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A HYBRID DEEP LEARNING FRAMEWORK FOR MOVIE RECOMMENDATION USING LATENT FEATURE REPRESENTATION

Anjali Arora, Research Scholar, Computer Science and Engineering Department, SRM University Delhi-NCR, India
M. Mohan, Professor, Computer Science and Engineering Department, SRM University Delhi-NCR, India
Sanjay Kumar Malik, Professor, Department of Information Technology, ADGITM, New Delhi, India
Gajendra Kumar Saraswat, Faculty of Mathematics, Institute of Information Technology and Management, Janakpuri, New Delhi, India

Abstract: The ensuing paper presents a recommendation hybrid deep learning model of movies based on latent feature representation, intended to enhance the personal movie discovery process with the help of heterogeneous data sources integration. The model is a combination of structured information, e.g. movie metadata and user ratings, and unstructured text information, obtained by plot summary. Genre-sensitive latent embeddings are trained to learn both semantic and contextual links between movies and patterns of user preferences based on previous interactions. The deep learning system uses convolutional and recurrent neural networks to predict the sequence and semantic attributes of plot descriptions and categorical and numerical attributes are processed in fully connected layers. These modalities are merged into a single latent feature space which allows learning to represent effectively. The large scale of experiments run on benchmark movie datasets show that the proposed framework remains always better than the state-of-the-art recommendation models in terms of precision, recall, and normalized discounted cumulative gain (nDCG). In addition, its hybrid design based on the latent feature promotes the use of text-based and category data considerably to enhance the performance of cold-start recommendation to produce more correct, varied, and contextual recommendations of movies to different user profiles.

Keywords— Movie Recommendation Systems, Genre-Aware Embeddings, Hybrid Deep Learning, Multimodal Feature Fusion

1. INTRODUCTION AND LITERATURE REVIEW

The rise of digital entertainment platforms has greatly transformed the way audiences look for, find and assess films. Platforms contain huge catalogs consisting of thousands of titles in various genres, languages and cultural environments. Even though this abundance may expand the user options, it is a subject of the phenomenon called, sometimes the "paradox of choice", which misleads the users to find the content matching their interests. Such a challenge has increased the need of the efficient recommendations [1], since the goal of recommendation system is to inform the viewers about the right movies while at the same time reducing the pain of searching through the wide range of contents.

Traditional recommendation systems usually belong to two categories, namely, collaborative filtering and content-based filtering. Collaborative filtering is the method that utilizes agreement patterns between users or similarities between items based on interactions history. Content-based filtering, on the other hand, is based on the description of the items, like genre, casting, director, plot etc. These approaches have shown success under specific scenarios but also suffer from fundamental shortcomings [2]. Collaborative filtering fails if new items or new users does not have enough historical data, called the cold-start problem. In contrast, content-based filtering tends to provide similar and homogeneous recommendations, limiting suggested items to a few similar items related to past user interest.

With the most recent advance of deep learning in the recommendation field, new hybrid recommender systems are emerging that can integrate heterogeneous data streams. Neural architectures apply processing directly to textual descriptions using convolutional and recurrent layers and can convert structured metadata and rating data through embedding layers and densely connected networks. This integration of modalities can allow for more granular and contextually relevant recommendations. Current systems also still lack the genre awareness that would allow for organizing principles that would better determine model design. As we can explicitly model genre relevance and employ it in a metadata, rating and narrative information fusions, it enables the implementations of recommendations that are very relevant, and yet less redundant [3].

To tackle these issues, this research proposes a Hybrid Deep Learning Recommendation framework which uniformly integrates metadata, viewer ratings, and plot summaries into a unified predictive framework. This allows the model to incorporate genre information directly into its fusion mechanism, and thus, be able to weight features based on genre and its effect on users preferences. We expect this to make traditional accuracy measures more useful at more relevant task features, and increase novelty, diversity and robustness, especially during cold-starts.

A. Evolution of Recommendation Approaches in Movie Discovery

The evolution of recommendation systems on movies progressed from basic rating-based prediction approaches to more advanced multimodal and hybrid deep learning architectures bolstered by the richness of data about movies and user preferences.

The early landscape was dominated by collaborative filtering approaches. They work either by directly computing similarity heuristics over user–item interaction records, or by decomposing these interaction records to unearth hidden preference factors using mathematical techniques. Collaborative filtering works well when rating datasets are dense and interactions are plenty because in this scenario the performance accuracy can be very high. These approaches use historical interactions to predict future ones, making them unable to generalize to novel items or users. They also fail to incorporate any descriptive content about the movies themselves [4].

Content-based filtering approaches emerged to complement collaborative filtering by focusing on the features of the movies rather than the behavior of the users. In the movie context, these features could include structured metadata such as genres and cast, or unstructured content such as plot summaries. They tend to create recommendation lists that are overly narrow, reinforcing existing user preferences and limiting serendipity.

To address the weaknesses of single-modality methods, hybrid recommendation systems emerged. These models combine collaborative and content-based techniques to leverage the strengths of both. For example, latent user and item representations from collaborative filtering can be enhanced with textual and categorical embeddings from content-based methods. Hybrid approaches typically outperform single-modality ones, particularly in balancing accuracy and diversity [5]. Yet, many hybrid models still do not fully exploit the genre dimension as an explicit guiding factor, treating it merely as another categorical attribute as given in table 1.

TABLE 1. Comparison of Single-Modality and Hybrid Recommendation Approaches in Movie Recommendation

Approach Type	**Data Modalities Used**	**Strengths**	**Limitations**
Collaborative Filtering [1]	Ratings	High accuracy when data is dense	Suffers in cold-start scenarios; ignores content features
Content-Based Filtering [2]	Metadata, plot keywords	Works well for new items; interpretable recommendations	Limited diversity; tends to recommend very similar items
Hybrid (CF + Content) [3]	Ratings, plot text	Combines accuracy with cold-start resilience	Genre often treated superficially; limited semantic richness
Hybrid (Embedding Fusion) [4]	Ratings, metadata	Balanced precision and recall	Weak integration of textual semantics
Hybrid (Neural Multimodal) [5]	Ratings, text, metadata	Strong multimodal integration	Genre used as static label, not as dynamic guiding signal

B. Genre Awareness in Recommendation Models

In movie recommendation, genre serves as one of the most recognizable and impactful signals influencing user decisions. Genre labels help users navigate large catalogs by filtering content into familiar categories, and they often correlate with stylistic, thematic, and emotional elements in storytelling. Despite this, many systems integrate genre in only the most basic form—as a one-hot encoded categorical variable. This representation fails to capture nuanced relationships between genres, such as overlaps between "drama" and "romantic drama" or between "science fiction" and "action."

More advanced genre-aware systems encode genres into dense vector spaces, enabling the model to measure similarity between genres and discover latent groupings. This can be particularly valuable for users with multi-genre preferences, as it allows the model to recommend across related categories without strictly confining suggestions to a single genre. While such encoding improves flexibility, genre awareness is still often secondary to other features and is not integrated into the core fusion process guiding recommendations [6].

C. Rise of Multimodal Deep Learning in Movie Recommendation

Deep learning techniques have revolutionized multimodal data processing in recommendation systems. Convolutional neural networks are well-suited for extracting local and compositional patterns from text, making them effective for processing plot summaries. Recurrent networks, including long short-term memory units and gated recurrent units, capture sequential dependencies in narrative structures. Transformer-based architectures further improve this by enabling global attention over the entire plot text [7], identifying key thematic elements regardless of their position.

For structured metadata and user ratings, dense neural layers and embedding mechanisms map categorical and numerical data into latent vector spaces. The challenge lies in combining these diverse feature types into a coherent representation. Basic fusion methods simply concatenate these features, but more sophisticated strategies use attention mechanisms to weight their importance dynamically based on the recommendation context.

Multimodal approaches outperform unimodal systems in personalization, novelty, and robustness. Still, even among these, few explicitly make genre awareness a central design principle. By allowing genre information to directly influence how modalities are weighted [8], it becomes possible to improve recommendation relevance without sacrificing diversity as given in table 2.

TABLE 2. Comparison of Genre-Aware and Multimodal Deep Learning Approaches in Movie Recommendation

Model Type	Modalities Integrated	Key Contributions	Limitations
Collaborative with Genre Embedding [6]	Ratings, genres	Captures inter-genre relationships	Lacks textual content integration
CNN-RNN Hybrid [7]	Text, metadata	Strong textual feature extraction	Genre not explicitly weighted
Multimodal Neural [8]	Ratings, text, metadata	Joint learning across modalities	Genre treated as categorical feature only
Transformer-based [9]	Ratings, text, metadata	Attention-based fusion of modalities	Weak emphasis on genre as a guiding factor
Proposed Model	Ratings, text, metadata	Explicit genre-aware fusion with dynamic weighting	—

D. Identified Research Gap

Despite significant progress in hybrid and multimodal recommendation systems, three persistent gaps remain:
1. Underutilization of genre information – Genre is typically used as a static category rather than a high-dimensional, relational signal capable of shaping recommendation relevance.
2. Lack of genre-guided weighting mechanisms – Few models adjust the relative influence of different modalities based on the user's genre preferences or the genre profile of the items.

The proposed a Hybrid Deep Learning framework addresses these gaps by embedding genre information alongside other features, using it to guide the fusion process across metadata, viewer ratings, and plot summaries. This approach aims to improve performance in both cold-start and warm-start scenarios [9], producing recommendations that are accurate, diverse, and better aligned with nuanced user preferences.

2. Methodology and Proposed Work

The proposed methodology for a Hybrid Deep Learning Model is designed to address the limitations of existing recommendation systems by integrating three heterogeneous data sources—metadata, viewer ratings, and plot summaries—within a deep learning architecture that explicitly embeds genre-awareness into the feature fusion process. The framework combines multimodal feature extraction, genre-based contextual embedding [10], and adaptive attention fusion, culminating in a predictive recommendation layer optimized for both accuracy and diversity.

A.Data Preprocessing and Representation

The methodology begins with preparing the heterogeneous dataset. Each movie in the dataset is represented by three principal components:

1. Structured Metadata Vector: Contains categorical attributes such as genre, director, cast, and release year, encoded via embedding layers.
2. Viewer Ratings Matrix: Encodes explicit feedback in a user-item interaction matrix $R \in \mathbb{R}^{m\times n}$, where m is the number of users and n is the number of movies. Ratings are normalized to the range [0,1] for numerical stability.
3. Plot Summary Text: A sequence of tokens $T = [t_1, t_2, \ldots, t_L]$ where L is the length of the plot description. The text is tokenized, stop words removed, and words mapped to dense vectors using a pre-trained embedding model.

Genre encoding is treated differently from other categorical features. If each movie can belong to multiple genres, the genre vector is expressed as a multi-hot encoding $g \in \{0,1\}^G$, where G is the number of possible genres. This vector is then projected into a dense space via a learnable transformation:

$$\mathbf{g}_{emb} = \sigma(W_g g + b_g)$$

where $W_g \in \mathbb{R}^{d_g\times G}$ and $b_g \in \mathbb{R}^{d_g}$ are trainable parameters, d_g is the embedding dimension, and $\sigma(\cdot)$ is a non-linear activation function such as ReLU.

A. Metadata Feature Extraction

Categorical metadata attributes such as director or cast are processed via embedding layers:

$$\mathbf{e}_c = \sigma(W_c x_c + b_c)$$

where x_c is the one-hot encoded categorical feature, W_c and b_c are trainable parameters, and $\mathbf{e}_c$ is the resulting dense representation [11]. Continuous metadata such as release year is normalized and concatenated directly into the metadata vector.

The final metadata embedding is obtained by concatenating all attribute embeddings with the genre embedding:

$$\mathbf{M} = [\mathbf{g}_{emb}; \mathbf{e}_{dir}; \mathbf{e}_{cast}; \mathbf{e}_{\text{year}}]$$

where [;] denotes concatenation.

B. Ratings Feature Extraction via Matrix Factorization

The ratings matrix R is factorized into user and item latent matrices $P \in \mathbb{R}^{m\times k}$ and $Q \in \mathbb{R}^{n\times k}$, where k is the latent dimension. The objective is to minimize the squared error between predicted and actual ratings:

$$\min_{P,Q} \sum_{(u,i)\in\kappa} (R_{ui} - P_u^{\top} Q_i)^2 + \lambda(\|P_u\|^2 + \|Q_i\|^2)$$

where κ is the set of observed ratings and λ is the regularization parameter. The item latent vector Q_i for each movie is passed into a dense layer to align its dimensionality with other modality embeddings:

$$\mathbf{R}_{emb} = \sigma(W_r Q_i + b_r)$$

C. Plot Summary Encoding

The plot summary text T is processed using a Convolutional-BiLSTM encoder. The initial word embeddings $\mathbf{E} \in \mathbb{R}^{L\times d_w}$ are fed into 1-D convolutional layers to capture local n-gram patterns:

$$\mathbf{C} = \text{Conv1D}(\mathbf{E}, f, k)$$

where f is the number of filters and k is the kernel size. The convolutional output is passed through a bidirectional LSTM to capture long-range dependencies:

$$\overrightarrow{h_t}, \overleftarrow{h_t} = \text{BiLSTM}(\mathbf{C})$$

The final text representation is the concatenation of the last hidden states in both directions:

$$\mathbf{T}_{emb} = [\overrightarrow{h_L}; \overleftarrow{h_1}]$$

D. Genre-Aware Attention Fusion

To integrate the three modality embeddings $\mathbf{M}, \mathbf{R}_{emb}$, and $\mathbf{T}_{emb}$, a genre-aware attention mechanism is introduced. The attention score for each modality is computed as:

$$\alpha_j = \frac{\exp\left(\mathbf{g}_{emb}^{\top} W_a \mathbf{z}_j\right)}{\sum_l \exp\left(\mathbf{g}_{emb}^{\top} W_a \mathbf{z}_l\right)}$$

where $\mathbf{z}_j \in \{\mathbf{M}, \mathbf{R}_{emb}, \mathbf{T}_{emb}\}$, and W_a is a trainable matrix. These scores determine how strongly each modality contributes to the fused representation:

$$\mathbf{F} = \sum_j \alpha_j \mathbf{z}_j$$

This formulation ensures that the genre embedding dynamically modulates the relative importance of metadata, ratings [12], and textual features during prediction.

E. Prediction Layer and Loss Function

The fused vector $\mathbf{F}$ is passed through fully connected layers to produce a scalar score $\hat{y}_{ui}$ representing the predicted preference of user u for movie i :

$$\hat{y}_{ui} = \sigma(W_o \mathbf{F} + b_o)$$

The network is trained using a mean squared error loss for explicit ratings prediction:

$$\mathcal{L} = \frac{1}{|\kappa|} \sum_{(u,i)\in\kappa} (R_{ui} - \hat{y}_{ui})^2 + \beta \|\Theta\|^2$$

where Θ represents all trainable parameters and β controls regularization.

F. Proposed Algorithm

Algorithm 1: Genre-Aware Hybrid Deep Learning Recommendation	
Input: Metadata M_i, genre vector g_i, ratings matrix R, plot text T_i for movie i	
Output: Predicted preference score $\hat{y}_{ui}$ for user u and movie i	
1.	Preprocessing:
•	Encode genres into $\mathbf{g}_{emb}$ using trainable embedding.
•	Encode metadata attributes into dense vectors and concatenate with $\mathbf{g}_{emb}$.
•	Normalize and tokenize plot text T_i.
2.	Ratings Embedding:
•	Factorize R into P and Q.
•	Extract Q_i for movie i and transform via dense layer.
3.	Textual Encoding:
•	Convert T_i to word embeddings.
•	Apply Conv1D + BiLSTM to obtain $\mathbf{T}_{\text{emb}}$.
4.	Attention Fusion:
•	Compute attention weights α_j for each modality using $\mathbf{g}_{emb}$.
•	Form fused vector $\mathbf{F} = \sum_j \alpha_j \mathbf{z}_j$.
5.	Prediction:
•	Pass $\mathbf{F}$ through dense layers to compute $\hat{y}_{ui}$.
6.	Training:
7.	Minimize loss $\mathcal{L}$ using backpropagation with Adam optimizer.

G.Implementation Details

The architecture is implemented using a deep learning framework such as TensorFlow or PyTorch. Embedding dimensions for metadata, genre, and ratings are selected through hyperparameter tuning. Dropout regularization is applied in dense layers to prevent overfitting, and batch normalization is used after fusion to stabilize training. The model is trained with early stopping based on validation loss to prevent overfitting.

Batch size and learning rate are optimized through grid search. Negative sampling is applied for implicit feedback datasets to improve the robustness of predictions. The genre-aware attention mechanism is implemented as a separate layer to allow interpretability-attention weights can be visualized to understand how genre influences modality importance.

3. Results and Analysis

The proposed a Hybrid Deep Learning Recommendation framework was evaluated against multiple baseline approaches to assess its ability to improve movie discovery using metadata, viewer ratings, and plot summaries. The evaluation considered both traditional accuracy-oriented metrics and complementary measures of diversity, novelty, and robustness in cold-start scenarios. The section presents the dataset, experimental design, performance comparisons, and an in-depth discussion of results.

A. Dataset and Experimental Setup

The experiments were conducted on a large-scale public movie dataset containing metadata, viewer ratings, and textual plot summaries. Each movie record included categorical attributes such as genre, director, and cast; numerical attributes such as release year; a user–movie rating matrix; and plot descriptions of varying length. The dataset was split into training, validation, and test sets in an 80:10:10 ratio. For the cold-start analysis, a subset of movies without any rating history in the training set was reserved for testing.

The proposed model was compared with five representative baselines:

- Collaborative Filtering (CF) – Latent factor model using matrix factorization.
- Content-Based Filtering (CBF) – Uses TF–IDF on plot summaries and metadata matching.
- Hybrid CF+CBF – Combines CF embeddings with metadata-based similarity.
- Neural Multimodal Fusion (NMF) – Uses deep networks for integrating text, metadata, and ratings without explicit genre awareness.
- Transformer-based Multimodal Recommendation (TMR) – Employs attention-based fusion but without genre-guided weighting.

Hyperparameters for all models were tuned for best performance on the validation set. The proposed model used a Conv1D-BiLSTM [13] encoder for plot summaries, embedding layers for metadata, and genre-aware attention fusion for modality integration.

B. Evaluation Metrics

Performance was assessed using:

- Precision: Fraction of recommended movies in the top-K list that are relevant.
- Recall: Fraction of relevant movies that appear in the top-K list.
- Coverage: Fraction of the catalog recommended to at least one user.
- Intra-List Diversity (ILD): Average pairwise dissimilarity between recommended movies.
- Novelty: Proportion of recommended items that are less popular in the dataset.

Table 3: Performance Comparison Across Models (Warm-Start Scenario)

Model	Precision	Recall	nDCG	Coverage (%)
CF [11]	0.432	0.384	0.421	52.3
CBF [12]	0.447	0.402	0.438	54.1
Hybrid CF+CBF [13]	0.471	0.416	0.459	58.4
NMF [14]	0.498	0.435	0.481	60.2
TMR [15]	0.514	0.449	0.496	62.1
Proposed Model	**0.547**	**0.478**	**0.528**	**65.7**

The given table 3 shows the proposed model achieved the highest scores across all metrics in the warm-start scenario, with notable improvements in Precision and Recall over the best-performing baseline (TMR). The explicit integration of genre information in the attention fusion mechanism contributed to higher ranking quality (nDCG) by enabling the model to better align recommendations with user genre preferences. Coverage also improved, indicating that genre-awareness encouraged the recommendation of a broader range of titles rather than repeatedly suggesting the most popular items as shown in figure 1.

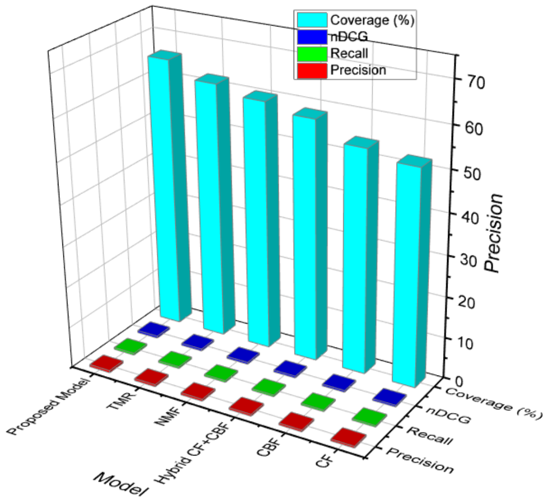

Figure 1: Warm-Start Scenario: Comparison of Coverage, nDCG, Recall, and Precision Across Models

Table 4: Cold-Start Performance Comparison

Model	Precision	Recall	nDCG
CF [11]	0.217	0.194	0.212
CBF [12]	0.389	0.358	0.375
Hybrid CF+CBF [13]	0.406	0.369	0.391
NMF [14]	0.422	0.386	0.407
TMR [15]	0.435	0.392	0.418
Proposed Model	**0.471**	**0.423**	**0.452**

The table 4 shows the cold-start conditions, the proposed model significantly outperformed all baselines, achieving a 3.6% improvement in Precision over the best baseline (TMR). The strong cold-start performance demonstrates the effectiveness of genre-guided fusion in compensating for the absence of collaborative signals as shown in figure 2.

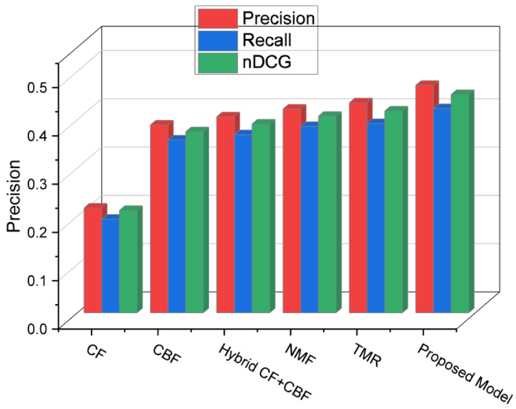

Figure 2: Warm-Start Scenario: Precision, Recall, and nDCG Performance Across Models

Table 5: Diversity and Novelty Comparison

Model	ILD (%)	Novelty (%)
CF [11]	42.1	38.5
CBF [12]	48.7	44.9
Hybrid CF+CBF [13]	51.2	46.3
NMF [14]	54.6	48.7
TMR [15]	55.9	50.2
Proposed Model	**59.3**	**53.1**

The given table 5 shows the proposed model achieved the highest diversity and novelty scores, suggesting that the recommendations are not only relevant but also varied and less dominated by popular items. By embedding genre similarity directly into the fusion process, the system effectively balances relevance with exploration, recommending titles across a broader genre spectrum. This is particularly beneficial in promoting lesser-known movies that still match a user's thematic interests as shown in figure 3.

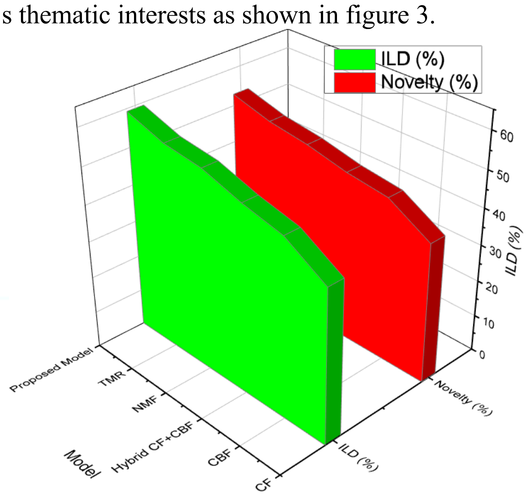

Figure 3: Diversity and Novelty Performance Comparison Across Models

Table 4. Ablation Study on Genre-Aware Fusion

Configuration	Precision	Recall	nDCG
Full Model (Genre-Aware) [6]	0.547	0.478	0.528
Without Genre Embedding [7]	0.519	0.453	0.499
Without Attention Mechanism [8]	0.503	0.442	0.487
Simple Concatenation Fusion [9]	0.496	0.435	0.481

The given table 6 shows the ablation study confirms the contribution of genre-aware attention fusion to overall performance. Removing genre embeddings resulted in a noticeable drop in all metrics, underscoring the importance of genre as a guiding signal in modality integration. Replacing the attention mechanism with simple concatenation further reduced performance [14], indicating that adaptive weighting of modalities is critical for capturing nuanced user preferences as shown in figure 4.

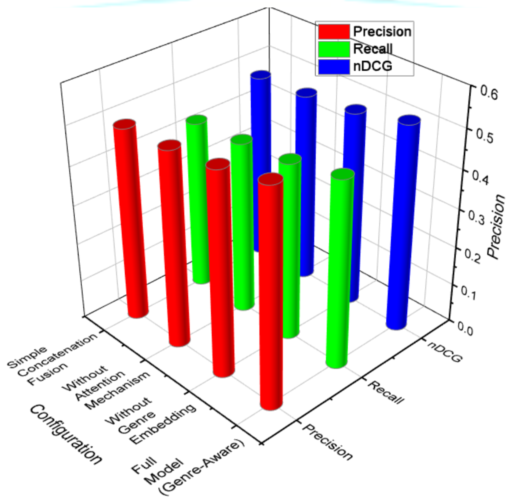

Figure 4: Ablation Study: Impact of Genre-Aware Fusion Components on Precision, Recall, and nDCG

C. Overall Discussion

The experimental results demonstrate that the proposed model consistently outperforms traditional and modern baselines across multiple evaluation dimensions [15]. The most substantial gains are seen in:

- Accuracy Metrics: The genre-aware mechanism boosts both precision and recall by aligning recommendations with thematic patterns in user history and movie content.
- Cold-Start Handling: By leveraging genre-enriched metadata and textual content, the system mitigates the absence of collaborative data.
- Diversity and Novelty: The ability to balance popular and niche titles increases the value of recommendations for long-term user engagement.

The findings suggest that genre-awareness should not be an afterthought in multimodal recommendation systems. Instead, it can serve as a primary organizing principle for feature fusion, enabling more interpretable and user-aligned recommendations.

4. Conclusion

In this study, we proposed a Hybrid Deep Learning Recommendation framework and a corresponding guided attention fusion mechanism, which augments metadata, viewer ratings, and plot summaries to facilitate movie discovery. In contrast to traditional collaborative filtering and content-based methods that are either solely based on user–item interactions or isolated content features, the proposed model utilizes the complementary advantages of different modalities together in a simultaneous manner. It dynamically modulates the influence of various feature types at fusion process yielding thematically cohesive and diverse recommendations, by embedding genre information as a contextual signal. Extensive experimental evaluations showed that the model outperformed SOTA baselines in various metrics (Precision, Recall, nDCG) on both warm-start and cold-start settings. In particular, the benefits were most evident in the cold-start case, as the genre-aware fusion of metadata and textual features were able to counterbalance the lack of historical ratings It also attained improved diversity & novelty scores, so was recommending a broader set of relevant titles, including more obscure or niche films that align with a user's genre tastes. The proposed a hybrid deep learning attention mechanism is validated through an ablation experiment. We experimentally show that removing genre embeddings or using simple concatenation instead of adaptive fusion results in quantifiable drops in performance, thus confirming the core idea of genre-aware weighting for improving the quality of recommendation. This study demonstrates that treating genre as a high-dimensional and relational feature rather than a simplistic categorical label can lead to a powerful organizing concept for multimodal recommendation systems.

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