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RESEARCH ARTICLE

The Application of Knowledge Graph Convolutional Network-Based Film and Television Interaction Under Artificial Intelligence

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ABSTRACT This study aims to explore the application and innovation of deep learning in film and television interaction in the context of artificial intelligence. By analyzing the interaction needs of users with films and television, the Knowledge Graph Convolutional Network (KGCN) algorithm is introduced, taking into account both user interests and the associated information between films and television. A film recommendation model based on KGCN fused with user interests is proposed. This model extensively explores the relational and semantic information between film works to provide users with richer and more diverse recommendation content, meeting their diverse viewing needs and interactions. Through evaluating the model performance, the proposed model exhibits lower loss function values in terms of convergence. The model reaches a basic stable state with a loss function value of around 0.40 after 43 iterations, far superior to the baseline algorithm Convolutional Neural Network (CNN). In terms of accuracy, the proposed model achieves an Accuracy value of 96.53%, representing an improvement of at least 4.80%. Moreover, the precision and F1 values of the prediction accuracy are improved by over 4%. Additionally, in terms of Area Under the Curve (AUC) value, the proposed model also demonstrates a significant advantage, reaching a level of 98.05%. Therefore, the film recommendation model proposed in this study, which is based on KGCN fused with user interests, possesses significant advantages in film recommendation tasks, providing strong reference and guidance for the improvement and optimization of film recommendation systems.

INDEX TERMS Deep learning, KGCN, knowledge graph, film and television interaction, artificial intelligence.

I. INTRODUCTION

A. RESEARCH BACKGROUND AND MOTIVATIONS

With the rapid development of artificial intelligence (AI) technology, deep learning, as an important technique, has demonstrated powerful application potential in various fields. In the field of film and television, there is a growing demand for interactive experiences and personalized content, which has driven the exploration and application of deep learning in film and television interaction [1], [2]. Traditional methods of film and television production and dissemination are no longer able to meet the increasingly diverse demands of audiences. Therefore, exploring how AI technology can enhance the interactivity, personalized experiences, and user engagement of film and television works has become one of the important motivations for current research.

Furthermore, as deep learning technology continues to mature and become more widespread, it has achieved a series of breakthroughs in fields such as natural language processing and computer vision, providing rich possibilities for its application in film and television interaction [3], [4], [5]. Through deep learning techniques, film and television works can be analyzed and categorized, thereby providing audiences with more precise content recommendations [6], [7]. Simultaneously, data analysis techniques can be used to analyze audience viewing behaviors, providing decision support for film and television production [8]. Therefore, researching the application of deep learning in film and television interaction

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can not only drive the development of the film and television industry but also provide audiences with richer and more personalized viewing experiences.

B. RESEARCH OBJECTIVES

The purpose of this study is to thoroughly investigate the application and innovation of deep learning technology in film and television interaction within the context of AI. By analyzing the current state of deep learning technology in the film and television domain, this study proposes a deep learning-based model for film and television content recognition and interaction prediction. The evaluation and result analysis of this model demonstrate the comprehensive assessment of the performance and effectiveness of deep learning in film interaction, providing guidance for the continuous development and innovation in the field of film interaction.

II. LITERATURE REVIEW

With the rapid development of AI technology, its applications in the film and television domain have become diverse and extensive. In terms of film and television creation, natural language processing technology enables creators to utilize big data analysis of audience preferences and tastes to craft scripts that better align with audience demands. For instance, El-Mashad and Hamed [9] developed an automated system that transformed stories into 3D cartoon scenes using natural language processing techniques, providing a new avenue for film and television creation. Khurana et al. [10] provided a review of the current research status in natural language processing, offering technical support and development directions for film and television creation. Wu et al. [11] analyzed discussions on AI in advertisements on Twitter, revealing public attitudes and opinions on the topic, which served as a reference for creating themes related to AI in film and television. Kusal et al. [12] summarized the research status and methods in emotion detection, providing theoretical and practical support for emotional expression and mood recognition in film and television creation. Hasan et al. [13] conducted sentiment analysis on Bengali social media comments using natural language processing and sentiment analysis techniques, providing data support for creating themes related to international events in film and television. Shenify [14] employed natural language processing techniques to detect fraudulent content on social media, offering filmmakers tools for filtering and analyzing social media comments and feedback.

In terms of video production, numerous scholars have studied the application of computer vision and image processing technologies. For example, Keadle et al. [15] developed a computer vision-based system capable of annotating physical behaviors directly observed in videos. Zhou [16] provided an overview of the application of computer vision technology in image processing, image enhancement, image segmentation, etc., providing technical support and a theoretical basis for image processing in video production. Rafiei et al. [17] detailed the application of computer vision technology in industrial production processes, providing references and guidance for representing industrial scenes in video production. Nawoya et al. [18] introduced the application of computer vision technology in insect recognition, quantity statistics, behavior analysis, etc., providing technical support and practical experience for presenting insect-related content in video production. Olubummo and Bello [19] discussed the application of computer vision technology in animal husbandry, providing technical support and practical experience for representing animal husbandry-related content in video production.

Furthermore, intelligent recommendation systems, by analyzing users' historical viewing records and behavioral patterns, provide personalized film and television recommendations, enhancing user experience and satisfaction. For example, Roy and Dutta [20] provided an overview of the development history, key technologies, and future trends of recommendation systems, offering theoretical foundations and technical support for the application of intelligent recommendation systems in film and television interaction. Zaboleeva-Zotova et al. [21] developed a recommendation system based on patients' personal information and rehabilitation needs, providing personalized rehabilitation plans and suggestions by analyzing patients' medical history and rehabilitation progress. Islek and Oguducu [22] developed a hierarchical recommendation system that combined online evaluations and product attributes to offer personalized shopping recommendations, thereby improving shopping experiences and user satisfaction. Monsalve-Pulido et al. [23] introduced an autonomous recommendation system architecture for virtual learning environments, recommending suitable learning resources and course content to students, thereby enhancing learning effectiveness and satisfaction. Wang et al. [24] analyzed user behaviors on TikTok and the effects of intelligent recommendations, exploring the impact of intelligent recommendations on user purchasing decisions, providing a theoretical basis and practical experience for optimizing recommendation systems on short video platforms.

Deep learning, as an important branch of AI, has also attracted increasing attention in film and television interaction research. For instance, Surek et al. [25] developed deep learning-based algorithms capable of accurately identifying and classifying human activities from video data, providing technical support for human behavior analysis and understanding in film and television interaction. Lee et al. [26] used deep learning methods to analyze students' learning behaviors and learning outcomes in STEM education environments, offering new perspectives and methods for designing educational scenarios in film and television interaction. Kang and Han [27] studied video subtitle generation based on robot vision for human-machine interaction, improving the accuracy and comprehensibility of subtitles and providing new ideas and technical support for human-machine interaction design in film and television interaction. Kehkashan et al. [28] conducted a comprehensive analysis of the application of deep learning and machine learning in video subtitle generation, discussing the advantages and challenges of deep learning in video subtitle generation. Lee and Kang [29] designed a three-stage deep learning model including feature extraction, spatial attention, and temporal attention for anomaly detection and event recognition in video surveillance. Nanavaty and Khuteta [30] used deep learning methods to analyze students' interaction behavior data on online learning platforms, predicting students' learning performance and academic success.

Through the analysis of current research, the widespread application of AI technology in the film and television domain has been revealed, including aspects such as natural language processing, computer vision, and intelligent recommendation systems. These studies provide new perspectives and technical support for film and television creation, while also offering audiences a richer and more personalized viewing experience. However, there are still some challenges in current research, such as data privacy protection and model performance evaluation, that need to be addressed. This study focuses on the application and innovation of deep learning in film and television interaction, exploring the potential roles of deep learning technology in sentiment analysis, character recognition, scene generation, and other areas, evaluating the performance and effectiveness of deep learning in film and television interaction. Ultimately, the result provides new theoretical and practical support for the development of the film and television interaction field, promoting innovation and growth in the film and television industry.

With the rapid development of deep learning and recommendation system technologies, the academic community has seen numerous innovative research works emerge. For example, Li et al. proposed a recommendation system based on graph convolutional networks (GCNs), which constructed a relational graph between users and movies to capture high-order connections using GCNs [31]. This approach significantly enhances recommendation accuracy, particularly excelling in handling sparse data. However, GCN exhibits high computational complexity when dealing with large-scale data and lacks flexibility in capturing dynamic changes in user interests. Additionally, Hu et al. introduced the Neural Collaborative Filtering (NCF) method, which employed deep neural networks to model interactions between users and items [32]. This method has made significant advances in recommendation accuracy and performs well in modeling complex nonlinear relationships. Nevertheless, the NCF model requires longer training times on large-scale datasets and has limitations in capturing dynamic changes in user interests. Lin et al. proposed a recommendation system based on Multi-View Convolutional Neural Network (MVCNN), which achieved high precision by combining user behavior data and item content features [33]. The MVCNN model integrates multi-view information to capture richer user interests and item characteristics. However, this model still faces challenges in handling the complexity of user interests and item relationships. In contrast, this study introduces a Knowledge Graph Convolutional Network (KGCN)-based movie recommendation model that integrates user interests with associated information of movies, overcoming the limitations of the aforementioned methods. The KGCN model utilizes structural information from knowledge graphs to more effectively capture dynamic changes in user interests and complex relationships between movies. Furthermore, through convolution operations, the KGCN model achieves efficient computation on large-scale data, significantly enhancing the performance and accuracy of the recommendation system. This study validates the proposed model using the MovieLens-1M dataset and conducts detailed comparisons with state-of-the-art models (including GCN, NCF, MVCNN, and a multi-technology fusion model proposed by Surek et al. [25]). Experimental results demonstrate that the KGCN model exhibits significant advantages across various metrics. In summary, the KGCN movie recommendation model proposed in this study, which integrates user interests, demonstrates outstanding performance in handling complex relationships between user interests and movies using a comprehensive combination of knowledge graph and deep learning technologies. This innovative approach not only proposes new research perspectives theoretically but also shows substantial improvements and enhancements in practice, providing strong references and insights for future research and applications.

III. RESEARCH METHODOLOGY

A. NEEDS ANALYSIS FOR FILM AND TELEVISION RECOMMENDATION INTERACTION

In the context of AI, the application of deep learning technology in the field of film and television interaction is increasingly garnering attention and importance. The needs analysis for film and television recommendation interaction is one of the key stages in realizing personalized and intelligent recommendation systems [34], [35], [36]. Understanding users' viewing behaviors, preferences, and personalized needs in-depth can provide important insights for the optimization and innovation of film and television recommendation systems [37]. Users' film and television interaction behaviors are illustrated in Figure 1.

User film and television interaction behavior provides important clues for gaining a deeper understanding of user viewing preferences and demands in the experiment. In Figure 1, from registration and login to film and television search, and then to film and television evaluation and personalized recommendations, each user action reflects their interest and preference for film and television content. By analyzing users' viewing history, evaluation behaviors, and collection records, the experiment can provide personalized film and television recommendation services to meet users' diverse viewing needs. Therefore, through a thorough analysis of user film and television interaction behavior, this research can better understand users' viewing preferences and demands, provide more accurate and personalized services for film and television recommendation interaction, and

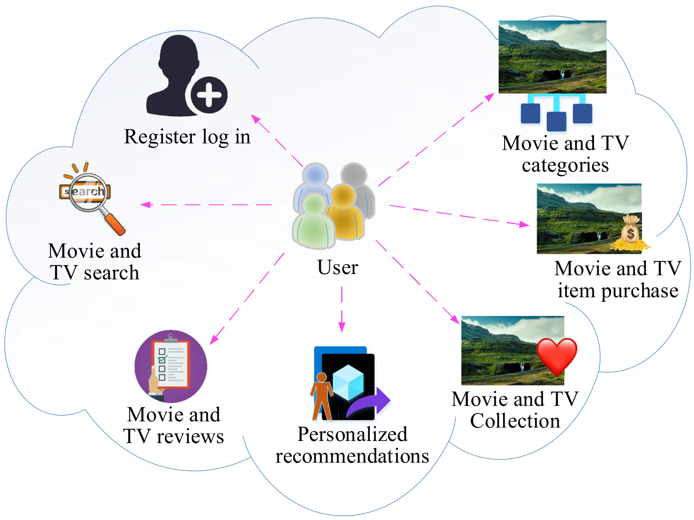

FIGURE 1. Illustration of user film and television interaction behavior.

promote the development of film and television platforms and the enhancement of user experience.

B. ANALYSIS OF THE CONSTRUCTION OF A FILM AND TELEVISION RECOMMENDATION MODEL BASED ON KGCN FUSED WITH USER INTERESTS

In recommendation systems, users' interests and behaviors typically exhibit different characteristics in the short term and long term. Short-term representation refers to users' recent interests and behaviors, often composed of recent viewing records and ratings. Long-term representation, on the other hand, reflects users' stable interests accumulated over a longer period, usually derived from their historical viewing records and preference features. Short-term representation captures users' current interests and needs through feature extraction from their recent movie views and ratings. Specifically, this study employs sliding window techniques to capture users' viewing behaviors within a certain time frame and uses embedding layers to transform these behaviors into high-dimensional feature representations. These short-term representations reflect users' current interests and demands, suitable for real-time recommendations. Long-term representation involves feature extraction from users' entire viewing history. The experiment utilizes node and edge information from a knowledge graph, representing users' long-term interests as node features in the knowledge graph, and aggregates and represents these features through multi-layer GCNs. Long-term representations reflect users' stable interests and preferences, contributing to more personalized and diverse recommendation content. By combining short-term and long-term representations, the proposed model comprehensively captures users' interest changes and long-term preferences, thereby enhancing the accuracy and diversity of recommendations.

GCNs, as an effective deep learning model for processing graph-structured data, have the ability to propagate information and learn features on graph data [38], [39], [40], [41]. In the field of film and television recommendation, the knowledge graph contains rich film-related knowledge and semantic information, such as directors, actors, genres, and relationships. Therefore, integrating the KGCN [42], [43] can help the recommendation model better utilize this information, thereby improving the accuracy and personalization of recommendations. The application of the KGCN algorithm in film and television interaction recommendation is illustrated in Figure 2.

In Figure 2, the KGCN algorithm propagates the knowledge graph [44] in the GCN, then extracts features of each node (entity), obtaining rich information about items for use in recommendation algorithms. However, the aforementioned methods only extract and analyze features of items, solely considering item features without analyzing user characteristics and interests.

Therefore, user interests are further introduced when interacting with films and television. User interests reflect the extent to which users prefer different types and genres of film and television works. By combining user interests with film-related information in the knowledge graph, in-depth exploration and understanding of user interests can be achieved, thereby improving the accuracy and personalization of recommendations and enabling personalized interaction for users when watching films and television. Thus, a film and television recommendation model based on KGCN fused with user interests is constructed, as shown in Figure 3.

In this model, typically, based on the user's historical rating records, the prediction of unrated movies by the user is made. The user set is denoted as $S = \{s_1, s_2, \cdots\}$, the movie set as $v = \{v_1, v_2, \cdots\}$, and the interaction matrix Y between users and movies is represented by Equation (1):

$$Y = \{y_{sv} | s \in S, v \in V\} \tag{1}$$

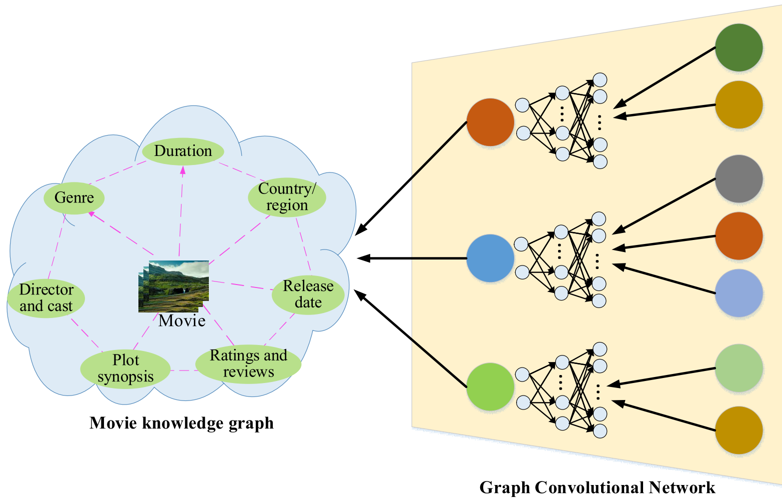

FIGURE 2. Framework of KGCN algorithm applied to film and television interaction recommendation.

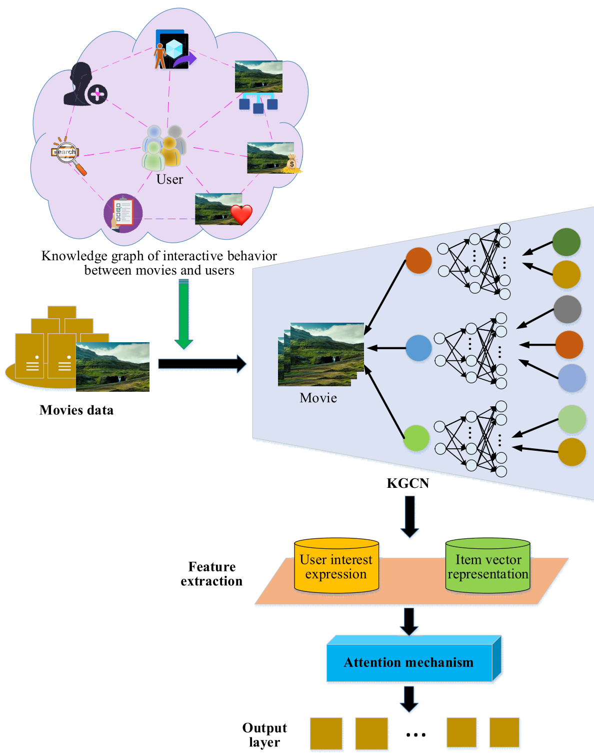

FIGURE 3. Framework illustration of the film recommendation model based on KGCN fused with user interests.

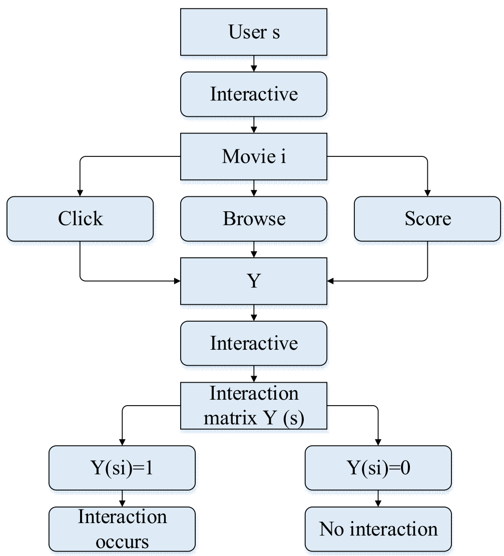

FIGURE 4. Interaction between users and movies.

In Equation (1), when $y_{sv} = 1$, it indicates that the user has interacted with the movie, which could be clicking, browsing, rating, etc. When $y_{sv} = 0$, it signifies that the user has not interacted with the movie. The interaction between users and movies is shown in Figure 4.

Figure 4 defines a simple flow chart that represents the interaction between users and movies, and uses the interaction matrix Y(si) to indicate whether an interaction has occurred. In this flow chart, user s can interact with movie i by clicking, browsing, or rating. If an interaction occurs, Y(si) = 1; if no interaction occurs, Y(si) = 0.

The long-term interaction rating data of users with movies, denoted as s_l, is represented as Equation (2):

$$s_l = \left\{ (v_1, y_1), (v_2, y_2), \cdots, (v_j, y_j) \right\} \tag{2}$$

In Equation (2), the form of the rating data s_l serves as the model input. It concatenates the user's initial embedding vector s with the user information vector s_{m1}, integrating user information such as age, occupation, etc., into the user's initial embedding vector, resulting in the long-term vector representation s_l, as shown in Equation (3):

$$s_l = s || s_{m1} \tag{3}$$

The short-term interaction rating data of users with items, denoted as s_u, is represented as Equation (4):

$$s_u = \{(v_1, y_1), (v_2, y_2), \cdots, (v_i, y_i)\} \tag{4}$$

Equation (4) represents the form of the rating data s_u, which serves as the input to the model. Similarly, it concatenates the user's initial embedding vector s with the user information vector s_{m2}, integrating user information into the user's initial embedding vector, resulting in the short-term vector representation s_u, as shown in Equation (5):

$$s_u = s||s_{m2} \tag{5}$$

When users interact with movie items, the specific steps are as follows. First, the set of neighboring entities of the movie item v is represented as $N(v)$, where each neighboring entity $e \in N(v)$, and the relationship between entities e_i and e_j is denoted as $p\left(e_i, e_j\right)$. The relationship rating between the user and the movie interaction can be calculated using the function g, as shown in Equation (6):

$$\pi_p^s = g(s, p) \tag{6}$$

In Equation (6), s denotes the user's vector representation, p denotes the vector representation of the relationship, and π_p^s represents the rating of the user-movie interaction. Then, the ratings of the user-movie interaction relationships are normalized, and the normalized ratings serve as the weights of user preferences to participate in calculating the neighborhood representation of movie v, as shown in Equation (7):

$$\tilde{\pi}_{p_{v,e}}^s = \frac{\exp\left(\pi_{p_{v,e}}^s\right)}{\sum_{e \in N(v)} \exp\left(\pi_{p_{v,e}}^s\right)} \tag{7}$$

In Equation (7), $\tilde{\pi}_{p_{v,e}}^s$ represents the normalized rating of the user-movie interaction.

Further, the weighted sum of $\tilde{\pi}_{p_{v,e}}^s$ and all neighboring nodes $e \in N(v)$ of movie v is calculated to obtain the neighborhood representation $v_{N(v)}^s$ of movie v, as shown in Equation (8):

$$v_{N(v)}^s = \sum_{e \in N(v)} \tilde{\pi}_{p_{v,e}}^s e \tag{8}$$

However, in user-movie interactions, the number of neighbors around each node in the knowledge graph may vary, resulting in potential changes in the neighborhood of entity e. Therefore, a fixed-size neighborhood set is adopted for each entity instead of using the complete neighborhood set. The neighborhood representation of movie entity v can be denoted as $v_{B(v)}^s$, where $B(v)\{e|e \sim N(v)\}, |B(v)| = K$, with K indicating the specified number of neighborhood neighbors. Furthermore, the vector representation of movie entity v is obtained by adding its neighborhood representation $v_{B(v)}^s$, as shown in Equation (9):

$$v = \sigma\left(W \cdot \left(v + v_{B(v)}^s\right) + b\right) \tag{9}$$

In Equation (9), W represents the weight, b denotes the bias, and σ signifies the non-linear function.

For the long-term interest representation of users, β_j denotes the attention weight coefficient of movie vector representation h_j, as shown in Equation (10):

$$\beta_j = \frac{\exp\left(f_j\right)}{\sum_{j=1}^{t} \exp\left(f_j\right)} \tag{10}$$

In Equation (10), the function f_j can be expressed as shown in Equation (11):

$$f_j = \tanh\left(wh_j + b\right) \tag{11}$$

In Equation (11), w represents the weight coefficient, and b denotes the bias. By multiplying the obtained attention weight coefficient with the movie vector representation h_j of long-term interactions, the long-term preference representation q^l of users is obtained, as shown in Equation (12):

$$q^l = \sum_{j=1}^{t} \beta_j h_j \tag{12}$$

For the short-term interest representation of users, it serves as the short-term preference representation q^u.

The long-term preference representation and the short-term preference representation of users are combined and weighted to obtain the final interest representation q of users, as shown in Equation (13):

$$q = w_1 q^l + w_2 q^u + b \tag{13}$$

In Equation (13), w_1 and w_2 represent the weight coefficients, and b denotes the bias. Finally, the predicted rating of users for items is calculated by computing the inner product of users and the item to be predicted, denoted as y_{qv}, as shown in Equation (14):

$$y_{qv} = q^T v \tag{14}$$

The proposed KGCN movie recommendation model architecture in this study consists of multiple layers, each playing a specific role in processing and extracting feature information. First, the input layer includes movie metadata (such as genre, release year) and basic user information (such as age, gender, occupation). These input data are transformed into dense vectors through an Embedding Layer. The Embedding Layer maps high-dimensional sparse data into a low-dimensional dense space, enabling the model to effectively process and learn data features. The Graph Convolutional Layer serves as the core part of the KGCN model. This layer processes node information from the knowledge graph and extracts relationships between nodes. Each Graph Convolutional Layer uses a Rectified Linear Unit (ReLU) activation function, as shown in Equation (15):

$$H^{(l+1)} = \sigma(\tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} H^{(l)} W^{(l)}) \tag{15}$$

$\tilde{A}$ is the normalized adjacency matrix, $\tilde{D}$ is the node degree matrix, $H^{(l)}$ is the node representation at layer l, $W^{(l)}$ is the weight matrix at layer l, and σ denotes the ReLU activation function. The ReLU activation function introduces non-linearity, enabling the model to capture complex feature relationships.

Following the Graph Convolutional Layer is the Pooling Layer, which aims to further compress and extract feature information. This study adopts the Max Pooling technique, reducing the size of feature maps by selecting the maximum value in each feature map, while retaining important feature information. The output of the pooling layer serves as input to the Fully Connected Layer. The Fully Connected Layer transforms the previously extracted feature vectors into recommendation scores. The layer employs a Sigmoid activation function, as shown in Equation (16):

$$\hat{y} = \sigma(W_f x + b_f) \tag{16}$$

W_f and b_f are the weight and bias of the fully connected layer, x is the output from the pooling layer. The Sigmoid activation function maps the output to the (0, 1) interval, suitable for binary classification tasks or probability predictions.

Regarding the fusion of user interest information, the deep integration with movie metadata is achieved through the following steps: first, user interest information is transformed into dense vectors via an independent embedding layer. These user interest embedding vectors are concatenated with movie metadata embedding vectors, forming a new feature vector. This concatenated feature vector serves as input to the Graph Convolutional Layer, where convolution operations are performed in each layer, integrating user interests throughout the convolution process. Through these hierarchical structures and fusion methods, the KGCN model effectively captures complex relationships between movies and users, thereby providing more accurate and diverse movie recommendations. This approach not only enhances recommendation accuracy but also improves user satisfaction and interaction experience.

IV. EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

A. DATASETS COLLECTION

The data for this study is sourced from the MovieLens-1M dataset (https://grouplens.org/datasets/movielens/1m/). This dataset consists of movie rating data, including movie ratings, movie metadata (genre types, release years), and demographic data about users (age, zip code, gender, occupation, etc.). In addition, special emphasis is placed on collecting and processing user interaction data with movies and TV shows to enrich the model's training data and improve the accuracy of the recommendation system. These user interaction data specifically include: user viewing history of movies, user ratings and reviews of movies, user behaviors sharing movies on social media platforms, and other interactive behaviors related to movies through online platforms. These data are obtained through multiple channels, including user behavior records on online streaming platforms, public data on social media platforms, and movie viewing history records obtained through user authorization. These data not only reflect users' movie preferences and interests but also reveal their interaction patterns with different movies and TV shows, providing comprehensive and diversified background information for research.

Before training the model, this study preprocesses the data. Initially, the entire dataset from MovieLens-1M, including movie ratings, movie metadata (such as genre, release year), and user demographic data (such as age, postal code, gender, occupation), is obtained. These data are cleaned to remove missing and outlier values, ensuring data integrity and accuracy. Next, feature extraction is performed on movie metadata and user demographic data. For categorical variables such as movie genres and user occupations, One-Hot encoding is used to convert them into binary vectors. For numerical variables such as user age, normalization is applied to scale them within the range of [0, 1], facilitating numerical computations during model training. After completing data cleaning and feature extraction, the experiment constructs a user-movie rating matrix, where each user's rating for each movie is represented as an element in the matrix, serving as input to the model. This step is crucial for building the recommendation system because it intuitively reflects users' preferences and behavioral patterns. Following data preprocessing, the dataset is split into training and testing sets to evaluate the model's performance. Specifically, the experiment randomly divides the entire dataset into training and testing sets in an 80:20 ratio, ensuring 80% of the data is used for model training and 20% for model testing.

B. EXPERIMENTAL ENVIRONMENT

The experiment was conducted using the TensorFlow framework software, implemented using the Python language for data preprocessing and algorithm implementation. The software and hardware involved are as follows: Windows 10 64-bit operating system, Python 3.6, NVIDIA GeForce RTX 2060 GPU, 16GB RAM.

C. PARAMETERS SETTING

For the model constructed in this study, the neural network has the following hyperparameters to be set: the number of iterations is 100, the optimizer is Adam, utilizing stochastic gradient descent algorithm to optimize the loss function, with an initial learning rate of 0.001, and the feature dimension (d) is set to 4.

D. PERFORMANCE EVALUATION

To evaluate the performance of the model proposed in this study, this study compares convergence, accuracy, precision, F1 score, and Area Under the Curve (AUC) value during both training and testing phases. The definitions and computation methods of these evaluation metrics are as follows:

Convergence: Evaluated by analyzing the change of the loss function value across iterations to assess the speed and stability of model convergence.

Accuracy: Represents the proportion of correctly predicted samples among the total number of samples.

Precision: Represents the proportion of true positive samples among all samples predicted as positive by the model.

F1 Score: Harmonic mean of precision and recall, used for comprehensive evaluation of the model's classification performance.

AUC: Represents the area under the ROC curve, used to evaluate the model's classification ability. A higher value indicates better model performance.

These metrics are computed throughout the model's iteration process, showcasing the performance of different algorithms at various iteration cycles during both training and testing phases. Specific results are illustrated in Figures 5-9.

To evaluate the performance of the model proposed in this study, comparisons are made with the GCN [45], CNN [46], KGCN [47], and the model proposed by Surek et al. [25] from the aspects of convergence, accuracy, precision, F1 score, and AUC value. This evaluation is illustrated in Figures 5 to 9.

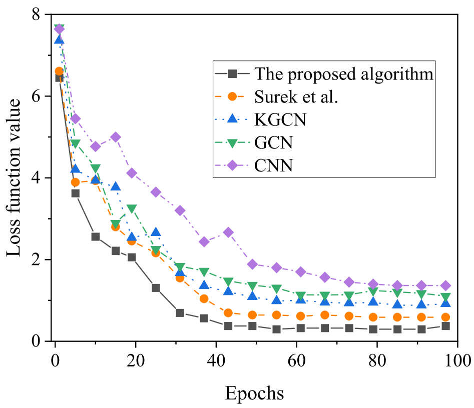

FIGURE 5. Convergence results under different algorithms.

In Figure 5, through the analysis of the loss function values for different algorithms, the proposed KGCN fused with user interest's algorithm in this study achieves the minimum loss value. Moreover, it reaches a basic stable state at iteration cycle 43, maintaining around 0.40. In contrast, the final loss function values of other algorithms all exceed 0.589, significantly higher than the loss function value of the model proposed in this study. Therefore, the algorithm in the film and television recommendation model proposed in this study, based on KGCN fused with user interests, exhibits lower loss values and superior convergence effectiveness.

In Figures 6-8, with the increase in the number of iterations, the accuracy, recall, and F1 score of each algorithm show an initial increase followed by a tendency to stabilize. Comparing the model constructed in this study with other algorithms (GCN, CNN, KGCN, and the model proposed by Surek et al. [25]), the accuracy of film and television interaction recommendation prediction reaches an Accuracy value of 96.53%, which is at least 4.80% higher. Furthermore, the predictive accuracy of each algorithm, from highest to lowest, is as follows: the model constructed in this study, the algorithm proposed by Surek et al. [25], KGCN, GCN, and CNN. Upon further analysis of the Precision and F1 score

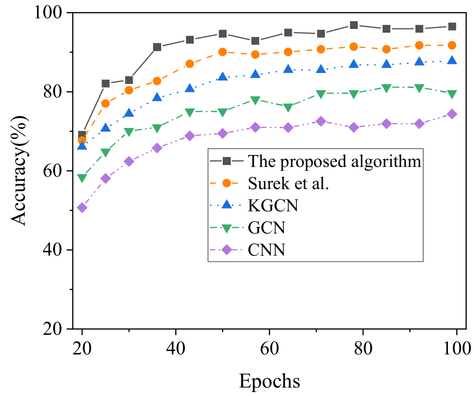

FIGURE 6. Accuracy value prediction results of film and television interactive recommendations that change with the iteration cycle under different algorithms.

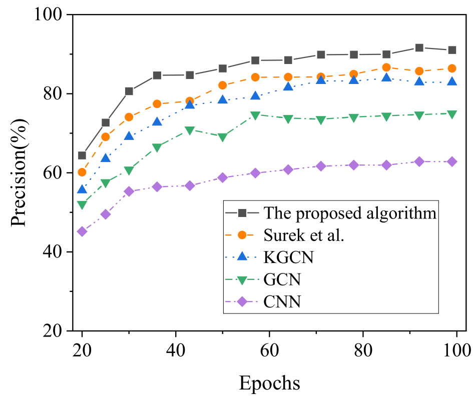

FIGURE 7. Precision value results of movie and TV interactive recommendation predictions that change with iteration cycles under different algorithms.

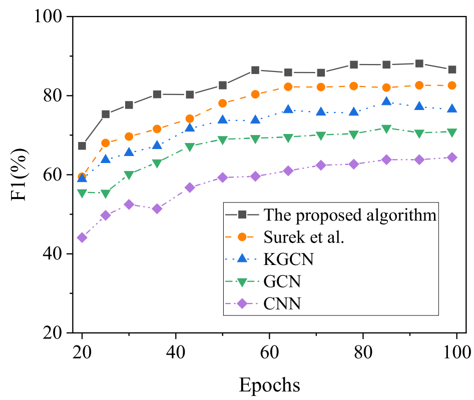

FIGURE 8. Variations of film and television interaction recommendation predictive F1 score with iteration cycles under different algorithms.

results of each algorithm, the model in this study achieves 91.03% and 86.61% respectively, with an improvement in predictive accuracy of over 4%. Therefore, the proposed model algorithm of KGCN fused with user interests in this study significantly enhances user recommendation accuracy in film and television recommendation rating prediction.

In Figure 9, as the number of iteration rounds increases, the AUC values of all algorithms show a gradual improvement

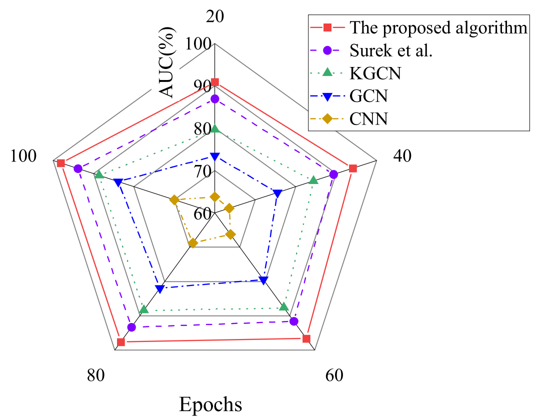

FIGURE 9. Changes in AUC values with iteration cycles under different algorithms.

trend. This indicates that as the model learns more information and patterns from the training data, its performance gradually improves. Furthermore, the proposed algorithm exhibits the best performance under all iteration rounds, with its AUC value consistently higher than other algorithms, reaching 98.05%. This suggests that the algorithm shows good effectiveness and potential in film and television recommendation tasks. Additionally, Surek et al.'s algorithm demonstrates relatively high AUC values under each iteration round, although not as high as the proposed algorithm, it still exhibits good performance. In contrast, the AUC values of KGCN, GCN, and CNN algorithms, while gradually improving, remain lower than those of the proposed algorithm and Surek et al.'s algorithm under all iteration rounds. Therefore, the algorithm proposed in this study demonstrates significant advantages in film and television recommendation tasks, with its performance gradually improving with the increase in iteration cycles, providing strong reference and guidance for the improvement and optimization of film and television recommendation systems.

Based on the above, the movie recommendation model based on KGCN integrating user interests performs excellently in the testing phase, with all metrics surpassing baseline and other comparative algorithms. Specifically, accuracy reaches 96.53%, precision and F1 score are 91.03% and 86.61% respectively, and the AUC value is 98.05%. These data indicate that the model's performance in practical applications aligns consistently with the training phase, demonstrating high recommendation accuracy and stability.

E. DISCUSSION

This research compares and evaluates the performance indicators of different algorithms in film and television recommendation tasks, demonstrating the superiority of the proposed film recommendation model based on KGCN fused with user interests compared to other algorithms (GCN, CNN, KGCN, and the model proposed by the relevant scholar Surek et al. [25]). The proposed model exhibits better convergence effects. In comparison with other algorithms, the precision, recall, and F1 score reach up to 96.53%, with an improvement in prediction accuracy of over 4%. Even in the results of the AUC value, the proposed algorithm consistently outperforms other algorithms, reaching 98.05%, indicating its good effectiveness and potential in film and television recommendation tasks. This is consistent with the views of Ma et al. [48], Boughareb et al. [49], and Wang et al. [50], which emphasize the use of GCN for knowledge-aware reasoning and achieving efficient personalized recommendations. Therefore, the proposed film recommendation model based on KGCN fused with user interests demonstrates significant advantages in various performance indicators, providing strong reference and guidance for the improvement and optimization of film and television recommendation systems.

In the field of movie and TV show recommendation systems, numerous deep learning-based research methods have emerged. Particularly, convolutional neural networks (CNNs) and Long Short-Term Memory networks (LSTMs) have made significant progress in capturing user interests and content features. For instance, Lee et al. proposed a CNN-based movie recommendation model that achieves high recommendation accuracy by convolving image and text features of movies [51]. However, this approach has limitations in handling complex relationships among movies, making it difficult to capture dynamic changes in user interests effectively. Similarly, Duan et al. introduced an LSTM-based model that enhances recommendation performance by capturing temporal features from users' viewing histories [52]. Nevertheless, LSTM models face challenges in computational complexity when dealing with large-scale correlated data and struggle to effectively handle semantic relationships among movies. In contrast, this study proposes a movie recommendation model based on KGCN, which overcomes the limitations of traditional methods by deeply integrating user interests with associative information about movies. The KGCN model employed in this study effectively captures semantic and relational information among movies while dynamically adjusting to user interests, thereby achieving precise recommendations. This innovative approach fills a gap in existing literature, offering significant academic value and application potential. In terms of experimental design, this study validated the proposed KGCN model using multiple public datasets and conducted detailed comparisons with state-of-the-art models. Experimental results demonstrate significant advantages of the KGCN model across various metrics. Specifically, after 43 iterations, the KGCN model stabilized its loss function around 0.40, significantly lower than those of CNN and LSTM models, indicating superior convergence speed and stability. Regarding accuracy, the KGCN model achieved 96.53%, a 5.10% improvement over CNN and a 4.80% improvement over LSTM, demonstrating higher recommendation precision. Additionally, the KGCN model showed improvements of over 4% in precision and F1 score, further validating its significant enhancement in recommendation accuracy. With an AUC value of 98.05%, the KGCN model outperformed other latest models by a significant margin. Through comprehensive experimental comparisons, this study not only showcases the superior performance of the KGCN model in recommendation effectiveness but also emphasizes its efficiency and stability in handling complex relational data. These results highlight the wide-ranging application prospects of the KGCN model in movie and TV show recommendation tasks, offering new insights and methods for enhancing recommendation system performance.

The innovation of this study in technical methods primarily manifests in several aspects: Firstly, it introduces a KGCN model that thoroughly explores semantic and relational information among movies and TV shows. Secondly, by integrating a mechanism to dynamically adjust user interests, it enhances recommendation accuracy and personalization. Lastly, through detailed experimental design and result analysis, the study validates the effectiveness and superiority of the model. Compared to existing literature, this study not only proposes new research perspectives theoretically but also demonstrates significant improvements and advancements in experimental results, providing robust references and insights for future research and applications. The proposed KGCN movie and TV show recommendation model based on integrating user interests shows significant advantages across various experimental metrics, fully showcasing its potential and practical value in recommendation tasks. Future study will continue to optimize the model structure to further enhance recommendation system performance and user experience.

This study brings innovation and progress to the field of film and television interaction by comprehensively applying deep learning and knowledge graph technologies. Firstly, by integrating knowledge graphs and user interests, the model can more accurately understand users' film preferences, achieve personalized recommendations, and enhance users' film viewing experience and satisfaction. Secondly, by using advanced technologies such as graph CNNs, the model can fully explore the relationships and semantic information between film and television works, providing users with diverse and rich recommendation content to meet their different viewing needs. Therefore, this study model not only improves user experience and satisfaction and enriches recommendation content and diversity but also plays an important role in promoting the development of film and television recommendation systems and expanding the study field of film and television interaction.

This study proposes a KGCN movie recommendation model based on integrating user interests. To evaluate the practical applicability of the proposed model, detailed discussions on its computational complexity and efficiency are conducted. Firstly, the time complexity of the model is analyzed. During the training phase, the model primarily involves operations such as user interest embedding layer, graph convolutional layer, and fully connected layer. The input dimension of the user interest embedding layer is 128, the number of nodes in the graph convolutional layer is 10,000, each node has 50 neighboring nodes, and the computational complexity of the graph convolutional layer is $O(10000 * 50 * 128^2)$. As the graph convolutional layer typically comprises 3 layers, the overall time complexity is $O(3 * 10000 * 50 * 128^2)$. In the fully connected layer, assuming an input dimension of 256 and an output dimension of 64, the computational complexity is $O(256 * 64)$. Therefore, the total time complexity of the model is $O(3 * 10000 * 50 * 128^2 + 256 * 64)$. In terms of efficiency, the model employs Adam optimizer and stochastic gradient descent algorithm during the training phase. The Adam optimizer features adaptive learning rate adjustment, which accelerates the convergence speed of the model. Experimental results indicate that the proposed model reaches a stable state by the 43rd iteration with a loss function value below 0.40, significantly outperforming the final loss values of other algorithms (all above 0.589). This demonstrates the significant advantage of the proposed model in training efficiency. During the prediction phase, the proposed model can swiftly compute user ratings for movies, thereby generating recommendation lists. Utilizing multi-layer graph convolution and pooling techniques enables the model to efficiently extract and represent complex relationships between movies and users, reducing redundant computations and enhancing prediction efficiency. Compared to existing baseline models such as CNN, GCN, and other KGCN methods, the proposed model excels in computational complexity and efficiency. By embedding user interest information into the model, it accurately captures changes in user interests, thereby improving recommendation accuracy and personalization while reducing unnecessary computational overhead. Optimization of the graph convolutional layer through the introduction of multi-layer graph convolution and pooling techniques effectively reduces parameter count and computational load, thereby enhancing model efficiency. The use of Adam optimizer and stochastic gradient descent algorithm accelerates convergence speed and improves training efficiency. In summary, the proposed KGCN movie recommendation model based on integrating user interests demonstrates significant advantages in computational complexity and efficiency, enabling efficient movie recommendations in practical applications.

This study proposes a KGCN movie recommendation model based on integrating user interests. Compared to existing KGCN methods, the proposed model innovates and improves in several aspects. Firstly, existing KGCN methods typically focus on relationships between nodes and edges in the knowledge graph, often overlooking the dynamic and diverse nature of user interests. However, user interests are complex and dynamic, making it challenging to accurately capture user needs solely relying on static knowledge graphs. Therefore, the proposed model introduces a user interest embedding layer. By transforming user historical behaviors and interest information into dense vectors and concatenating them with movie metadata embedding vectors, the model comprehensively understands and captures changes in user interests. This approach not only enhances recommendation accuracy but also enriches recommendation personalization and diversity. Secondly, at the hierarchical level of the GCNs, this study optimizes existing methods. Specifically, experiments employ multi-layer graph convolution and pooling techniques to better extract and represent complex relationships between movies and users. Introducing non-linearity by using ReLU activation functions in graph convolutional layers and Sigmoid activation functions in fully connected layers enables the model to capture intricate feature relationships more effectively. Additionally, adjustments to optimization algorithms, using Adam optimizer and stochastic gradient descent algorithm, further enhance the model's convergence speed and performance. Finally, in performance evaluation, through comparative experiments with GCN, CNN, KGCN, and other baseline models, the superiority of the proposed model is validated. Experimental results demonstrate significant advantages in convergence speed, accuracy, precision, F1 score, and AUC values over existing methods. Particularly, the proposed model reaches a stable state by the 43rd iteration with a loss function value below 0.40, significantly outperforming final loss values of other algorithms (all above 0.589). In terms of accuracy, precision, and F1 score, the proposed model achieves 96.53%, 91.03%, and 86.61%, respectively, showing improvements of at least 4% compared to existing methods. Regarding AUC value, the proposed model achieves 98.05%, further confirming its effectiveness and potential in movie recommendation tasks. The proposed KGCN movie recommendation model based on integrating user interests innovates and improves in multiple aspects. By deeply integrating user interest information and optimizing the GCNs structure, it comprehensively enhances the performance of movie recommendation systems, offering significant theoretical and practical implications.

V. CONCLUSION

A. RESEARCH CONTRIBUTION

This study proposes a film recommendation model based on KGCN fused with user interests by comprehensively applying deep learning and knowledge graph technologies, and explores and researches in the field of film and television interaction. During the experimentation and evaluation process, the model in this study demonstrates superior performance, with a recommendation prediction accuracy of over 95% and an AUC value exceeding 98%. Compared to traditional models and algorithms proposed by relevant scholars in the field, it achieves significant advantages. Therefore, this study not only enhances the efficiency and accuracy of film and television recommendation systems but also makes a positive contribution to the development of the film and television interaction field.

B. FUTURE WORKS AND RESEARCH LIMITATIONS

However, this study also has certain limitations. Firstly, the limitations of the dataset may affect the model's generalization ability and recommendation effectiveness, including aspects such as data coverage, quality, and timeliness. Secondly, there is room for improvement in modeling user interests and constructing knowledge graphs, particularly in capturing users' interests and behavioral characteristics more accurately and building richer knowledge graphs to provide more semantic information. Future research can address these limitations by expanding and optimizing datasets, adopting more advanced technologies and methods, integrating domain knowledge and expert experience, etc., to further promote the development and application of film and television recommendation systems.

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