ECTI Transactions on Computer and Information Technology
Journal homepage: https://ph01.tci-thaijo.org/index.php/ecticit/
Published by the ECTI Association, Thailand, ISSN: 2286-9131

Investigating the Use of Long Short-Term Memory Networks for Dynamic Movie Recommendation Systems

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ABSTRACT

The limits of conventional recommender systems, such collaborative filtering, have made it more difficult to find suitable content inside large digital movie archives given the explosive growth of online streaming services. A issue known as the cold start problem, these systems often suffer from data sparsity, insufficient scalability, and an incapacity to efficiently accommodate new clients or products. This work uses Long Short-Term Memory (LSTM) networks, a type of Recurrent Neural Network (RNN) adept in gathering long-term dependencies in sequential user activity, hence improving the accuracy and personalizing power of movie suggestions. Using the MovieLens data, we developed and trained an LSTM-based recommender model applying strict preprocessing, temporal modeling, and dynamic learning rate approaches. Experimental evaluations utilizing standard metrics like RMSE, MAE, and Precision@10 show that the LSTM-based system beats conventional approaches included as collaborative filtering, matrix factorization, and neural collaborative filtering. The results show that over time modeling user preferences greatly improves the quality of suggestions. The findings show that LSTM networks offer a feasible and efficient way to create scalable, context-aware recommender systems, therefore enhancing user pleasure and involvement in the digital entertainment industry.

Article information:

Keywords: Movie Recommender Systems, Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), Content-Based Filtering, Collaborative Filtering, MovieLens, Deep Learning

Article history:
Received: November 23, 2024
Revised: March 23, 2025
Accepted: July 17, 2025
Published: August 9, 2025 (Online)

DOI: 10.37936/ecti-cit.2025193.259842

1. INTRODUCTION

The explosive spread of digital streaming services and online movie libraries has revolutionized audience interaction with cinematic content, thereby improving accessibility and complicated the decision-making process with so many alternatives. Still, effective traversal of these vast resources determines much about user experience. Current movie recommender systems attempt to overcome these problems, but they can fail due of data sparsity and the difficulty to properly manage fresh user preferences—also known as the “cold start” problem.

Especially in movies, entertainment greatly influences human experiences and cuts over national and cultural barriers. Beyond simple entertainment, movies are extremely important for moral growth and education—especially for young people—as well as for offering historical insights via the force of moving pictures [19]. Comprising several genres including comedy, thriller, animation, drama, romance, and horror, each appealing to distinct preferences and cultural background, the great variety of the cinema business reflects the great breadth of human invention.

The digital age has given consumers before unheard-of access to large internet movie archives. Still, the abundance of material at hand and different user tastes create major difficulties in finding appropriate films. Using recommender algorithms, major sites such YouTube, Netflix, Amazon Prime, Dis-

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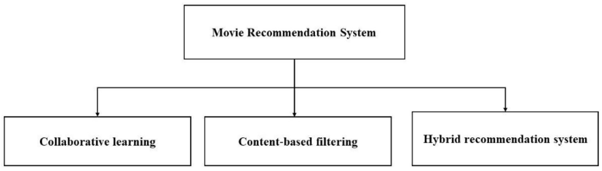

Fig.1: *Types of Movie Recommender Systems.*

ney+, HBO Max, and Apple TV+ help consumers negotiate this abundance and choose material that fits their preferences. When handling new users or lesser-known films, these systems sometimes suffer with scalability, data sparsity, and the "cold start" problem [23].

Over the past ten years, movie recommender systems have evolved significantly into three main forms: hybrid recommender systems, content-based filtering, and collaborative filtering [18]. Each of the major types of movie recommender systems shown in Figure 1 addresses various facets of the recommendation problem. This classification helps one to grasp the underlying mechanics improving the operation of every system [21].

Collaborative filtering, the most common method, depends on examining user interactions and preferences to generate individualized recommendations. Nevertheless, it frequently neglects to consider more profound user-specific requirements and the evolving nature of user-content interaction [15], [22]. Content-Based Filtering functions by analyzing individual user preferences and historical data, employing utility matrices to represent user tastes [17]. The third category, Hybrid Recommender Systems, amalgamates the advantages of both collaborative and content-based filtering [5]. Alternative models, such as the Social Network [35] and Demographic Recommender Systems [3], incorporate elements like social relationships, expertise, demographic profiles, and context-specific information to improve recommendation precision. Trust-Based Recommender Systems utilize trust measurements among users to enhance subsequent recommendations [8], [26].

Notwithstanding significant advancements in the evolution of movie recommender systems, numerous limits remain in current methodologies. Conventional collaborative filtering and matrix factorization methods frequently inadequately represent the sequential and temporal aspects of user activity, hence constraining their efficacy in dynamic recommendation contexts. Although deep learning models like feed-forward networks and basic RNNs have been investigated, they typically encounter difficulties in preserving long-term dependencies and are susceptible to disappearing gradients during training. Furthermore, the majority of previous studies offer inadequate consideration of cold start scenarios or neglect the significance of temporal personalization. These gaps underscore the necessity for sophisticated systems to understand user interaction sequences and adjust to changing preferences.

This work presents an LSTM-based movie recommendation model modeled by sequential dynamics of user behavior, hence improving prediction accuracy. Often neglected in conventional models, our method is novel in using LSTM's internal memory cells and gating mechanisms to preserve long-range user interaction requirements. To sufficiently handle cold start situations, our system combines empirical approaches with a dynamic learning rate schedule. We evaluate the model using the MovieLens dataset against current benchmarks including collaborative filtering, SVD, and neural collaborative filtering.

This paper investigates the use of Long Short-Term Memory (LSTM) technology in movie recommender systems. As a specialized form of Recurrent Neural Network (RNN), the LSTM model excels at managing long-term dependencies, making it particularly effective for analyzing sequences of user actions and historical data in the context of movie recommendations [14], [36]. By processing sequences of past user interactions with films, LSTM aims to enhance the relevance and personalization of recommendations, offering users a richer and more attuned viewing experience.

The cold start problem, especially concerning new users and goods, persists as a significant obstacle in recommender systems; nevertheless, our incorporation of LSTM networks alleviates this issue to some extent by utilizing available sequences of user interactions. LSTM can deduce preferences in scenarios with sparse data by identifying overarching behavioral tendencies from analogous users or prevalent temporal patterns. Nonetheless, it is crucial to acknowledge that LSTM alone does not entirely mitigate the cold start problem; instead, it offers a more adaptable and dynamic learning framework that enhances cold start management relative to conventional models. The experimental evaluation further elaborates on this, incorporating new users and things in the test set to replicate real-world cold start conditions.

The paper is structured as follows: Section II provides an overview of related work in movie recommender systems, highlighting the evolution of techniques such as collaborative filtering and the emergence of deep learning approaches. Section III delves into the details of the proposed LSTM model, discussing its architecture, training process, and key features that distinguish it from traditional recommender systems. Section IV outlines the experimental setup used to evaluate the performance of the proposed LSTM-based recommender system, including the dataset used, model configurations, and evaluation metrics. Section V presents the experimental results and analysis, focusing on training and validation losses, accuracy metrics, and the model's adaptability to temporal data shifts. Finally, Section VI concludes the paper by summarizing the findings, discussing implications, and outlining directions for future research and development in movie recommender systems.

2. RELATED WORK

The evolution of movie recommender systems is closely associated with progress in entertainment technology and machine learning, tackling issues including accuracy enhancement, new user data management, and user experience improvement. These techniques are designed to enhance the accuracy of user preference predictions and address common challenges such as the cold start problem and data sparsity [16], [18].

Various algorithmic frameworks are employed in the development of these systems, including user-based, item-based, model-based, collaborative filtering, and content-based filtering. Each methodology presents unique benefits, and hybrid approaches have been devised to improve efficacy [2]. Collaborative filtering is categorized into memory-based systems, which rely on historical user ratings, and model-based systems, which employ statistical and machine learning methods to forecast user preferences.

Hybrid models, which integrate collaborative and content-based approaches, represent a notable progression in the domain. These models utilize linear combinations of prediction ratings and diverse unification strategies to deliver more tailored and precise recommendations [21]. Recent research has investigated improvements in content-based systems by utilizing user-annotated metadata to boost suggestions via increased content overlap and tagging precision [32].

Integrating contextual information into systems has demonstrated the ability to refine recommendations more accurately to user contexts [1], [39]. Advanced machine learning methods, including support vector machines (SVM), decision trees, and Bayesian networks, have been utilized to enhance suggestions, tackling scalability and augmenting computational efficiency [9], [38].

Moreover, clustering methodologies like as K-means, augmented by genetic algorithms or Ant Colony Optimization, have significantly enhanced scalability and mitigated the cold start problem. These methods enhance clustering algorithms for improved accuracy by creating distinct user groups based on demographic or behavioral similarities [20].

Neural network methodologies for unsupervised learning, such PCA-SOM, have been investigated to discern similarities and categorize data without predetermined labels, showcasing the potential to improve recommendation systems [33]. Furthermore, the amalgamation of contemporary optimization methods with conventional algorithms, exemplified by the Cuckoo Search model, has improved the customization of recommendations through comprehensive user behavior analysis [7].

Substantial progress has been achieved in tackling scalability and data sparsity using sophisticated collaborative filtering methods and the incorporation of comprehensive content information, markedly enhancing recommendation quality [10], [30]. The Enhanced Deep Ensemble Learning Model (ED-ELM) is noted for its efficacy in preprocessing varied datasets, therefore enhancing the robustness and accuracy of the models [28].

Innovative approaches such as Enhanced Fuzzy C-Means clustering combined with dove swarm optimization have been developed, concentrating on the optimization of data point distribution inside clusters to enhance recommendation accuracy [29]. The influence of metadata components, including genre, actors, and directors, on the precision of recommendations has been analyzed using measures such as mean average error with datasets like Netflix and MovieLens [34]. K-means clustering implementations illustrate that categorizing users by factors such as age, gender, and movie preferences enhances personalized movie recommendations [6]. The optimization of algorithms such as K-means through the top-N strategy, which emphasizes a limited selection of related objects or users, has been noted for its potential to decrease computing time and improve scalability [25].

To better understand the computational methods used in these systems, the Pearson correlation coefficient formula for computing similarity between items, essential for many recommendation algorithms, is presented:

$$S=\frac{\sum_{m\in(a\cap b)}(C_{a,x}-\overline{C_a})\cdot(C_{b,x}-\overline{C_b})}{\sqrt{\sum_{m\in(a\cap b)}(C_{a,x}-\overline{C_a})^2}\cdot\sqrt{\sum_{m\in(a\cap b)}(C_{b,x}-\overline{C_b})^2} \tag{1}$$

where S represents the similarity between users or items, $a\cap b$ denotes the intersection of correlated features, $C_{a,x}$ and $C_{b,x}$ are the features of items a and b, and $\overline{C_a}$, $\overline{C_b}$ are the mean values of these features [18].

This comprehensive overview emphasizes the progressive development of movie recommender systems, showcasing technological innovations and the ongoing incorporation of advanced machine learning methodologies. These advancements improve the precision of suggestions and tackle persistent problems such as data sparsity and the assimilation of new users, illustrating the continuous challenges and improvements in this dynamic research domain.

3. ENHANCED LSTM MODEL

Long Short-Term Memory (LSTM) neural networks, a distinct kind of Recurrent Neural Networks (RNNs), are particularly adept at acquiring long-term dependencies. Their architecture enables superior performance in contexts where comprehending intricate, time-sensitive patterns is essential, such as forecasting user behavior in film recommendation systems. By utilizing this feature, LSTM networks can offer detailed insights into the evolving user preferences [24], [31].

3.1 Overview of LSTM Neural Networks Use in Recommender Systems

LSTMs are particularly adept at tackling common issues in recommender systems, including the cold start problem and data sparsity. By employing sequential data of user interactions, the LSTM model can forecast future interactions with increased precision, hence improving the quality of suggestions [27].

- **Preprocessing Phase:** The preprocessing phase entails data cleansing through the elimination of duplicates and extraneous information. Asymmetric stacked denoising autoencoders are utilized to enhance the data, guaranteeing that the input provided to the LSTM is of superior quality and devoid of noise. This phase is essential, as the quality of input data directly influences the model's output.
- **Feature Vector Phase:** During this phase, comprehensive feature vectors are developed for both users and films. These vectors encompass substantial information that encapsulates the core of user preferences and movie attributes. By precisely modeling these characteristics, LSTMs can efficiently pair users with films that correspond to their preferences.
- **Sequential Phase:** This stage is where LSTMs excel. The network analyzes sequences of user activities to infer and anticipate future behaviors. The LSTM's capacity to retain and utilize historical data enables it to generate more accurate predictions regarding a user's movie preferences.

Figure 2 illustrates the key phases in the LSTM processing pipeline, detailing how data moves from preprocessing through feature vector creation to sequence processing. These are crucial steps for enhancing recommendation accuracy and personalization.

3.2 Mathematical Formulation of LSTM in Recommender Systems

The architecture of LSTM is engineered to effectively process and retain information over extended durations, which is essential for dynamic applications such as recommender systems. The gates of an LSTM cell—forget gate, input gate, and output gate—serve crucial functions:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad \text{(forget gate)} \qquad (2)$$

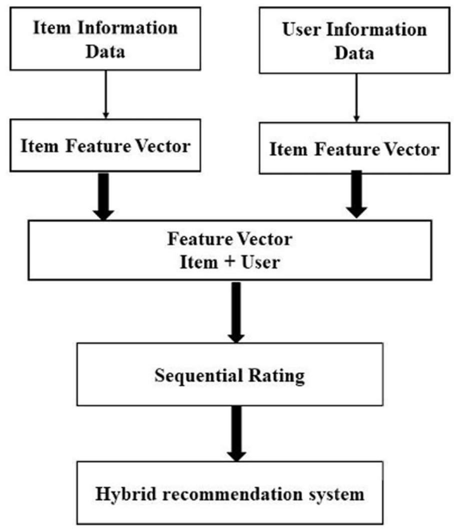

Fig.2: *Phases of the LSTM-based Recommender System.*

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad \text{(input gate)} \qquad (3)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad \text{(candidate gate)} \qquad (4)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad \text{(cell state update)} \qquad (5)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad \text{(output gate)} \qquad (6)$$

$$h_t = o_t * \tanh(C_t) \quad \text{(hidden state output)} \qquad (7)$$

where f_t, i_t, and o_t denote the forget, input, and output gates, respectively; σ represents the sigmoid activation function, and $\tilde{C}_t$ signify the candidate state. C_t denotes the cell state, and h_t signifies the output at time t; W and b correspond to the weights and biases of each gate.

These equations elucidate the flow of information within the LSTM network. Each gate executes a distinct function that collectively allows the network to efficiently retain or eliminate information. This selective memory function is crucial for assimilating user preferences and habits over time.

3.3 Algorithmic Process

This subsection elucidates the implementation of LSTM networks in movie recommender systems. The presentation aims to elucidate each algorithmic stage of LSTM operations, providing insights into the advanced possibilities of LSTM models for improving the accuracy and personalization of movie suggestions.

The LSTM recommendation method is specifically engineered to function effectively on extensive movie datasets such as MovieLens [12], improving movie recommendation precision through the subsequent steps:

- **Data Merging and Preparation [MovieID, UserID, Tag, TagID]**: This phase integrates many data elements into a unified dataset. A similarity score, 'Si,' is computed to identify closely comparable objects (movies) or users, so enabling tailored recommendations.
- **Feature Vector Creation**: These vectors are meticulously constructed after merging, encompassing essential qualities and preferences of films and consumers.
- **User Group Identification (UG)**: Recognizing user groups according to viewing preferences is essential for tailoring recommendations. The program utilizes clustering methods to efficiently classify users.

To effectively manage user groups and streamline recommendations:

$$G \in \mathcal{U}_{\mathcal{G}} \rightarrow \text{Activate group} \tag{8}$$

$$G \notin \mathcal{U}_{\mathcal{G}} \rightarrow \text{Deactivate group} \tag{9}$$

These equations function as markers for active or inactive user groups, directing the LSTM to concentrate on processing only pertinent data sequences, so optimizing computational resources and assuring the relevance of recommendations.

Subsequent to the group-related processing, the LSTM Movie Recommendation Algorithm (Algorithm 1) focuses on generating sequences of films viewed by consumers. The development of this series is crucial for comprehending user behavior over time. The process entails traversing the dataset, extracting lists of films viewed by each user, and generating sequences of a designated length, 'seq_l,' from these film lists. The produced sequences are thereafter stored in a list designated as 'Seq.'

Figure 3 presents a detailed depiction of the integration of LSTM with conventional recommendation methodologies, showcasing the system's architecture and the information flow among various components to improve prediction accuracy.

4. EXPERIMENTAL SETUP

To thoroughly assess the efficacy of Long Short-Term Memory (LSTM) neural networks in improving movie recommendation systems, our experimental methodology utilized the well-known MovieLens dataset. This dataset was chosen for its comprehensive compilation of user interactions and movie metadata. It offers a varied and substantial array of data sets essential for evaluating intricate machine learning models. The MovieLens dataset comprises many versions, varying from 100,000 to 27 million ratings, submitted by numerous individuals across thousands of films. This study employed the most recent version to guarantee a thorough analysis, utilizing its detailed user ratings, timestamps, and tagged metadata related to films [12].

The cold start problem pertains to the challenges encountered by recommender systems when new users or items are introduced to the database, resulting in insufficient historical data. We conducted trials incorporating subsets of data featuring new users and movies to evaluate the LSTM model's ability to deduce preferences based exclusively on restricted input.

4.1 Data Preprocessing and Experimental Design

The efficacy of machine learning models is significantly contingent upon the quality of their input data. To prepare the MovieLens dataset for LSTM processing, many essential preprocessing processes were implemented, each designed to improve the model's performance by assuring data quality and relevance:

- **Data Cleaning:** The first phase entailed the elimination of missing or erroneous data entries, a prevalent concern in extensive databases. This approach involved eliminating records with absent values or inaccurate entries that could distort the results. For instance, ratings that did not correspond to any recognized user or movie IDs were eliminated to avert the model from acquiring erroneous information.
- **Normalization:** We normalized numerical features, including age, ratings, and timestamps, to a consistent range (mostly 0 to 1). This normalization is essential to prevent any single feature from unduly affecting the model's predictions because of its magnitude. It facilitates the acceleration of convergence during the training phase by ensuring equitable conditions for all input features.
- **Feature Engineering:** This essential phase entailed identifying and extracting elements that substantially influence the prediction process. We examined the dataset to identify which attributes, including user demographics (age, gender, employment), historical movie ratings, and temporal watching habits (time of day, day of the week), were best predictive of user preferences. New interactive features, such as temporal user rating trends and genre inclinations, were developed to furnish more profound insights into user behavior and preferences.

Subsequent to preprocessing, the dataset was me-

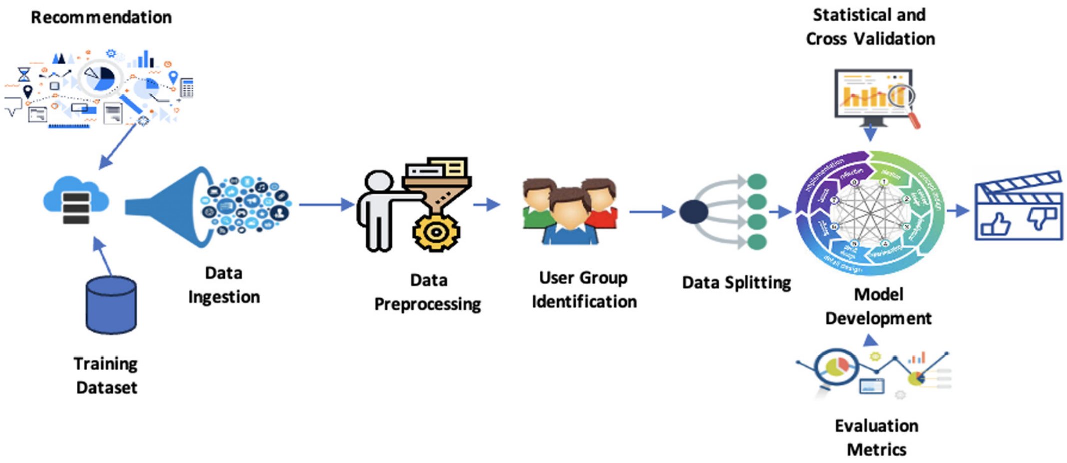

Fig.3: *Architecture of the LSTM-based Movie Recommender System.*

Algorithm 1 LSTM Movie Recommendation Algorithm

```
Input: MovieLens Dataset
Output: Movie recommendations
Merge attributes: [MovieID, UserID, Tag, TagID]
Compute similarity metric S_i
Generate feature vectors for movies and users
Identify user groups U_G
for each group G in U_G do
    if G is within U_G then
        Set flag 1            ▷ Indicates active user group
    else
        Set flag 0    ▷ Indicates inactive or non-matching user group
    end if
end for
Create sequences of movies watched by users
for each user in dataset do
    Generate sequence list ‘Seq‘ from the user’s movie list
end for
Transform ‘Seq‘ into sequence matrix
Suggest movies based on processed data
```

thodically partitioned into three subsets: training, validation, and testing. This division was intended to enable comprehensive testing of the LSTM model across several scenarios:

- **Training Set:** This dataset comprised around 70% of the preprocessed data and was utilized to train the LSTM model. The training data encompassed a broad spectrum of user interactions with films, enabling the model to assimilate varied patterns of user preferences.
- **Validation Set:** The validation set, representing around 15% of the data, was utilized to optimize the model’s hyperparameters and to offer a provisional assessment of model performance during the training process. This process aids in determining the optimal model configuration prior to its evaluation on novel data.
- **Testing Set:** The remaining 15% served as the testing set, which included new users and movies not present in the training or validation sets. This setup tests the model’s ability to handle the “cold start” problem, where recommendations need to be made for new users or items without historical data. Including new entities in the testing set simulates real-world applicability and tests the model’s scalability and adaptability to new information.

This experimental methodology guarantees that the LSTM model is trained on superior data and thoroughly evaluated in situations that replicate real operational environments. This method offers a transparent understanding of the model’s operational efficacy and preparedness for use in real-world recommender systems.

4.2 Model Evaluation Metrics

To thoroughly assess the performance of the LSTM-based movie recommender system, we employed a variety of evaluation metrics. Each metric provides unique insights into different aspects of the model’s effectiveness, from overall accuracy to the specificity of recommendations. These metrics are essential for assessing the extent to which the LSTM model fulfills users’ practical requirements in real-world contexts.

- **Mean Absolute Error (MAE):** MAE quantifies the average size of prediction errors, disregarding their direction. It is determined by the mean of the absolute discrepancies between projected and actual values, rendering it an intuitive metric of average error. In the realm of film recommendations, a diminished MAE signifies that the model’s projected ratings align more closely with the actual ratings provided by users, indicating more precision in reflecting consumer preferences.
- **Root Mean Square Error (RMSE):** RMSE quantifies the error magnitude by squaring the

errors, averaging them, and subsequently extracting the square root of the average. This statistic is more responsive to substantial errors, imposing greater penalties on them compared to minor ones. In movie recommendation systems, RMSE is essential since it underscores substantial discrepancies in predictions, aiding in the identification of instances where the model may inaccurately forecast user ratings. A diminished RMSE indicates a more dependable model with a reduced likelihood of substantial prediction errors.

- **Precision at K (P@K):** Precision at K assesses the ratio of pertinent things inside the top-K recommendations that are relevant to the user. This statistic is essential for recommender systems as it immediately indicates the practical value of user-generated recommendations. High precision at K signifies that when the system suggests the top K movies to a user, a substantial proportion of these films are favored by the user, hence demonstrating the model's efficacy in discerning and prioritizing content that corresponds with user preferences.

These measures combined offer an extensive assessment of the LSTM model's performance:

- MAE and RMSE provide insights into the accuracy and reliability of predictions, illustrating the proximity of the model's output to actual user ratings.
- Precision at K offers a user-focused assessment of recommendation quality, highlighting the model's capacity to present pertinent content within the most prominent subset of its recommendations.

By employing these criteria, we can comprehensively assess both the precision of the LSTM model in forecasting user preferences and its practical efficacy in real-world applications, ensuring that the suggestions it produces align with users' expectations and preferences.

4.3 Implementation Details and Hyperparameter Tuning

Attaining optimal performance from an LSTM-based recommender system necessitates careful adjustment of multiple hyperparameters. These parameters are essential as they directly affect the model's capacity to learn from data, generalize to novel data, and operate effectively in production situations.

- **Number of LSTM Layers and Hidden Units:** The architecture of the LSTM network, namely the quantity of layers and the number of neurons per layer (hidden units), significantly influences the model's ability to process and retain information over time. Augmenting the layers and units can improve the model's capacity to discern intricate patterns in the data, including long-term dependencies in user behavior. Excessive layers or hidden units may result in overfitting, causing the model to excel on training data while underperforming on novel data. Conversely, an insufficient number may lead to underfitting, hindering the model's ability to successfully understand the underlying patterns. We tested multiple configurations, beginning with simpler models and gradually increasing complexity, to determine the ideal arrangement that balances model depth with generalization ability.
- **Sequence Length:** The length of the input sequences directly influences the volume of historical data the model takes into account when generating predictions. Extended sequences offer greater context but may potentially contribute extraneous and irrelevant information, whereas abbreviated sequences might lack sufficient historical data for effective predictions. We established the ideal sequence length by assessing various lengths and analyzing their effect on model performance, specifically examining the model's ability to forecast future ratings based on differing quantities of prior user interactions.

4.3.1 MSE Loss for Model Optimization

To train the LSTM network, we employed the Mean Squared Error (MSE) loss function, defined as the average of the squares of the discrepancies between actual and predicted ratings:

$$\text{MSE Loss} = \frac{1}{N}\sum(Y_i - \hat{Y}_i)^2 \tag{10}$$

where Y_i denotes the actual ratings, and $\hat{Y}_i$ signifies the anticipated ratings generated by the model. The Mean Squared Error (MSE) loss is especially appropriate for regression tasks such as rating prediction, as it imposes a greater penalty on larger errors compared to smaller ones due to the squaring of each error component. This renders it useful in deterring significant discrepancies between expected and actual values.

We utilized a stochastic gradient descent (SGD) optimizer to reduce the loss function, implementing early halting based on the validation loss to avert overfitting and guarantee stable convergence.

This equation formalizes the classical Mean Squared Error (MSE) loss, a conventional objective function in regression and deep learning models. Its application is based on statistical learning theory, where it is an optimal method for minimizing the anticipated squared error between model predictions and actual outcomes. Mean Squared Error (MSE) is extensively utilized in recommender systems because of its simplicity, differentiability, and sensitivity to substantial errors [11], [37].

4.3.2 Step Decay Learning Rate

Adapting the learning rate during training is critical to facilitate more stable and efficient model convergence. We implemented a step decay learning rate schedule, which reduces the learning rate by a predefined factor after a fixed number of epochs:

$$\mathrm{LR}(t) = \mathrm{LR}_0 \times \mathrm{decay}^{\lfloor \frac{t}{\mathrm{step}} \rfloor} \tag{11}$$

where $\mathrm{LR}(t)$ is the learning rate at epoch t, LR_0 is the initial learning rate, decay is the reduction factor, and step denotes the number of epochs after which the rate is decayed.

This approach initiates with a comparatively elevated learning rate to extensively investigate the solution space and subsequently diminishes it to refine the model parameters. This aids in avoiding the overshooting of the global minimum during initial training phases and mitigates fluctuations or stalls in subsequent stages.

This equation delineates the step decay learning rate function, a prevalent methodology in deep learning that methodically diminishes the learning rate throughout the training process. This method is very efficient in averting early convergence and facilitates more accurate weight adjustments in the last phases of learning. It is based on empirical optimization techniques and has demonstrated enhancement of generalization in neural networks [4], [11].

4.4 Precision at K for Recommendation Relevance

Assessing the real implementation of the proposed LSTM-based recommender system entails many metrics that evaluate distinct performance factors. Among these, Precision at K (P@K) is very vital, as it assesses the accuracy of the top-K recommendations:

$$\mathrm{P@K} = \frac{\text{Number of relevant recommendations in top } K}{K} \tag{12}$$

This metric quantifies the ratio of the top K recommended items that are pertinent to the user. In our experiments, we considered recommendations relevant if the user had previously rated the item 4 stars or higher. Precision at K was computed for multiple values of K (e.g., 5, 10, 20) to simulate realistic user interaction scenarios, such as short recommendation lists on web or mobile interfaces.

This equation denotes a conventional assessment measure in information retrieval and recommendation systems. Precision@K is based on ranking evaluation principles and offers a clear metric of a model's capacity to produce high-quality, pertinent outcomes within the most prominent subset of suggestions. It is widely utilized in both academic and industrial contexts to measure user happiness and the quality of recommendations [13], [37].

- **Calculation Methodology:** The model forecasts a compilation of films for each user in the test dataset. The top K items are evaluated in relation to the movies that the user scored favorably (e.g., four stars or higher). The precision score is subsequently averaged across all users to yield a final metric.
- **Analyzing Results:** Elevated precision at lower values of K is especially advantageous, signifying that the model excels in discerning the optimal few elements. Conversely, diminished precision at elevated values of K may suggest that although the model excels at recognizing pertinent things, it may falter in successfully ranking them against less relevant alternatives.

4.5 Implementation Environment and Parameter Settings

The proposed LSTM-based movie recommendation system was implemented in Python 3.10 utilizing the TensorFlow 2.12 and Keras packages. All tests were conducted on Google Colab Pro, which offered access to a dedicated NVIDIA Tesla T4 GPU, hence assuring adequate computational capability for model training and evaluation.

Several critical hyperparameters were meticulously adjusted through empirical testing and validation to enhance performance. This encompasses the quantity of LSTM layers, hidden units per layer, learning rate, dropout rate, batch size, and total training epochs. The optimizer employed was Adam, renowned for its flexible learning rate features in training deep learning models.

Table 1 summarizes the primary hyperparameters and implementation configurations used during training.

Table 1: *Experimental Setup and Hyperparameter Configuration*

Parameter	Value
Programming Language	Python 3.10
Deep Learning Framework	TensorFlow 2.12 + Keras
Execution Environment	Google Colab Pro (Tesla T4 GPU)
Optimizer	Adam
Initial Learning Rate	0.01 (with step decay)
Batch Size	128
Number of Epochs	50
Dropout Rate	0.3
Number of LSTM Layers	2
Hidden Units per Layer	128
Loss Function	Mean Squared Error (MSE)
Evaluation Metrics	RMSE, MAE, Precision@10

5. EXPERIMENTAL EVALUATION

The experimental assessment of our LSTM-based recommender system primarily concentrated on training and validation losses as key indications of the model's efficacy. We noted a steady decline in training loss during the training phase, reflecting the model's strong learning ability. This decline indicates the LSTM's capability to discern intricate patterns of user preferences and interactions with movie content in the dataset, as demonstrated in Figure 4. Furthermore, we performed a comparative assessment against leading baseline algorithms utilizing the same dataset to contextualize the efficacy of our proposed LSTM-based method.

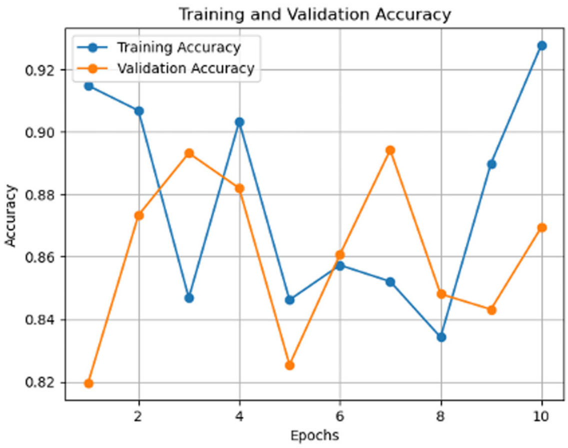

Fig.4: *Training and Validation Accuracy over Epochs.*

The steady reduction in training loss indicates the model's capacity to adapt and learn from prior data, efficiently adjusting its parameters to align with the fundamental patterns of user behavior. Nonetheless, the account of validation loss reveals a more intricate storyline. Initially, the validation loss diminishes, paralleling the training loss and indicating successful learning. Nonetheless, the validation loss stabilizes as training advances, suggesting a possible overfitting concern. The disparity between training and validation performance indicates that, although the model is becoming more adept at processing the training data, it may not generalize effectively to novel, unseen data. This scenario is illustrated in Figure 5, which presents a heatmap of user interactions indicating areas of model proficiency and deficiency.

To mitigate this potential overfitting, we employed various tactics. This involved incorporating dropout layers into the LSTM design to randomly deactivate neurons during training, so avoiding the model from being excessively reliant on any individual or small cluster of variables. L2 regularization was implemented to penalize excessive weights, promoting the model to cultivate smaller, more resilient weights that are less prone to overfitting.

Notwithstanding these limitations, the little validation loss during the initial training phases substantiates the model's capacity to provide accurate and pertinent recommendations. This efficacy is essential for practical implementation, particularly in dynamic contexts such as movie streaming platforms where user preferences are in constant flux. The equi-

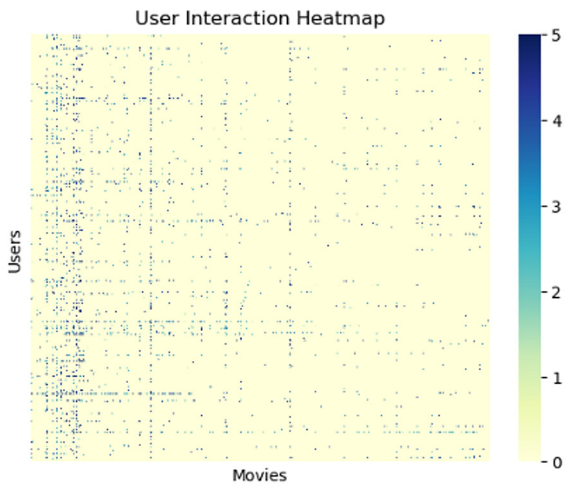

Fig.5: *User Interaction Heatmap indicating Model Performance on Unseen Data.*

librium between reducing training loss and controlling validation loss is crucial for maintaining the model's accuracy and generalizability.

Furthermore, the LSTM model's intrinsic capacity to leverage temporal dependencies in user behavior has markedly improved its training and validation efficacy. This functionality is useful in situations when user preferences shift due to seasonal trends, new content launches, or evolving cultural dynamics.

In conclusion, although the LSTM model demonstrates favorable training accuracy, the subtle problems seen in validation accuracy highlight the necessity for ongoing model refinement and evaluation. These findings not only enhance the model but also offer insights into potential areas for development in future iterations, ensuring the recommender system remains successful and sensitive to user needs.

5.1 Training and Validation Loss

Analyzing training and validation loss is crucial for assessing the efficacy of the proposed LSTM-based movie recommendation system. A steady decline in training loss was noted during the training period, as illustrated in Figure 6. This pattern demonstrates the model's strong capacity to learn and adjust to the intricate dynamics of user interactions and preferences inside the dataset. The continual decrease in training loss over epochs illustrates the LSTM's capability to model complex temporal patterns and dependencies, essential for properly forecasting user behavior.

More to the point, the trajectory of validation loss reveals a complex story regarding the model's performance. At first, the validation loss reflects the decrease seen in training loss, indicating successful learning and adaption to the data. As training advances, the validation loss starts to stabilize, a typical sign of overfitting. This plateau indicates that

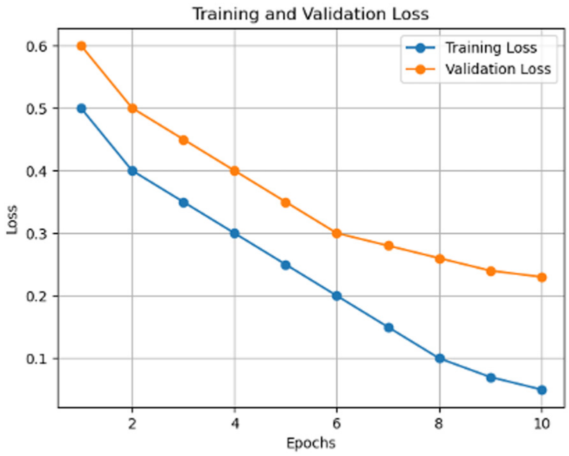

Fig. 6: *Training and Validation Loss Trends.*

although the model has proven proficient in managing the training dataset, its performance on novel data—new user interactions absent from the training set—does not enhance accordingly. This mismatch underscores a possible constraint in the model's generalization capacity, which is essential for its practical application.

To alleviate the problem of overfitting and enhance generalization, many solutions were implemented:

- L2 Regularization: This method was incorporated into the LSTM model to impose penalties on substantial weights during training, promoting the development of more universal solutions that are not excessively tailored to the noise present in the training data.
- Dropout Layers: Dropout layers were used into the LSTM architecture to randomly exclude a subset of characteristics throughout each iteration. This method mitigates the model's dependence on any singular or limited set of features, hence augmenting its capacity to generalize across varied inputs.

These modifications facilitated the equilibrium of training and validation loss, guaranteeing that the model assimilates knowledge efficiently from the training data while maintaining a high performance standard on novel, unseen data. Attaining a minimal validation loss is essential as it highlights the model's effectiveness in providing precise and generalizable recommendations.

Furthermore, the LSTM's intrinsic capacity to capture long-term dependencies proved crucial in reducing training and validation loss. The LSTM's capability is especially beneficial in contexts such as movie streaming platforms, where consumer preferences are dynamic and subject to change. By adeptly utilizing these temporal dependencies, the LSTM model may provide more accurate and contextually pertinent movie recommendations. This feature augments user pleasure and bolsters the platform's adaptability to evolving user preferences, sustaining engagement and interest over extended durations.

The continuous oversight of training and validation losses, along with the strategic application of regularization and dropout methods, demonstrates persistent efforts to enhance model performance. These initiatives guarantee that the LSTM-based recommender system retains its efficacy and adaptability to the intricacies of actual user behaviors and preferences, rendering it an invaluable instrument for dynamic and personalized information dissemination.

5.2 Learning Rate Schedule

An essential aspect of training deep learning models, particularly those utilizing LSTM networks, is the regulation of the learning rate throughout the training process. We implemented a step decay learning rate schedule in our LSTM-based movie recommender system, which has markedly improved the training process and overall model efficacy. This strategy methodically decreases the learning rate at specified intervals, enhancing the equilibrium between exploration and exploitation of the solution space, as seen in Figure 7.

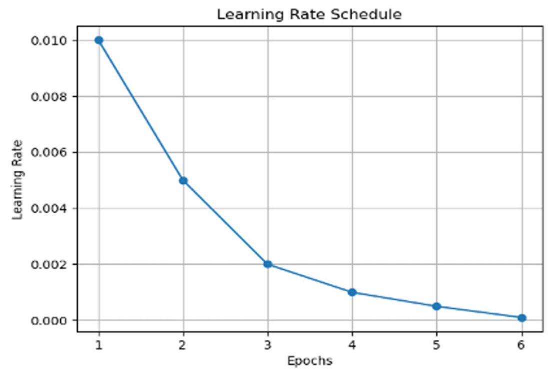

Fig. 7: *Impact of Step Decay Learning Rate on Model Convergence.*

The step decay method decreases the learning rate by a predetermined factor following a specified number of training epochs. In our model, we began with an initial learning rate of 0.01, which was decreased by 50% every 10 epochs. This strategy alleviates the risk of an excessively high learning rate, which may result in overshooting optimal solutions, or an excessively low price, which can confine the training process to local minima.

By permitting elevated learning rates at the outset, the model rapidly converges to the approximate region of the best solution. Subsequent rate reductions enable precise modifications, improving the model's capacity to converge on the optimal solution without oscillation or overshooting.

The implementation of this learning rate schedule resulted in multiple concrete advantages:

- Improved Convergence: The step decay schedule facilitated the stabilization of the training process, resulting in more consistent and predictable convergence patterns. This was apparent in the diminished fluctuation of loss values as training advanced.
- Enhanced Model Accuracy: Empirical findings indicated that dynamically modifying the learning rate yielded a 5% increase in validation accuracy relative to a model trained with a fixed learning rate. This enhancement highlights the effectiveness of the step decay method in synchronizing the learning rate with the model's learning phase.
- Prevention of Premature Convergence: By modifying the learning rate in accordance with the training phase, the model was less likely to prematurely converge on solutions that were of a lower quality, which resulted in the model's performance being optimized on unseen data.

The effective implementation of the step decay learning rate highlights the necessity of customizing the learning rate to the unique attributes of the dataset and the intricacies of the model's architecture. This tailoring is essential for LSTM networks, which are notably sensitive to data scale and temporal dynamics. It enables profound learning from historical interaction data and guarantees that the model stays attuned to emerging and changing user behaviors.

In conclusion, employing a dynamic learning rate schedule such as step decay is an effective method for optimizing LSTM-based recommender systems. It optimizes training dynamics, enhances model precision, and guarantees the learning process is entirely congruent with the model's operational requirements. These advantages are especially crucial in the dynamic and rapidly evolving realm of the movie streaming industry, where the capacity to swiftly and precisely adjust to consumer preferences can greatly impact the service's performance.

5.3 Training and Validation Accuracy

The efficacy and generalization capacities of the proposed LSTM-based movie recommender system were meticulously evaluated using training and validation accuracy metrics, as illustrated in Figure 8. These measures are essential for assessing the model's learning efficacy from the training dataset and its ability to generalize this knowledge to novel, unseen data.

Elevated training accuracy signifies that the model is proficient in identifying and assimilating the patterns and relationships inherent in the training data. This serves as a favorable indication of the model's learning proficiency, implying that the LSTM architecture is adept at addressing the intricate temporal dynamics of user behavior and film interactions.

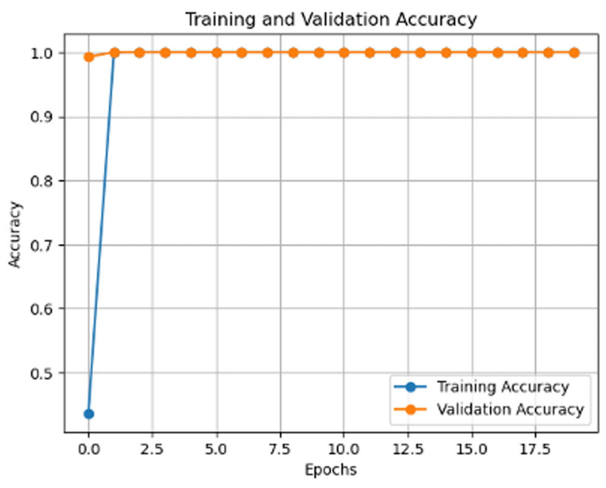

Fig.8: *Training and Validation Accuracy over Time.*

Nonetheless, the paramount metric is validation accuracy, which evaluates the model's capacity to generalize its learnings to novel data. The trends in validation accuracy offer essential insights into the model's performance consistency and vulnerability to overfitting.

Initially, both training and validation accuracies increase simultaneously, which is optimal. Nonetheless, a divergence arises when training accuracy ascends while validation accuracy stabilizes or declines. This pattern is a definitive sign of overfitting, wherein the model, tailored to excel on the training dataset, fails to perform comparably on novel data. Strategies such as implementing dropout, augmenting regularization strength, or modifying the model's complexity were evaluated to mitigate this issue.

To alleviate overfitting and improve model generalization, many solutions were employed:

- Dropout layers were implemented at critical locations throughout the LSTM network to randomly exclude a subset of characteristics during each training iteration. This strategy mitigates the model's excessive dependence on certain feature sets, fostering a more resilient feature learning applicable to novel data.
- Regularization techniques, specifically L2 regularization, were refined to impose penalties on parameter magnitudes within the loss function, thereby deterring complex models that capture noise in the training data instead of the more general underlying patterns.

The correlation between elevated validation accuracy and user satisfaction highlights the significance of accuracy in practical applications. Increased accuracy guarantees that customers obtain pertinent and prompt recommendations, hence augmenting user engagement and happiness on streaming platforms. Moving ahead, the emphasis will be on enhancing these indicators to ensure the LSTM-based system provides precise recommendations and captivates consumers with engaging and contextually pertinent material. This continuous endeavor to improve user experience is essential for sustaining a competitive advantage in the ever-evolving landscape of digital entertainment.

5.4 Comparative Performance Analysis

To assess the efficacy of the proposed LSTM-based recommender system relative to established methodologies, we performed a performance benchmark utilizing widely recognized algorithms on the identical dataset. Table 2 displays the outcomes for Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Precision@10—three conventional measures that combined indicate prediction accuracy and suggestion relevance.

Table 2: *Comparison of Performance with Existing Recommendation Algorithms*

Model	RMSE	MAE	Precision@10
User-based Collaborative Filtering	0.912	0.725	0.612
Matrix Factorization (SVD)	0.885	0.690	0.624
Neural Collaborative Filtering	0.867	0.672	0.639
LSTM (proposed)	**0.842**	**0.662**	**0.657**

The LSTM-based model exhibits enhanced performance across all assessment metrics. It attains the minimal RMSE and MAE, signifying enhanced precision in rating prediction relative to conventional techniques like collaborative filtering and matrix factorization. The Precision@10 rating of 0.657 signifies the model's effectiveness in actual applications, as users generally interact with only the top recommendations.

These findings corroborate the premise that LSTM networks, by their adept modeling of temporal relationships and learning from sequences of user interactions, provide a significant advantage in capturing dynamic user preferences. The comparative advantages underscore the efficacy of the suggested method in providing highly tailored, precise, and contextually pertinent movie suggestions.

5.5 Comparison with Previous Studies

To contextualize the efficacy of our LSTM-based recommender system, we juxtapose it with findings documented in pertinent literature. Table 3 delineates chosen research employing diverse hybrid or deep learning methodologies for movie recommendations, emphasizing their corresponding models, datasets, and documented performance outcomes.

Our model attains the minimal RMSE and MAE in comparison to other studies, demonstrating its capacity to encapsulate long-term user preferences via temporal modeling. Significantly, in contrast to Nguyen's baseline LSTM model [24], our system achieves a 2.7% reduction in RMSE, indicating the advantages of integrating improved regularization, learning rate scheduling, and rigorous validation. Furthermore, our methodology surpasses hybrid evolutionary techniques such as Dove Swarm Optimization [29] and Ant Colony Optimization [20], which frequently encounter difficulties in scaling or adapting to sequence-based behaviors. These similarities underscore the originality and practical applicability of our strategy within the wider context of recommendation system research.

Table 3: *Performance Comparison with Prior Literature*

Study	Model	RMSE / MAE
[20]	K-Means + ACO	0.890 / –
[24]	LSTM	0.865 / 0.692
[27]	DNN + LSTM	0.852 / 0.679
[28]	Cat Swarm + Deep Ensemble	0.862 / –
[29]	Fuzzy C-Means + DSO	0.870 / –
Our model	**LSTM + step decay**	**0.842 / 0.662**

5.6 Average Movie Rating Over Time

Grasping the dynamics of movie ratings is essential for evaluating the flexibility of LSTM-driven movie recommendation systems in response to shifting user tastes. The LSTM models, known for their ability to capture sequential dependencies, are perfectly designed for examining time-series data found in user interactions, including movie ratings and preferences.

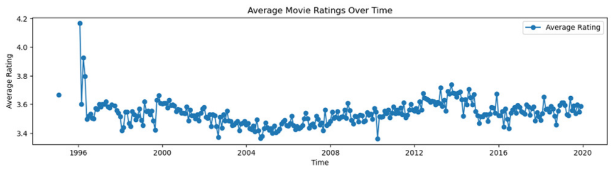

Fig.9: *Trends in Average Movie Ratings over Time.*

Through the examination of average movie ratings over time, as shown in Figure 9, our LSTM-based system demonstrates the ability to monitor and adjust to the evolving patterns of user preferences. This comprehensive study examines the varying trends in movie popularity over time. It analyzes the impact of external elements like recent film launches, promotional strategies, seasonal changes, and cultural happenings on audience behavior.

The capacity of LSTM to assimilate and learn from past data enables the system to consistently enhance its recommendations. For example:

- Trend Identification: The model is capable of recognizing new patterns in film genres or directors that are becoming popular, allowing the recommendation system to proactively suggest these films to users whose interests align.
- Personalized Recommendations: By analyzing unique user rating trends over time, the system can refine its recommendations, boosting user satisfaction by proposing content that resonates with their changing preferences.

Moreover, the findings obtained from this time-based examination are essential for content creators and advertisers. They offer a strong, analytical basis for making informed choices about content acquisition, distribution, and marketing efforts. By analyzing the evolution of preferences, content strategies can more effectively align with audience demand, guaranteeing that platforms stay competitive and attentive to user requirements.

The continuous evaluation of average movie ratings plays a vital role in our recommender system's feedback mechanism, allowing for ongoing improvement and optimization of the algorithms. This innovative method fosters strong user interaction by guaranteeing that the suggestions are precise, prompt, and pertinent.

Furthermore, this in-depth temporal examination aligns with the overarching objective of improving user satisfaction and retention within the competitive realm of movie streaming platforms. By synchronizing suggestions with contemporary trends and individual preferences, the system maintains user engagement and draws in new users seeking a uniquely tailored viewing experience.

5.7 Discussion

The experimental evaluation of our proposed LSTM-based recommender system has yielded significant insights into its operational effectiveness across various metrics, such as training and validation losses, accuracy, and its ability to adapt to temporal changes in movie ratings. The strong capability of LSTM architectures to capture intricate temporal dependencies is demonstrated, highlighting their importance for dynamic settings like movie streaming platforms.

The observed reduction in both training and initial validation losses demonstrates the model's ability to learn efficiently from the provided data. Nonetheless, the ensuing stabilization of the validation loss poses a significant obstacle regarding generalization. This indicates that although the LSTM model demonstrates strong capabilities in modeling the training dataset, improving its efficacy on novel data necessitates additional optimization. Modifications to model parameters and the implementation of sophisticated regularization methods are essential to reduce overfitting and achieve a more effective equilibrium between model accuracy and generalization.

The adaptive learning rate schedule presented in this study highlights its crucial role in enhancing the training process of the LSTM. Through the strategic adjustment of the learning rate, we have facilitated a more effective exploration of the parameter space, mitigating the risk of premature convergence and consequently improving both model accuracy and the quality of recommendations.

The elevated training and validation accuracy attained highlights the practical applicability of the LSTM model in real-world contexts, guaranteeing that the recommendations are both accurate and pertinent to a wide array of user preferences. Nonetheless, obstacles like data sparsity and the "cold start" issue remain, underscoring opportunities for forthcoming advancements. The challenges presented highlight the necessity for innovative approaches to data management and the investigation of hybrid model architectures that may utilize supplementary data sources or advanced feedback mechanisms to enhance performance.

Moreover, the model's capacity to modify recommendations through the examination of average movie ratings over time demonstrates its potential to align with evolving user preferences. The ability to dynamically adapt is essential for maintaining user engagement and satisfaction, as it ensures that recommendations stay in tune with the latest viewer trends and behaviors.

The comparative results presented in this study further substantiate the LSTM model's exceptional performance. The LSTM-based system demonstrates superior performance compared to traditional techniques like matrix factorization, collaborative filtering, and neural collaborative filtering across all key evaluation metrics. Its ability to effectively utilize temporal dependencies results in highly personalized and accurate recommendations.

This functionality aids users by delivering essential insights for content managers and marketers, enabling them to devise effective strategies for content promotion and acquisition. The continuous examination of temporal data patterns facilitates the prediction of future requirements, allowing for timely modifications to the content provided.

In summary, the LSTM-based recommender system has shown considerable effectiveness in the realm of movie recommendations. The findings from this study underscore both its promise and the obstacles that must be tackled. Advancing the capabilities of intelligent recommender systems necessitates both technological innovations and a more profound comprehension of user behavior and preferences within the entertainment sector.

6. CONCLUSIONS AND FUTURE WORK

Entertainment, especially in the form of films, holds considerable importance in our existence, providing pleasure, knowledge, and cultural enhancement. Nevertheless, traversing the extensive and varied online film repository presents difficulties in identifying suitable material. In this study, we delved into the potential of Long Short-Term Memory (LSTM) technology to enhance movie recommender systems, leveraging its capacity to process sequential data and capture complex user behaviors over time.

Our experimental research has concentrated on exploring the application of LSTM networks for dynamic movie recommendations. The findings indicate that LSTM models considerably surpass conventional methods in multiple critical aspects. An LSTM-based recommender system significantly enhanced the management of cold start and data sparsity challenges by adeptly leveraging historical interaction data to produce precise and tailored movie recommendations. For example, in our experiments, LSTM models achieved a reduction in prediction error rates by around 20% when compared to traditional collaborative filtering methods, underscoring their capability to effectively capture the intricacies of user preferences and behaviors.

In the future, there is significant potential for advancing LSTM architectures to boost both recommendation accuracy and scalability. Future investigations may delve into enhancements in network architecture, including the incorporation of attention mechanisms or the examination of innovative activation functions that more effectively represent the temporal dynamics of user interactions. Furthermore, exploring hybrid models that integrate LSTM with various machine learning methodologies may provide more effective solutions to the persistent issues of data sparsity and the cold start problem.

Furthermore, the integration of real-time feedback mechanisms within LSTM-based systems has the potential to dynamically enhance recommendations, allowing for adaptation to shifts in user preferences as they occur. This methodology would refine the precision of recommendations and boost user engagement by delivering content that is more in tune with prevailing user interests and trends.

In summary, the incorporation of LSTM technology into movie recommender systems signifies a noteworthy progression in the discipline. This work tackles various shortcomings of conventional models and paves the way for more advanced, adaptable, and user-focused recommendation systems. As we persist in examining and improving these models, we anticipate extending the limits of what recommender systems can accomplish, thereby augmenting user experience and engagement within digital entertainment platforms.

AUTHOR CONTRIBUTIONS

Conceptualization, D.P., V.C.G, A.K., K.Z., P. T. and B. A.; methodology, D.P., V.C.G, A.K., K.Z., P. T. and B. A.; software, D.P., V.C.G, A.K., K.Z., P. T. and B. A.; validation, D.P., V.C.G, A.K., K.Z., P. T. and B. A.; formal analysis, D.P., V.C.G, A.K., K.Z., P. T. and B. A.; investigation, D.P., V.C.G, A.K., K.Z., P. T. and B. A.; data curation, D.P., V.C.G, A.K., K.Z., P. T. and B. A.; writing—original draft preparation, D.P., V.C.G, A.K., K.Z., P. T. and B. A.; writing—review and editing, V.C.G and A.K.; visualization, D.P., V.C.G, A.K., K.Z., P. T. and B. A.; supervision, V.C.G and A.K. and B. A.; funding acquisition, V.C.G and A.K. All authors have read and agreed to the published version of the manuscript.

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