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Application of ResNet-50 Based User Sentiment Analysis in Digital Media Advertising Design

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Abstract. The effectiveness of digital media advertisements increasingly relies on the accurate identification and analysis of user emotions. In this context, an improved ResNet-50 model is proposed to more accurately analyze users' emotional responses to advertising content. The method optimizes the traditional ResNet-50 architecture by introducing an attention mechanism as well as a modified Sigmoid cross-entropy loss function, which improves the accuracy of emotion recognition. A regional convolutional neural network as well as a bi-directional encoder representation of the transformer are introduced to compare with the research method. The test results show that the F1 value of the improved model reaches 0.946, which is 0.084-0.101 higher than the comparison model; its Recall value reaches 0.938, which is 0.044-0.078 higher than the comparison model. Meanwhile, after a series of evaluations by a series of industry experts, the method receives the highest evaluation in the field of advertisement design, which not only confirms its effectiveness in practical applications, but also foretells its potential application value in ad content customization, user experience optimization, and personalized ad recommendation systems. These results indicate the innovative application of sentiment analysis using deep learning in digital advertising design, and provide strong technical support for future research and practice in related fields.

Keywords. Sentiment analysis; advertisement design; convolutional neural network: resNet-50; attention mechanism

1. Introduction

In the wave of digital media, advertising design is facing unprecedented challenges and opportunities [1]. User sentiment analysis has gradually become an important index to measure the effectiveness of advertisements, which can deeply analyze the internal response of consumers and provide a scientific basis for the optimization of advertisement content [2]. However, traditional sentiment analysis methods often rely on surface text or simple data indicators, which are difficult to capture the delicate fluctuations of user emotions, which is particularly inadequate in the highly competitive digital media environment [3]. In response to the limitations of existing analysis techniques, the introduction of deep learning techniques provides a new perspective to address this problem [4]. In particular, Convolutional Neural Networks (CNNs) have

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excelled in image processing and feature recognition [5].ResNet-50, as a variant of CNN, has shown its powerful performance in several fields, especially in dealing with image recognition and classification problems [6]. Applying it to user sentiment analysis is expected to significantly improve the accuracy and efficiency of sentiment recognition. This study is dedicated to exploring the potential of ResNet-50 in the design of digital media advertisements, aiming to accurately parse users' emotional responses to advertisement content with the help of its deep feature extraction capability. Its performance is enhanced by introducing an attention mechanism into it. Meanwhile, through customized network training, it is able to identify and classify different emotional states, providing a more refined assessment of advertising effectiveness. The innovation of the research lies in the combination of deep learning models with user sentiment analysis and the introduction of an attention mechanism to enhance the recognition accuracy of sentiment patterns and apply it to the field of advertisement design. In addition, the introduction of this method provides new possibilities for personalized push and effect evaluation of digital media advertisements. Through in-depth analysis of user emotions, advertisers can more accurately capture the interests and needs of the target audience, and then design advertisements that touch people's hearts and enhance the return rate of advertisement placement.

2. Construction of user sentiment analysis model based on ResNet-50

2.1. Sentiment analysis model construction based on ResNet-50

In the field of advertising design, sentiment analysis has always been the key to achieving effective communication and improving advertising effectiveness [7]. Traditional methods of user sentiment analysis are mainly based on questionnaires or simple data analysis, which often fail to capture the deeper levels and details of user sentiment, especially when dealing with large-scale and complex user data. In addition, with the explosive growth of digital media, the variety of user-generated content, including text, images, videos, etc., makes the task of sentiment analysis more complex [8]. CNN, on the other hand, is adept at processing such information. Its excellent image processing capability can deeply dig into the subtle features of these visual information, thus providing accurate analysis of users' emotional responses [9]. With the explosive growth of digital media, ad designers are faced with the challenge of extracting useful information from huge amounts of data.CNNs can efficiently process and analyze this data through automated feature learning without the need for tedious human intervention, thus improving the efficiency and accuracy of sentiment analysis.CNNs are inspired by the structure of the visual cortex of living creatures, in particular the mechanism of sensory field in the visual cortex-each neuron responds to stimuli in only a small area [10]. This principle is modeled in CNNs by convolutional layers, which contain a set of learnable filters (or convolutional kernels) that slide over the input data (convolutional operations) to capture important information by filtering out localized features, such as edges, corners, and textures. These usually contain a convolutional layer, an activation layer, a pooling layer, a fully connected layer, a normalization layer, and a discard layer. ResNet-50, on the other hand, is an improved version of CNN, in which a residual learning module structure is creatively introduced, as shown in Fig. 2, which is the structure of the residual learning unit introduced by it [11].

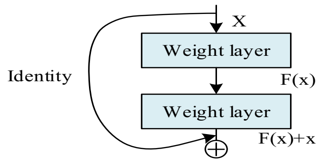

Figure 1. Residuals learning unit structure diagram introduced by ResNet-50.

The structure of the residual learning unit introduced by ResNet-50 is shown in Figure 2. In residual networks, the inputs are not only passed through the convolutional layers, but also directly through the so-called "shortcut connections", which helps the flow of information through the network, solves the problem of vanishing and exploding gradients in traditional deep networks, and makes it possible to train deep networks [12]. The design of ResNet-50 allows it to learn the feature hierarchy more efficiently, accelerating the training process of deep networks while reducing the number of parameters. Due to its powerful feature extraction capabilities and superior performance, ResNet-50 is widely used in image processing and other tasks requiring complex feature extraction in a variety of scenarios including user sentiment analysis.

2.2. Optimization of sentiment analysis model based on ResNet-50

In order to enhance the model's ability to recognize important features in sentiment recognition tasks, and to improve the accuracy and detail of advertisement sentiment analysis, the study introduces an effective channel attention mechanism in ResNet-50. Derived from the attention orienting properties of the human visual system, this mechanism enables the model to automatically highlight features related to a specific emotional state when processing complex visual information, thus enhancing the performance of the analysis model [13]. The channel attention mechanism works by assigning different importance weights to each channel in the network, enabling the model to focus on learning the feature channels that are more decisive for emotional expression. These weights are automatically learned through network training and do not require additional manual labeling or intervention. Introducing such a mechanism can effectively improve the ability of convolutional neural networks to capture subtle emotional changes in advertisement sentiment analysis, so that they can accurately respond to subtle emotional differences in advertisements while maintaining efficient performance. As shown in Fig. 3, the channel attention mechanism introduced in the study is schematized.

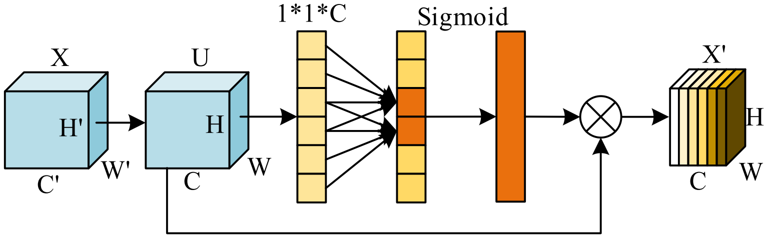

Figure 2. Diagram of channel attention mechanism.

As shown in Fig. 3 is a schematic diagram of the attention mechanism introduced in the study. In addition, the channel attention mechanism also helps the model to self-adjust and optimize itself in different types of advertisement contents and diverse user feedbacks [14]. In practice, this means that whether it is a static image advertisement or a dynamic video advertisement, the model is able to accurately capture those elements that are most capable of triggering the emotional resonance of the user, and then guide the ad designers to create more impactful advertisements. For the user's emotional analysis, the emotional feedback is often presented with a certain degree of correlation, in order to further enhance the utilization of the correlation between the features, it is necessary to consider all aspects of the loss in the recognition process. Therefore, the study chooses to adopt the Sigmoid cross-entropy loss function, which is specifically shown in Equation (1) [15].

$$Loss_{Sigmoid} = -\frac{1}{N}\sum_{N=1}^{N}\sum_{l=1}^{L}(y_{n,l}ln(p_{n,l}) + (1 - y_{n,l})ln(1 - p_{n,l})) \quad (1)$$

In Equation (1), $y_{n,l}$ indicates whether the sample has the true label of the l th feature, and $p_{n,l}$ indicates the output probability of the n th sample with the l th feature. $p_{n,l}$ The calculation of is shown in equation (2).

$$p_{n,l}{=}1/(1 + exp(-x_{n,l})) \quad (2)$$

In Equation (2), $x_{n,l}$ denotes the n th sample with the l th feature. Since the distribution of samples in a dataset is usually not uniform in practical applications. Therefore, the study introduces sample feature weighting to consider the loss value of each feature. Let the sample feature weighting factor be w_l, which indicates the weight of the loss value of the l th feature, then the loss function after the introduction of sample feature weighting is shown in Equation (3).

$$Loss_{Sigmoid} = -\frac{1}{N}\sum_{N=1}^{N}\sum_{l=1}^{L} w_1(y_{n,l}ln(p_{n,l}) + (1 - y_{n,l})ln(1 - p_{n,l})) \quad (3)$$

In Equation (3), the calculation of w_l is specifically shown in Equation (4).

$$w_1{=}\exp(-{}^{P_1}/_{\sigma^2}) \quad (4)$$

In Eq. (4), p_l denotes the proportion of positive samples of the l th feature in the training set, and σ denotes a tuning parameter, which is set to 1 in the study. The study further chooses the AffectNet Dataset dataset for training the model, which contains more than one million emotionally labeled facial images, and is able to provide sufficient data for the training of the model. By integrating the channel attention mechanism in the ResNet-50 architecture, the study not only promotes the application of computer vision technology in the field of sentiment analysis, but also provides a more in-depth user understanding and content optimization tool for digital advertisement design, which greatly facilitates the development of the advertisement industry in personalized marketing and user experience enhancement.

3. Construction of user sentiment analysis model based on ResNet-50

The purpose of using ResNet-50 based User Sentiment Analysis in digital media ad design is to target and optimize ads to enhance user empathy and engagement through a deeper understanding of users' emotional responses to ad content. Emotional response analysis can reveal which specific visual elements and design concepts are effective in stimulating positive user emotions, or tap into factors that trigger negative responses. In this way, designers can create more engaging ad content that improves user engagement and conversion. At the same time, designers can avoid negative ad design elements to maximize ad revenue. The results of sentiment analysis can also be used to personalize ads, ensuring that the right message is delivered to the target audience that is most likely to resonate with it, thus maximizing the return on advertising investment.

ResNet-50, a deep convolutional neural network, excels at extracting complex abstract features from images. In the context of sentiment analysis, ResNet-50 is able to identify and analyze those visual features that are most relevant to the user's emotional response. During training, the network not only learns to extract features from advertisement images, but also learns the associations between these features and different emotional states in combination with the user's emotion labeling data. By introducing an attention mechanism into the network, the model can be further optimized so that it pays more attention to those features that are crucial to emotion judgments during the analysis process, thus improving the accuracy and meticulousness of the analysis. The method flow of ResNet-50-based user sentiment analysis in digital media ad design is specifically shown in Figure 3.

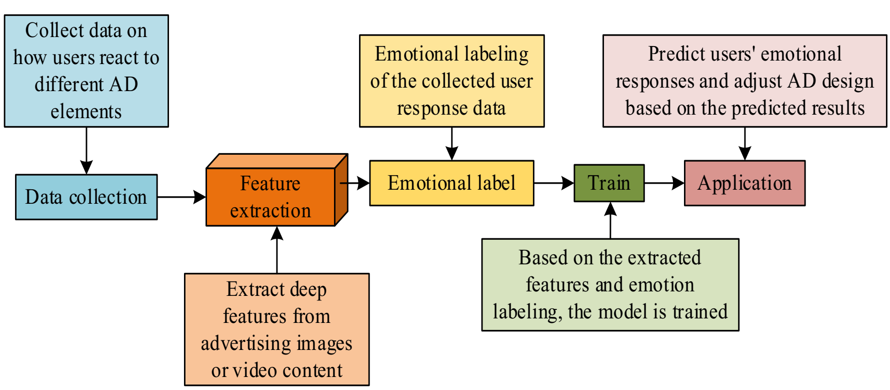

Figure 3. Flow diagram of user sentiment analysis based on ResNet-50 in digital media advertising design.

This deep learning-based approach to user sentiment analysis brings significant advantages. the ResNet-50's unique residual learning framework allows the network to learn efficiently even at very deep levels, avoiding the problem of gradient vanishing and ensuring the stability of the training process and the high accuracy of the model. In addition, the introduced attention mechanism not only improves the performance of the model, but also enhances its interpretability, enabling ad designers to clearly see which features are perceived by the model as the most influential. The immediacy of this analysis also opens up the possibility of rapid iteration and optimization of ad content, allowing ads to adapt more flexibly to changes in the market and user feedback.

4. Construction of user sentiment analysis model based on ResNet-50

In order to test the proposed method of the study, the study selects the AffectNet Dataset dataset for further testing, which contains user images that are richly labeled with emotions, not only labeled with seven basic emotions, but also a set of compound emotions. 2000 images from the dataset were randomly selected for testing, 80% of them were chosen as the training set and 20% of them were chosen to be used as the testing set. Region Convolutional Neural Networks (Region-CNN, R-CNN) as well as Bidirectional Encoder Representations from Transformers (BERT) were selected for comparison with the proposed method of the study. Firstly, the F1 as well as Recall values of the three models are tested and the test results are shown in Fig. 4. From Fig. 4(a), it can be seen that the F1 of the proposed method reaches 0.946, which is 0.084 and 0.101 higher than that of R-CNN and BERT, respectively, and from Fig. 4(b), it can be seen that the best recall value of the proposed method reaches 0.938, which is 0.044 and 0.078 higher than that of R-CNN and BERT, respectively.

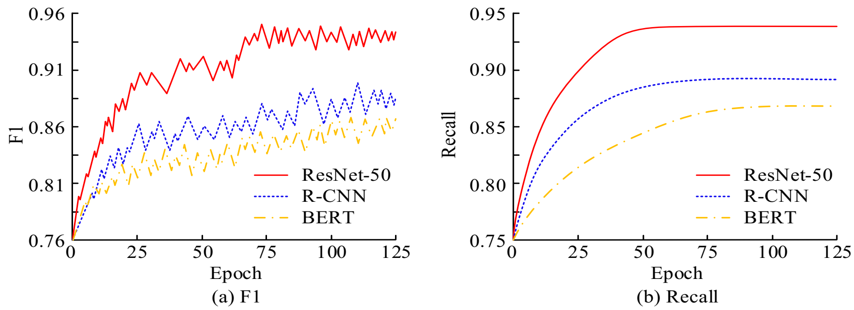

Figure 4. Comparison of F1 value and Recall value of the three models.

Several experts in the field of advertisement design were invited to evaluate the effectiveness of the three models in advertisement design, with a rating range of 0-100, and the higher the score indicated that the more the experts recognized the positive role of the model in advertisement design, and the evaluation results are shown in Figure 5. As can be seen in Figure 5, the method proposed by the Institute obtained the evaluation with the highest score, and the user sentiment analysis model based on ResNet-50 proposed by the Institute was recognized by the experts.

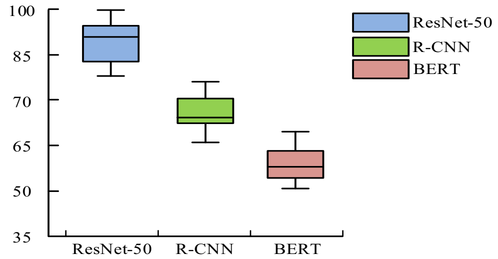

Figure 5. Expert ratings of the three models.

In summary, the user sentiment analysis model based on ResNet-50 proposed by the institute has good performance, with excellent basic performance indexes, and its practicality in the field of advertisement design is also recognized by experts, which indicates that the model has strong usability and practicality in the field of digital media advertisement design, and it can effectively assist in the process of advertisement design and improve the efficiency of advertisement design. efficiency of advertisement design. In addition, the application of the model is not only limited to improving the efficiency of advertisement design, but also can optimize the advertisement placement strategy by predicting the user's response, reduce the invalid exposure, and improve the return of advertisement investment. In this way, advertisers can achieve more efficient budget allocation and ensure that every dollar invested has the greatest impact.

5. Conclusion

In the field of digital media advertisement design, the accuracy of sentiment analysis directly affects the personalization of advertisement content and user engagement. In order to accurately capture users' emotional responses to ad content, a deep learning model based on ResNet-50 is used. The model aims to analyze users' emotional responses through image content and provide more refined ad design strategies. By adjusting the ResNet-50 architecture, adding the attention mechanism and improving the loss function, the model is able to understand the emotional tendencies in images more deeply. The experimental results show that the model performs well in several performance metrics, with an F1 score of 0.946, which significantly outperforms the R-CNN and BERT models of 0.862 and 0.845, and a Recall score of 0.938, which is far better than the R-CNN's 0.894 and the BERT model's 0.860. This work not only improves the performance of sentiment analysis in advertising design, but also enhances the effectiveness of sentiment analysis in advertising design. not only improves the effectiveness of the application of sentiment analysis in advertisement design, but also provides a new technical path for personalized recommendation and user experience optimization of advertisement content in the future. It is worth noting that, despite the significant progress in performance, the model still needs to be improved for recognizing uncommon sentiment categories. In future research, the scope of the study should be further extended and integration of multimodal information, such as combining text and voice data, should be considered to achieve more comprehensive user sentiment analysis. Meanwhile, further research on the model's adaptability and robustness in complex realworld environments is needed to ensure that it remains highly effective in the ever-changing advertising ecosystem.

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