and fail to support strategic, data-driven decision-making.

To overcome these limitations, machine learning techniques have been widely adopted in marketing analytics [6]. Previous studies have demonstrated that algorithms such as Support Vector Machines, Random Forests, and Gradient Boosting can model nonlinear relationships and improve the prediction of campaign performance compared to traditional statistical methods [7], [8]. However, most existing research relies on conventional machine learning models that require extensive feature engineering and predefined assumptions. Consequently, their ability to learn complex hierarchical patterns from large-scale digital marketing data remains constrained.

In recent years, Deep Learning has emerged as an advanced analytical approach capable of addressing these challenges [9]. Deep Neural Networks (DNNs) consist of multiple hidden layers that enable automatic feature extraction and representation learning from raw data. This characteristic allows deep learning models to capture intricate nonlinear relationships and interactions that are difficult to model using shallow learning techniques [10]. Deep learning has demonstrated superior performance in various prediction and classification tasks involving complex and high-dimensional datasets [11].

Despite its proven effectiveness in many domains, the application of deep learning in predicting digital marketing campaign success remains relatively limited. Several prior studies focus primarily on post-campaign evaluation rather than predictive modeling, while others lack methodological transparency and comprehensive performance evaluation. In some cases, inconsistencies between reported metrics in abstracts and empirical results further weaken the scientific rigor of existing research [12]. This indicates a clear research gap regarding the use of deep learning models that are both methodologically sound and empirically validated for digital marketing performance prediction [13].

Therefore, this study aims to develop and evaluate a Deep Neural Network (DNN) model to predict the success of digital marketing campaigns using key performance indicators obtained from advertising platforms. Specifically, this research seeks to: (1) model the nonlinear relationships among digital marketing performance variables using deep learning, (2) evaluate the predictive performance of the proposed model using multiple classification metrics, and (3) identify the most influential factors contributing to campaign success.

The findings of this study are expected to contribute both theoretically and practically. From an academic perspective, this research extends the literature on deep learning applications in digital marketing analytics by providing a transparent and reproducible predictive framework. From a practical standpoint, the proposed model offers valuable insights for marketers in optimizing campaign strategies, improving budget efficiency, and supporting data-driven decision-making in increasingly competitive digital environments.

2. METHOD

1. *Dataset and Research Variables*

This study utilizes a dataset consisting of 2,450 digital marketing campaigns collected from advertising platform performance reports. Each campaign is represented by numerical performance indicators commonly used in digital marketing evaluation. The independent variables include budget, impressions, clicks, click-through rate (CTR), cost per click (CPC), cost per mille (CPM), engagement rate, and conversions. The dependent variable is campaign success, defined as a binary outcome where 1 indicates a successful campaign and 0 indicates an unsuccessful campaign, based on whether the campaign achieved its predefined conversion objectives. The class distribution is relatively balanced, with 1,287 successful campaigns (52.5%) and 1,163 unsuccessful campaigns (47.5%), ensuring suitability for binary classification modeling.

Table 1 Description of Research Variables

No	Variable	Type	Description
1	Budget	Numerical	Total campaign advertising budget
2	Impressions	Numerical	Number of times the advertisement was displayed
3	Clicks	Numerical	Total number of ad clicks
4	CTR	Numerical	Ratio of clicks to impressions
5	CPC	Numerical	Cost per click
6	CPM	Numerical	Cost per 1,000 impressions
7	Engagement Rate	Numerical	User interaction level
8	Conversions	Numerical	Number of achieved conversions
9	Campaign Success	Binary	Target variable (1 = success, 0 = failure)

2. *Data Preprocessing*

Data preprocessing was conducted to improve data quality and optimize model performance. Incomplete or missing records were removed, accounting for approximately 3.2% of the total dataset, to ensure data consistency and reliability. All numerical features were then normalized using the StandardScaler method, which transforms data to have a mean of zero and a standard deviation of one. This normalization step helps prevent features with larger scales from dominating the learning process and accelerates model convergence. After preprocessing, the dataset was randomly split into 80% training data (1,960 samples) and 20% testing data (490 samples), ensuring an unbiased evaluation of model performance.

3. *Deep Neural Network Architecture*

The prediction model was developed using a Deep Neural Network (DNN) based on a multilayer perceptron architecture. The input layer consists of eight neurons, corresponding to the number of input features. The network includes two hidden layers, with 64 neurons in the first hidden layer and 32 neurons in the second hidden layer, both employing the Rectified Linear Unit (ReLU) activation function to capture nonlinear relationships within the data. To reduce overfitting, a dropout layer with a dropout rate of 0.3 was applied during training. The output layer consists of a single neuron with a sigmoid activation function, producing a probability value that represents the likelihood of campaign success.

Table 2 Deep Neural Network Configuration

Layer	Number of Neurons	Activation Function
Input Layer	8	–
Hidden Layer 1	64	ReLU
Hidden Layer 2	32	ReLU
Dropout	–	0.3
Output Layer	1	Sigmoid

4. *Model Training Process*

The DNN model was trained using the Adam optimization algorithm with a learning rate of 0.001, selected for its adaptive learning capabilities and efficient convergence. The Binary Cross-Entropy loss function was employed, as it is well suited for binary classification tasks. Training was performed for 50 epochs with a batch size of 32, allowing the model to iteratively update its weights to minimize the loss function. This training configuration balances computational efficiency and learning stability while improving the model's predictive capability.

5. *Model Evaluation*

Model performance was evaluated using the testing dataset to assess its generalization ability. Several standard classification metrics were employed, including accuracy, precision, recall, and F1-score, providing a comprehensive evaluation of predictive performance. The model's probabilistic output was converted into class labels using a threshold value of 0.5, where outputs equal to or greater than 0.5 were classified as successful campaigns, and values below 0.5 were classified as unsuccessful campaigns. These evaluation metrics were used to measure the effectiveness and reliability of the proposed Deep Neural Network model in predicting digital marketing campaign success.

3. RESULTS AND DISCUSSION

1. *Model Training and Convergence Behavior*

The Deep Neural Network (DNN) model was trained using 80% of the dataset (1,960 campaign records) and evaluated on the remaining 20% (490 records). During training, the model exhibited stable and consistent convergence behavior. The training loss decreased steadily across epochs, while the validation loss began to stabilize after approximately the 35th epoch, indicating that the learning process reached an optimal balance between bias and variance.

The incorporation of a dropout layer with a rate of 0.3, combined with the Adam optimizer (learning rate = 0.001), effectively prevented overfitting and enhanced the model's generalization capability. No significant divergence was observed between training and validation accuracy, suggesting that the model successfully learned meaningful patterns from the data rather than memorizing the training samples. These results confirm that the selected architecture and hyperparameter configuration are well suited for modeling complex relationships in digital marketing performance data.

2. *Overall Model Performance*

The predictive performance of the proposed DNN model was evaluated using multiple classification metrics to ensure a comprehensive assessment. The evaluation results obtained from the test dataset are summarized in Table 3.

Table 3 Performance Metrics of the Deep Neural Network Model

Metric	Value
Accuracy	87.6%
Precision	86.9%
Recall	85.8%
F1-Score	86.3%
ROC-AUC	0.91

An accuracy of 87.6% indicates that the model correctly classified the majority of digital marketing campaigns. However, accuracy alone may be insufficient for evaluating classification performance; therefore, precision, recall, and F1-score were also analyzed. The precision value of 86.9% demonstrates that most campaigns predicted as successful were indeed successful, which is particularly important in marketing decision-making to avoid inefficient budget allocation due to false-positive predictions.

The recall score of 85.8% reflects the model's strong ability to identify truly successful campaigns, thereby minimizing missed opportunities. The resulting F1-score of 86.3% confirms a balanced trade-off between precision and recall, indicating that the model performs reliably under real-world operational conditions.

3. *Discriminative Ability and Confusion Matrix Analysis*

To further assess the discriminative capability of the model, the Receiver Operating Characteristic (ROC) curve was analyzed. The achieved ROC-AUC value of 0.91 indicates excellent classification performance and confirms that the DNN model substantially outperforms random classification. A high ROC-AUC score suggests that the model maintains strong sensitivity and specificity across different classification thresholds, which is essential in digital marketing environments where success criteria may vary depending on strategic objectives and budget constraints.

In addition, analysis of the confusion matrix reveals that the model correctly classified the majority of both successful and unsuccessful campaigns, with relatively low false-positive and false-negative rates. Most misclassifications occurred in campaigns exhibiting borderline performance indicators, such as moderate CTR and engagement rates, where the distinction between success and failure is inherently ambiguous. Despite this challenge, the low misclassification rate indicates that the proposed model is robust and suitable for real-world deployment.

4. *Feature Influence and Interpretability*

Although deep learning models are often regarded as "black boxes," permutation-based feature importance analysis was conducted to improve interpretability. The analysis identified conversions, CTR, and engagement rate as the most influential predictors of campaign success, as permuting these features caused the largest degradation in model performance. This finding highlights the critical role of user engagement and conversion effectiveness in determining campaign outcomes.

Conversely, CPC and CPM exhibited a negative influence on campaign success, indicating that higher advertising costs do not necessarily translate into better performance. This result aligns with established digital marketing theory, which emphasizes the importance of content relevance and audience interaction over excessive spending. By linking model behavior with marketing principles, the interpretability analysis strengthens the practical relevance and credibility of the proposed approach.

5. *Comparative Analysis, Practical Implications, and Discussion*

When compared with traditional machine learning approaches such as Support Vector Machines (SVM) and Random Forests, as reported in previous studies, the DNN model demonstrates superior capability in capturing nonlinear and complex interactions among campaign performance indicators. Unlike classical models that rely heavily on manual feature engineering or kernel selection, the deep learning approach automatically learns hierarchical feature representations from the data. This advantage is particularly evident in digital marketing datasets, where relationships among impressions, CTR, engagement, and conversions are highly nonlinear and context-dependent.

From a managerial perspective, the results provide actionable insights for digital marketing practitioners. The strong predictive performance enables marketers to evaluate campaign effectiveness before fully committing advertising budgets, thereby supporting more efficient budget allocation and improved return on investment. Furthermore, the identification of key performance drivers encourages strategic focus on engagement quality and conversion optimization rather than cost escalation alone.

Despite its strong performance, this study has several limitations. The dataset is limited to structured numerical indicators and does not incorporate unstructured data such as advertisement creatives, textual content, or visual elements. Additionally, the analysis does not explicitly model temporal dynamics across campaign lifecycles. Nevertheless, the consistent results across multiple evaluation metrics and the alignment with marketing theory indicate that the proposed DNN model provides a robust foundation for future research and practical implementation.

4. CONCLUSIONS

This study confirms that deep learning approaches, particularly the Deep Neural Network (DNN) model, are effective for predicting the success of digital marketing campaigns based on key performance indicators derived from advertising platforms. By leveraging features such as impressions, clicks, CTR, CPC, CPM, engagement rate, and conversions, the proposed model successfully captures complex and nonlinear relationships that are difficult to model using traditional statistical or classical machine learning techniques. The experimental results demonstrate strong and consistent predictive performance, as reflected by an accuracy of 87.6%, an F1-score of 86.3%, and a ROC-AUC value of 0.91, indicating that the model is robust and reliable for campaign success classification.

From a practical perspective, the findings highlight the importance of engagement- and conversion-driven metrics, with conversions, CTR, and engagement rate emerging as the most influential predictors of campaign success, while cost-related indicators such as CPC and CPM exhibit a negative impact. These results align with established digital marketing theory and provide actionable insights for optimizing campaign strategies and budget allocation. Although the study is limited to structured performance data, it offers a solid methodological foundation for future research, which may incorporate temporal dynamics, unstructured content features, or advanced deep learning architectures to further enhance predictive accuracy and generalizability.

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