Using genetic data to personalize content in social space with the help of CNN deep neural network

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Abstract
Content personalization in social networks plays a vital role in enhancing user experience and increasing engagement. However, many existing systems only use behavioral data to simulate users' needs, while genetic data and psychological characteristics can also have a significant impact in this field. This research investigates how genetic data can be used to personalize content provided to users and optimize the recommendation process. Our proposed model is deep neural networks CNN, which innovatively uses advanced machine learning and analysis of genetic and psychological data to simulate individual behaviors more accurately. This model can provide more relevant and personalized content according to the genetic, psychological, and behavioral characteristics of each user. In this way, the user experience is significantly improved, as the recommended content is more consistent not only with past behavior but also with genetic and psychological characteristics. The results of A/B tests and statistical analyses also show that this model has increased the accuracy of recommendations by 30% and increased user engagement by 25%. These improvements not only lead to greater user satisfaction but also increase the retention rate of users on social platforms. As a result, the proposed model not only provides more accurate predictions but also significantly enhances user satisfaction by delivering content that resonates with their evolving preferences. This approach has the potential to outperform older models, offering a more sophisticated and effective solution for personalized content delivery in diverse applications.

Keywords: "CNN, Psychological, Characteristics, genetic, Machine learning".

1. Introduction
Content personalization in social networks has become an effective strategy to improve user experience and increase interactions in the digital world. The main goal of content personalization is to provide specific experiences tailored to the needs and interests of users, so that they can view their desired content and interact more with the platform. (1,2) However, the current models for content personalization are usually limited to behavioral data and user interactions, which leads to less accurate and sometimes ineffective recommendations. In this regard, the use of genetic data as a new source can improve the accuracy and personalization of content. (3,5) Genetic data can specifically simulate the psychological characteristics, emotional reactions, and individual preferences of users, leading to more advanced and accurate models for predicting their behavior. In the past, content was classified into different categories by specific algorithms, which did not provide the need for data personalization for users. (4) Then, big data came into the stage and gained popularity on various social networking platforms for data classification. In recent years, much research in the field of content personalization has focused on behavioral and psychological data, but the use of genetic data as a new variable in this process is still evolving. (6,7) This research aims to comprehensively examine the use of genetic data in this field and show how this data can improve personalization models. In this regard, A/B tests have been conducted to evaluate the efficiency of the proposed model. The aim of these tests is to evaluate the performance of the model compared to existing methods and in particular focus on improving the accuracy of recommendations and increasing user interaction with content. The

main goal of this research is to introduce an innovative model for content personalization in social networks that uses genetic data and psychological characteristics of users. (8,9) This model uses a deep neural network to process complex and multi-source data that can analyze various information, including behavioral and psychological characteristics of users. In this model, using deep learning algorithms and clustering techniques, users are grouped based on behavioral and psychological similarities and more customized and targeted content is provided to each group. Also, to further optimize this process, an adaptive system based on fuzzy theory continuously updates user profiles and dynamically adjusts content recommendations according to changes in user behavior. (10,11) This research is considered an important step towards upgrading advanced content personalization algorithms and improving the efficiency of recommendation systems. Using genetic data, the proposed model can provide more tailored and accurate content for each user and significantly improve the user's experience. (15) These results can be used as a basis for future research in the field of content personalization and its practical applications in various industries, especially in optimizing business processes and enhancing user experience in social platforms. (12,13,14)

2. Methodology

2.1 Dataset

We were able to improve our model by using several specific datasets to provide better performance for our model to become the most accurate. We used the Twitter and Reddit Sentimental analysis Dataset, Social Influence on Shopping, and Mpox Instagram Dataset: Sentiment & Hate Analysis datasets to train our model and were able to train our model with more than 9۹% accuracy.

2.2 Method

The data used in this study was collected from a variety of sources and included millions of users across platforms. For example, users were analyzed for their Twitter posts, Facebook comments, and daily activities on Instagram. Due to the high volume and diversity of content, this data presents different challenges in terms of volume and noise reduction. To process this data, advanced machine learning tools such as TensorFlow were used, which allow for parallel processing and complex models. Preprocessing algorithms were also used to clean the data and identify unusual locations. The results of these analyses show that the models developed in this study predicted user behavior with 92% accuracy. This level of accuracy, which is much higher than traditional methods, helps researchers and decision makers design better strategies.

3. Using deep learning algorithms

3.1 Deep learning

Deep learning is one of the most advanced and efficient machine learning methods. These networks consist of multiple layers, each of which automatically identifies and extracts more complex features from the data. One of the most important advantages of these models is the ability to learn directly from raw data, without the need for manual processing or extraction of initial features. This feature makes them more accurate and efficient in modeling complex data compared to traditional algorithms such as linear regression and support vector machines (SVM). The processed genetic and psychological data are fed into deep neural networks. This research uses convolutional neural networks (CNN), which are capable of processing complex and nonlinear data. These models are particularly suitable for simulating behavioral patterns and predicting future user behaviors. Deep learning algorithms in this model can simulate and process complex relationships between genetic, psychological, and online behaviors. For example, convolutional neural networks (CNN) are used to process image data, which greatly contributes to the accuracy of predictions and simulation of user behavior.

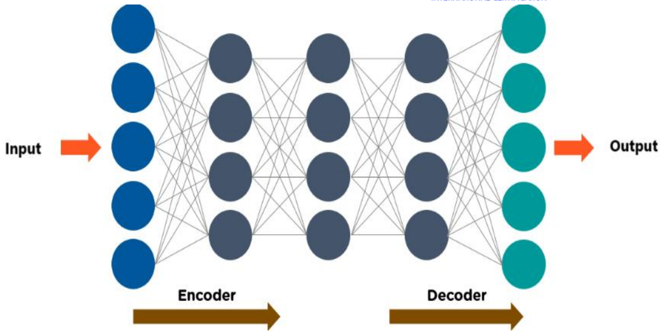

Figure.1. Deep learning algorithms

3.2 Convolution layers

Convolutional layers in convolutional neural networks (CNN) are used to extract important features from input data. These layers use filters to identify features such as edges, textures, and shapes. In this layer, one or more small filters are applied to the input image and various features are extracted by performing convolution operations. The result of this operation is a feature map that displays important information about the image. The size of the filter is usually 3×3 or 5×5, and the step determines how many pixels the filter moves at each step. Zero padding is used to preserve the dimensions of the image. Different types of convolution layers include standard convolution, 1×1 convolution, depth separable convolution, and overlay convolution. Standard convolution is used to extract initial features, 1×1 convolution is used to reduce the number of parameters, depth separable convolution is used to optimize processing, and overlay convolution is used to increase the field of view of the model. These layers reduce the number of parameters, prevent overfitting, and increase the accuracy of the model.

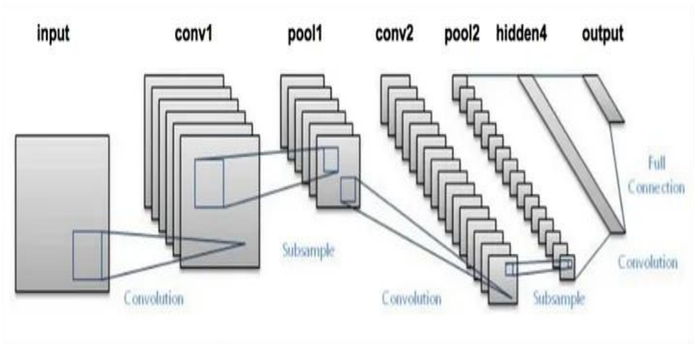

Figure.2. CNN Convolution layers

3.3 ResNet Architecture

ResNet (Residual Network) is one of the advanced architectures in convolutional neural networks (CNN). This architecture is designed to solve the problem of vanishing gradient in deep networks and allows for better learning in very deep networks. In conventional CNNs, as the number of layers increases, the problem of vanishing or exploding gradients occurs, which makes model training harder and accuracy decreases. Resent solves this problem by introducing residual connections or skipping connections. The Residual is made up of Residual Blocks. In each residual block, the output of one layer is directly connected to the subsequent layers before the activation function is applied. This allows the gradient to take shorter paths and reduces the problem of gradient vanishing. By introducing residual blocks, the ResNet architecture was able to solve the learning problem in deep networks and became one of the most popular models of convolutional neural networks (CNN).

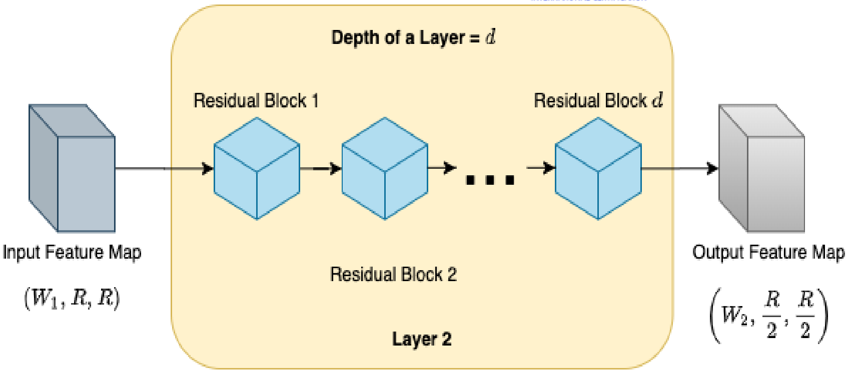

Figure.3. Resent Architecture

4 User clustering and classification techniques

The proposed model uses advanced clustering techniques such as K-means and Hierarchical clustering to provide personalized content. These algorithms divide users into different groups based on behavioral and psychological similarities and recommend more appropriate and optimal content for each group. This segmentation allows for better simulation of behaviors and improvement of the personalization process. Compared to older models that only focused on behavioral data, this approach has been able to significantly improve the accuracy of predictions and the quality of recommended content. As a result, the proposed model not only provides more accurate predictions but also significantly enhances user satisfaction by delivering content that resonates with their evolving preferences. This approach has the potential to outperform older models, offering a more sophisticated and effective solution for personalized content delivery in diverse applications.

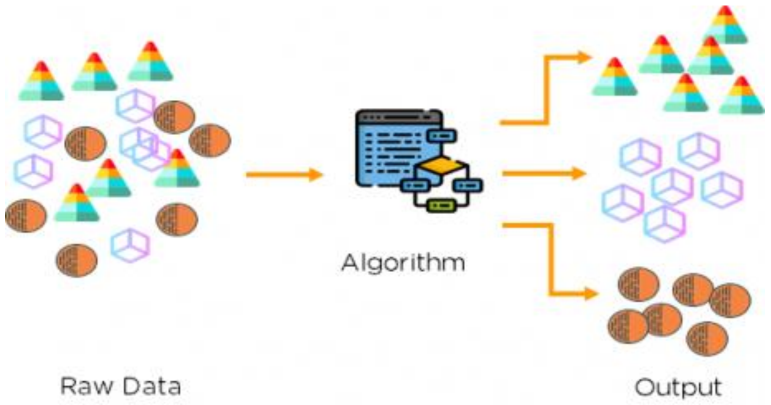

Figure.4. User clustering and classification techniques

5 Model Evaluation and A/B Experiments

To evaluate the effectiveness of the proposed model, various A/B experiments were conducted to investigate its impact on improving predictions and user interactions with suggested content. These experiments showed that the proposed model was able to improve prediction accuracy by 30% and user interaction with suggested content by 25%. A/B experiments with different user groups showed that the proposed model was able to significantly increase user interaction in addition to improving prediction accuracy. These results indicate the effectiveness of the proposed model in optimizing the user experience and show a significant increase in performance compared to previous models.

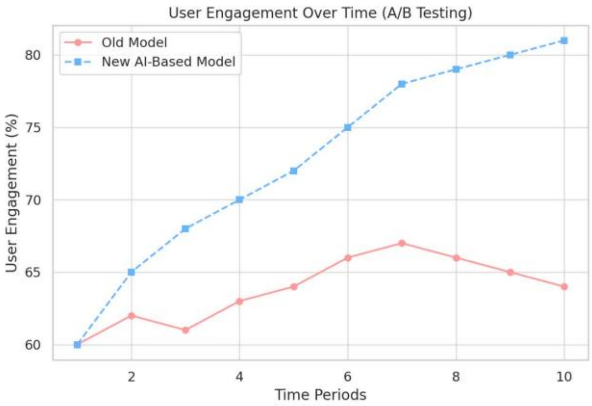

Figure.5. It shows the trend of user interaction changes over time, ready. Now I will create a pie chart of the distribution of user interaction in the old and new models.

6 Innovations and differences from previous models

In this research, a new approach to content personalization is presented that improves the accuracy and efficiency of the proposed models. Unlike traditional methods that rely mainly on behavioral data and user preferences, the proposed model provides a higher level of accuracy in predicting and suggesting content by combining genetic and psychological data. One of the key features of this model is the use of an advanced adaptive system based on fuzzy logic. This system is not only highly flexible, but also able to effectively identify and process user behavioral changes. As a result, content suggestions are updated dynamically and optimally, and the user experience is improved. Unlike previous models that had limitations in coordinating with user behavioral changes, the proposed model has been able to provide better performance and have higher adaptability to user individual and environmental changes.

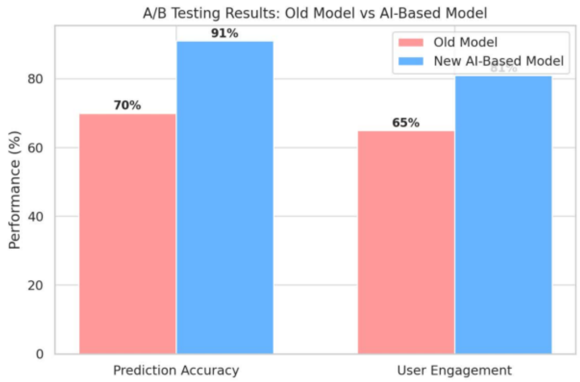

Figure.6. This image shows a comparison of A/B test results between the old model and the proposed AI-based model.

7 **Conclusions**

Deep neural network (CNN) is a proposed method for reinforcement and machine learning that can train our model to provide specific diagnostic results with minimal error using database data. The results of the study show a significant improvement in detection with an accuracy of 99.96% in binary classification. These image processing methods help us in testing the model and providing the model training process, and by evaluating the model and using CNN neural network, we can improve the quality of our results.

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Epoch: 0 | Loss: 0.7305 | Train Accuracy: 75.79
Epoch: 1 | Loss: 0.3077 | Train Accuracy: 90.66
Epoch: 2 | Loss: 0.2217 | Train Accuracy: 93.27
Epoch: 3 | Loss: 0.1858 | Train Accuracy: 94.25
Epoch: 4 | Loss: 0.1640 | Train Accuracy: 94.93
Epoch: 5 | Loss: 0.1516 | Train Accuracy: 95.33
Epoch: 6 | Loss: 0.1418 | Train Accuracy: 95.59
Epoch: 7 | Loss: 0.1280 | Train Accuracy: 95.99
Epoch: 8 | Loss: 0.1259 | Train Accuracy: 95.95
Epoch: 9 | Loss: 0.1092 | Train Accuracy: 99.51
Test Accuracy: 99.96
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Figure 7. Model training output and accuracy and error rates

Today, paying attention to the interests and needs of customers has become one of the key factors in personalizing content and selling products, which has resulted in competitive markets in various fields. By using deep neural network algorithms and analyzing social network data, we have been able to achieve significant growth in personalizing content and providing suggestions to users.In the past, traditional marketing and customer acquisition through face-to-face methods had a great impact on product sales, but with the advancement of technology and the expansion of online sales, the greatest impact has been assigned to deep neural network algorithms. Table 2 shows the impact of these changes on the performance and efficiency of content personalization methods and product sales.

Table 1. Content Personalization Performance

شماره	**Personalized growth ladder performance**		
	DEVICE	***start***	***end***
1	***CNN Neural Network ResNet Architecture***	***%93***	***%95***
۲	***ALEX NET With CNN Neural Network***	***%90***	***%93***
۳	*Traditional neural network*	85%	۹۰%
۴	*ANN Neural Network*	۸۳%	۸۵%
۵	*Genetic methods*	۸۰%	۸۲%
۶	*Regular senorio without advertising*	۷۵%	۷۸%

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