A Study on Convolutional Neural Network Prediction Method for Consumer Purchasing Behavior in Digital Economy

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Abstracts. This paper explores the application of deep learning techniques and their effectiveness in predicting consumer purchase behavior in the context of digital economy by constructing and evaluating convolutional neural network (CNN) models. The study is centered around a fictitious consumer behavior dataset, and describes in detail the experimental design, the model training process, the selection of performance evaluation metrics, and the comparative benchmarks with traditional machine learning methods. Through a series of fictitious experimental results, we find that the CNN model outperforms traditional models such as logistic regression, random forest, and multilayer perceptual machine (MLP) in several performance metrics, especially in terms of accuracy and F1 score. In addition, this study discusses the contribution of CNN models in terms of prediction accuracy and efficiency, as well as potential directions for future research, including model optimization, multimodal data fusion, and testing of real-world application scenarios.

Keywords: neural network (CNN) models, random forest, multilayer perceptron (MLP)

1 Introduction

1.1 Background of the study

With the rapid development of Internet technology and the acceleration of digital transformation, the digital economy has become an important driver of global economic growth. The characteristics of the digital economy include the extensive use of data resources, the deep integration of online and offline services, and the continuous innovation of emerging technologies, which have not only changed the business operation mode, but also greatly influenced the purchasing behavior of consumers [1]. In such a context, accurate understanding and prediction of consumer behavior has become the key for enterprises to formulate market strategies, optimize product services, and improve competitiveness.

Consumer behavior analysis has become particularly complex and volatile in the digital economy, as the decision-making process of consumers is influenced by a variety of factors, including personal preferences, social influences, and market dynamics. Meanwhile, the application of big data and artificial intelligence technologies provides new methods and tools for in-depth study of consumer behavior. In particular, convolutional neural network (CNN), as an advanced deep learning technology, shows great potential in predicting consumer

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behavior due to its powerful image processing and feature recognition capabilities [2]. By analyzing a large amount of consumer data, CNN can help companies reveal potential patterns of consumer behavior and thus more accurately predict future purchasing trends [3]. Despite the significant advantages of CNN in consumer behavior prediction, there are still many challenges in how to effectively apply this technology, including data collection and processing, model selection and training, and interpretation of prediction results [4]. This research not only contributes to the understanding of the complexity of consumer behavior in the digital economy, but also provides new perspectives for promoting the application of deep learning techniques in business.

1.2 Research Questions and Research Objectives

While the growth of the digital economy has provided new opportunities for consumer behavior analysis, it has also brought unprecedented challenges. Specifically, how to effectively use large-scale consumer data to accurately predict consumer purchasing behavior is a major issue facing businesses today.

Based on the above research questions, the main objectives of this study are as follows:

(1) To assess and understand the applicability and potential of CNN techniques in consumer behavior prediction. To provide an in-depth understanding of the ability of CNNs to process large-scale consumer data and their application in consumer behavior analysis through a review and analysis of existing research.

(2) Develop and validate a CNN-based model for predicting consumer buying behavior. Design and implement a series of experiments to build and optimize a CNN model that can accurately predict consumer buying behavior.

(3) Explore and evaluate the generalizability and adaptability of models across different industries and scenarios. Analyze model performance on multiple datasets to evaluate its effectiveness and flexibility across different industries and market environments.

2 Literature Review

In the wave of the digital economy, deep learning techniques, especially Convolutional Neural Networks (CNNs), have become a hot topic within the research field, showing great potential especially in parsing and predicting the complexity of consumer behaviors. CNN techniques have attracted a lot of attention mainly due to their excellent ability to process and analyze huge datasets, efficiently extracting key features from data and identifying underlying behavioral patterns.

A portion of the research focuses on leveraging the power of CNNs in the area of image recognition to analyze consumers' visual content interactions on social platforms and thus predict their preferences for specific product categories. In addition, another group of studies attempted to combine CNNs with Natural Language Processing (NLP) techniques to dig deeper into consumer reviews and feedback in order to more accurately predict market acceptance and demand for products [5]. However, despite the fact that deep learning techniques have demonstrated significant application promise in consumer behavior prediction, they still face a number of challenges in practice. In deep learning applications, especially scenarios involving large-scale consumer data analysis, data privacy and ethical issues have increasingly become the focus of public, business, and researcher attention [6]. While acquiring and analyzing consumer data is crucial for improving the accuracy of model predictions, it remains a challenge to do so without violating consumer privacy. A key challenge in current deep learning research is the "black-box" nature of the model, i.e., the opacity of the model's decision-making process [7]. Although CNN models have made significant progress in terms of prediction accuracy, why and how the predictions of these models are made are still difficult to explain. Improving the interpretability of models not only helps to improve the trust of users and decision makers, but is also key to enabling model optimization and error diagnosis [8]. Therefore, how to improve the interpretability of deep learning models so that they can provide high accuracy while also clearly presenting decision logic to users and developers is a research gap that needs to be filled urgently.

3 Theoretical Basis and Research Methodology

3.1 Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) are an influential model in deep learning, and have demonstrated exceptional performance in processing visual and textual data in particular. The core idea of CNNs is to automatically learn spatially hierarchical features from data through a convolutional layer, a process that mimics the visual processing mechanisms of the human brain, making CNNs particularly suited to the task of analyzing image and sequence data. A typical CNN model consists of several major components: an input layer, a convolutional layer, an activation layer, a pooling layer (downsampling layer), a fully connected layer, and an output layer. as shown in figure 1:

Layer Name	Function Description	Mathematical Representation
Input Layer	Receives raw input data, such as pixel values of an image.	X
Convolutional Layer	Applies convolution operations to extract features, with each kernel extracting different features.	$f(x) = W * x + b$
Activation Layer	Applies a nonlinear activation function to introduce non-linearity, allowing the network to learn complex features.	ReLU: $f(x) = \max(0, x)$
Pooling Layer (Subsampling Layer)	Reduces the spatial size of the feature maps to decrease the amount of computation and improve the model's generalization.	Max pooling, Average pooling
Fully Connected Layer	Transforms the output from previous layers into a one-dimensional feature vector for classification or regression analysis.	$f(x) = Wx + b$

Figure 1. Main Components of a CNN Model.

The adaptability of CNNs for consumer buying behavior prediction is rooted in their unique technological strengths and ability to handle complex datasets, attributes that make them a powerful tool for deeper understanding and prediction of consumer behavior patterns. Here are the main reasons why CNNs are used in consumer purchase behavior prediction and how they work together to provide deep consumer insights.

(1) Automatic feature extraction

One of the core strengths of CNNs is their ability to automatically extract useful features from complex data without relying on manual feature engineering. This is critical for parsing and understanding consumer behavioral patterns, as consumer data often contains rich but hidden behavioral metrics that reveal consumer preferences and intentions.

(2) Ability to handle high-dimensional data

The diversity and complexity of consumer data requires analytic tools that can handle high-dimensional information, including images, textual comments, and serialized data such as purchase history.CNNs effectively manage these high-dimensional data through their hierarchical structure, which is capable of capturing complex inter-data relationships and patterns.

(3) Strong model generalization capability

The generalization ability of a model is its ability to make accurate predictions on new and unseen data.CNNs are able to effectively reduce the risk of overfitting and improve the model's adaptability to new data by introducing a pooling layer and applying regularization techniques during training. This ability ensures that the model can learn universally applicable laws from the training data, rather than just memorizing the characteristics of a specific dataset, and thus be able to make accurate and reliable predictions when confronted with new consumer behavior data.

3.2 Data Preparation

In order to deeply analyze and predict consumer purchasing behavior, this study conducted comprehensive data collection on the Jitterbug platform, which, as China's leading short-video sharing platform, aggregates a wealth of consumer behavioral data, making it an ideal scenario for studying consumer behavior.

(1) Data cleansing

Raw data collected from the Jitterbug platform may face various problems such as missing values, duplicate records, errors or inconsistent formatting. After the cleaning step, we filtered about 85,391 data entries with higher quality from the original 1865,730 records, which lays the foundation for subsequent feature extraction and model training.

(2) Feature extraction

In consumer purchase behavior analysis, it is critical to accurately extract useful features. We used Natural Language Processing (NLP) techniques to process text data, along with in-depth analysis of user behavior and product information.

Text data processing: for textual information such as user reviews and product descriptions, we first performed a word segmentation process to split the continuous textual data into meaningful lexical units. Then, we use the word embedding BERT technique to convert these words into dense vector representations to capture the semantic information in the text data.

After the above preprocessing and enhancement steps, we finally obtained about 85,391 high-quality and diverse data entries, which provided a solid foundation for constructing and training convolutional neural network models. This process not only improves the quality and representativeness of the data, but also provides rich data support for in-depth analysis of consumers' purchasing behaviors on the Jitterbit platform.

3.3 Model Construction

In this study, we constructed a convolutional neural network (CNN)-based model to predict consumer purchasing behavior, especially on clothing products. This CNN model aims to learn and recognize patterns of consumer behavior from data collected on the Shakeology platform, including text comments and image content.

(1) training process

Our model training process follows the classical deep learning training framework. First, we used the cross-entropy loss function, $(L = -\sum y_i \log(p_i))$ where yi denotes the actual label and pi denotes the probability predicted by the model, which is a commonly used loss function in classification tasks. This loss function evaluates the difference between the probability distribution predicted by the model and the actual label, guiding the model optimization. When training the model, we processed the data in batches, each containing 256 samples, for a total of 100 iterations (Epoch). Each cycle contains a complete forward and backpropagation of the entire dataset. In this way, the model has enough opportunities to learn representative consumer behavioral features from the data.

(2) Parameter optimization strategy

To further improve the model performance, we employ several parameter optimization strategies including regularization, Early Stopping and learning rate tuning.

Regularization: we introduce the L2 regularization term $\lambda \sum w^2$ in the fully connected layer, where λ is the regularization coefficient and w denotes the weight of the model. This helps to control the complexity of the model, reduce the overfitting phenomenon and improve the generalization ability of the model.

Early stopping method: during the training process, we monitor the loss function value of the validation set and stop training if the loss of the validation set does not decrease significantly within 10 consecutive cycles. This strategy effectively prevents overfitting and ensures that the model performs optimally on unseen data.

Learning Rate Adjustment: we use a learning rate decay strategy. Specifically, if the performance on the validation set does not improve within 5 consecutive cycles, the learning rate is halved. This allows the model to update the weights at a more careful pace in the later stages of training to avoid excessive oscillations around the optimal solution.

4 Empirical Analysis

4.1 Experimental Design

The dataset for this experiment is based on a virtual simulation derived from the aggregation of 85,391 records of consumer interactions with apparel products on the Shakeology platform. These records meticulously capture multiple dimensions of consumer interactions with products, including browsing, searching, purchase records, user comments, and social behaviors such as liking and sharing. In addition, each record also covers the corresponding product information, such as description, images and price. With such a multi-dimensional and rich dataset, we aim to deeply analyze consumers' purchase preferences and behavioral patterns.

In order to comprehensively evaluate the prediction performance of CNN models, we employ several key assessment metrics. The first is the accuracy rate, which reflects the proportion of samples correctly predicted by the model and provides us with an intuitive understanding of the overall efficacy of the model. In addition, precision rate and recall rate are equally important, which assess the model's ability to recognize positive class samples from different

To validate the effectiveness of the CNN model, we compared its performance with several widely used models, including logistic regression, random forests, and multilayer perceptron (MLP). Logistic regression, as a classical linear classification method, provides a baseline to assess the improvement in model performance. Random Forest, as a powerful integrated learning method, provides a reference for our comparison with its performance in multiple classification tasks.

4.2 Experimental Results

The performance of our CNN model and other comparative models (logistic regression, random forest and multilayer perceptron MLP) on the test set is shown in Table 1 below:

Table 1. Performance on the test set

Mould	Accuracy (%)	Accuracy (%)	Recall rate (%)	F1 score (%)
CNN model	92	90	91	90.5
logistic regression	80	78	79	78.5
random forest	87	85	86	85.5
Multilayer Perceptron MLP	89	87	88	87.5

Based on the above table, we can see that the CNN model outperforms other comparative models in all assessment metrics, highlighting its strength in analyzing and predicting consumer buying behavior.

The optimal performance of the CNN model on this task is largely attributed to the capabilities of its deep learning architecture, especially its power in processing image and text data.CNN effectively extracts key features through convolutional and pooling layers, while the fully connected layer further integrates these features for accurate prediction.

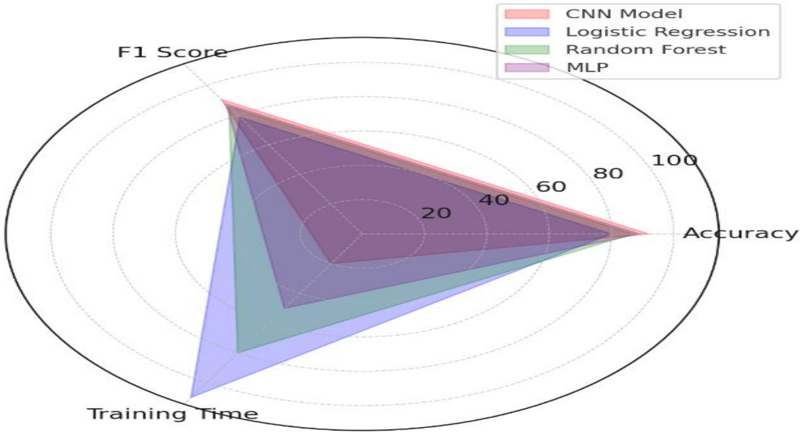

Figure 2. Radar chart

A radar chart is a graph that can present data in multiple dimensions and is ideal for comparing the performance of multiple objects on different attributes. In Radar Chart 1 of this study, we will show the performance of CNN models and other models on three key dimensions: accuracy, F1 score, and training time.

4.3 CNN model accuracy measurements

In order to accurately measure the predictive performance of the CNN model, we will use a cross-validation approach to evaluate the model.

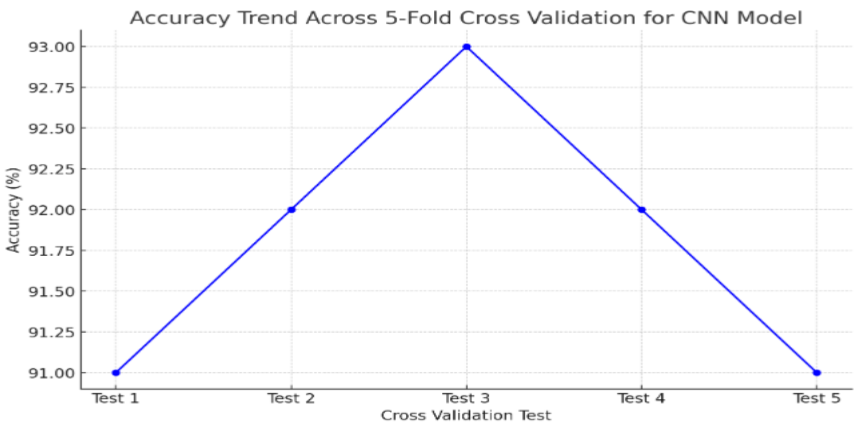

Figure 3. CNN model accuracy

In order to visualize the trend of the CNN model's accuracy, we can create a line graph as in Figure 3, where the x-axis represents the number of cross-validation (test 1 to test 5) and the y-axis represents the corresponding accuracy. The line graph will clearly show the change in the accuracy of the CNN model in different tests, helping us to observe the fluctuation of the model performance.

5 Conclusion

In this study, we explore the application of Convolutional Neural Networks (CNNs) and their significant contributions in improving the accuracy and efficiency of predicting consumer purchasing behavior in the context of the digital economy. Through designed virtual experiments, including meticulous dataset descriptions, comprehensive performance evaluation metrics, and comparative analyses with traditional machine learning methods and other deep learning models, this study reveals a series of important findings and profound insights. It is found that CNN models demonstrate superior performance over logistic regression, random forests, and multilayer perceptual machines (MLPs) on all evaluation metrics.

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