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ORIGINAL RESEARCH ARTICLE

LCNA-LSTM CNN based attention model for recommendation system to improve marketing strategies on e-commerce

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ABSTRACT

E-commerce industries have grown at an unpredicted and unprecedented rate in the 21st century, booming in the midst of the COVID-19 catastrophe and revolutionizing our way of life. The COVID-19 pandemic has demonstrated the widespread strong uptake of e-commerce. In today scenario, success of any business depends upon e-commerce platform. As e-commerce uses Machine learning algorithms for processing but they also encounter serious issues, i.e., cold start, sparsity, scalability and many more. In this research work, researchers address the cold start issue, as efficiency drops due to new users or lower engagement of users. Same is resolved in proposed LSTM CNN Based Attention Model (LCNA), a Longest short-term memory (LSTM) recurring neural networks, Convolution Neural Network (CNN) and deep attention layer based model for collaborative filtering to solve the problem of cold start for a new user. The proposed model in this study uses deep attention layer for semantic ranking with cosine similarity to improve the recommendation. Proposed framework primarily functions in stages, starting with the creation of interactive map matrices, then improving ranking using CNN, LSTM, and deep attention layer, and concluding with the framework's prediction of three key metrics: mean absolute error (MAE), root MSE (RMSE), and accuracy. The framework is put to the test in several metrices using various recommender metrics on the electronics dataset from the Amazon dataset.

Keywords: recommendation system; machine learning; longest short-term memory; Convolution Neural Network (CNN); deep attention layer

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1. Introduction

Considering the advancement in technology, every organization, regardless of industry, has gone online. The internet is now overloaded with items for both amusement and daily requirements. Additionally, individuals feel more at ease these days while shopping online at websites like Amazon, Netflix, Spotify, and Pandora. These e-commerce sites collectively provide hundreds of millions of items in numerous categories. Younger generations, in particular, purchase goods like apparel, food, gifts, electronics, or rent films and songs from internet retailers. Online buying is more appealing than shopping in real stores since it provides more options and takes less time.

This rapid explosive growth of electronic content available and the usage of Internet has resulted in a potential big data challenge, prohibiting quick access to information on the Internet platform. This has resulted in a higher-than-ever need for recommender systems.

Data filtering techniques called recommender systems address the issue of information overflow by separating useful data pieces from a massive amount of user-supplied data depending on the customer's preferences, hobbies, or account. A recommender system can predict if a user would choose an offering based on his or her profile[1].

Recommender systems help both utility companies and customers. They minimize the expenses of searching for and picking items in an e-commerce setting. It has also been demonstrated that recommendation systems improve the quality and quickness of decision. Because they are a promising strategy of marketing more products, recommender systems improve profitability in an e-commerce scenario[2,3].

Before making a purchase, people used to seek advice from friends, family, or specialists. Nonetheless, modern devices employ machine learning (ML) and artificially intelligent (AI) algorithms to give suggestions that are based on data[3,4].

The recommendation systems shorten the search period for items that a user might enjoy, benefiting both the provider and the customer. Therefore, an effective recommender system is crucial for all e-commerce platforms to aid customers in making shopping behavior. Therefore, it is impossible to overstate the importance of using accurate, productive, efficient, and timely recommendation system that wants to offer clients recommendations that are accurate as well as trustworthy.

The methodologies for recommendation can be divided into three categories[1] as shown in **Figure 1**: content-based (CB), collaborative filtering (CF), and hybrid approaches, depending on the types of data being gathered and the ways in which they are used in recommendation systems.

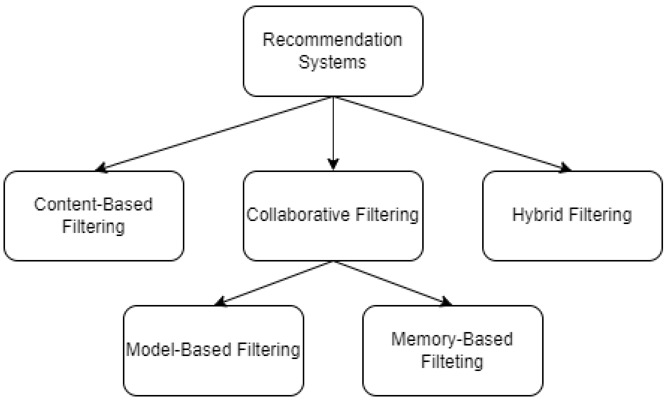

Figure 1. Categories of recommender systems.

The content of products is used in CB filtering to generate characteristics and traits that correspond to user details. Products are contrasted to items that users have previously enjoyed, and the closest matches are then suggested[1,5]. The requirement for recommendation systems (RS) is to identify preferences for those types of products and use these with other sorts of products, which is one of the main problems with the CB filtering approach. A user may not like too many similar movies, which causes CB filtering to struggle from the "bubble effect". For instance, if a person has seen Avengers-1, Avengers-2 will be suggested to him, and so forth.

The most well-liked strategy is CF. It makes predictions about the products customers would like by using a lot of information acquired from past user activities[1,5]. It is not essential to assess the contents of the things. Moreover, it is based on consumer behavior, which is frequently recorded in a rating feedback matrix where each component represents a particular user's viewpoint on a certain product. If the target user's taste has previously been matched with that of the second user, articles that the particular user strongly suggests will be presented to the target user in the future. There are issues with CF, scalability, cold start, and sparsity[1]. Only a small percentage of the scoring matrix's elements have values assigned to them. Only a few ratings are possible for even the most well-liked products. In fact, a significant Netflix ratings collection made accessible for the Netflix Prize contest by more than 480,000 subscribers has over 1 billion evaluations for approximately 18,000 videos. Only 1% or so of the rating matrix's elements receive ratings. Making appropriate recommendations while attempting to determine the connection between things and users in a sparse rating matrix is exceptionally hard.

The Cold Start (CS) problem, which can happen when new customers or new products are introduced, is another well-known issue for the CF technique[5]. Due to the system's lack of ratings for new users, new goods, or both, in order therefore for CF method to effectively suggest a product, a sizable number of user or item ratings are necessary. CS problems can also be separated into complete cold start (CCS) and incomplete cold start (ICS) problems depending on whether or not the frequency of rating entries is null. The rating sparsity for CS things is most often more than 85%, and for CCS objects, the rating sparsity is 100%.

Scalability, which is the ability of recommender systems to manage recommendations with changing environments where new users and items are continually being added to the dataset, causing the data to constantly grow, is another significant issue. With this kind of enormous and dynamic datasets, recommender systems become quite challenging to manage.

To solve their flaws and generate a more successful result, the hybrid strategy combines the CF approach and the CB filtering approach. Combining CBF for product traits and CF for user actions is known as a hybrid filtering technique[1,6]. Cold start issues and the bubble effect are both solved by hybrid approaches.

As a result of advancements in technology, traditional algorithms used in recommendation systems can no longer handle real world data. As a result of rising computational capabilities and huge information storage capabilities, artificial intelligence has started to garner a lot of interest. The researchers' accomplishments in creating and refining machine learning models help to advance machine learning as a developing field of computer science.

The area of machine-based recommendation systems appears to be remarkably interesting. Moreover, due to the large number of methodologies and versions suggested, researchers may find it very hard to monitor activity and the trends of ML algorithms in recommender systems as working of recommendation system is different for every type of application, so it makes difficult to choose techniques of recommendation system because it is fully dependent on the nature of service for which recommendation system is used[2,3].

In this research authors proposed LCNA, a new recommendation system using Longest short-term memory (LSTM) recurring neural network, Convolution Neural Network (CNN) and deep attention layer with cosine similarity for semantic ranking to improve the accuracy of recommendation systems by alleviating the cold start issue in CF.

Breakdown of the paper's structure: Section 2 explains the literature survey. Section 3 presents the proposed recommendation model. Section 4 provides the dataset for the proposed model. Section 5 explains the results and analysis of our model on the electronics dataset from the Amazon and Section 6 gives conclusion and future work.

2. Literature survey

On recommender systems, numerous research has been done. To increase the efficiency of recommender systems, numerous strategies have been put forth in earlier years.

Patro et al.[6] attempted to address the issues of cold start and sparsity, and the sparsity and cold start aware hybrid recommended system (SCSHRS) technique is presented for a precise suggestion. At first, it is assumed that by predicting unavailable scores will lessen data sparsity. After that, using an ALO-based *k*-means approach, comparable users are placed in categories according to their demographic information, such as race, their age, and their occupation. After Higher-Order Singular Value Decomposition (HOSVD) decomposes the tensor, Adaptive Neuro-Fuzzy Inference System (ANFIS) uses its fuzzy and utilizing machine learning to propose something to an upcoming novice consumer.

Singh et al.[7] used cross similarity value approach in collaborative filtering-based recommender system and tried to reduce not only the sparsity but also solve the cold start problem. The authors claim that their algorithm uses the target user's rating data from other domains, once obtainable, when the intended user is unable to locate relevant peers in the interest area.

Osman et al.[8] presented recommender system for electronic products is built on sentiment analysis-gathered context-specific information. The researchers used user feedback and preferences to make a suggestion.

Liu et al.[9] added to the semantic attributes acquired through feedback, take into account static features gained via user-item encounters. The author's model can extract adaptable semantic along with property characteristics from the static features in order to more accurately model a user when they are presented with various things. To enhance the efficiency of the recommendations, it was also suggested to extract complex relationships between the characteristics and by employing continuous sampling to build the model conducted tests using 16 open datasets.

Shoja and Tabrizi[10] proposed that although written customer reviews are unstructured data, they are a valuable resource of knowledge for recommender systems. The authors of this paper took those characteristics from feedback from consumers and used them to compare user similarity and, eventually, to generate recommendations. They created a glossary of features for each class of product, then used Latent Dirichlet Allocation to determine which words should be removed. In order to cope with sparsity, ambiguity, and redundancy, deep neural networks were used to utilize the reviews-characteristics matrix and derive extensive characteristics. In order to make suggestions, they also used matrix factorization as a collaborative filtering technique.

Liu and Zhao[11] attempted to address the issues of trustworthiness and data scarcity in collaborative filtering. It was suggested to use a recommendation system based on sentiment analysis and matrix factorization (SAMF), which completely mines the implicit data in reviews to enhance the rating matrix and support recommendations.

Lin et al.[12] proposed a novel recommendation which generates the top-N suggestions of courses suitable for the students' course choices using a sparse linear algorithm. Additionally, the existing recommendation system's observation of the course items leads to the use of the L0 regularization term as an optimization approach. To assess the efficiency of the strategy, they have used accuracy of various course numbers and themes.

Aguilar et al.[13] presented the concept of a knowledge-based recommender system, which is enhanced by an overall structure for an intelligent recommender system and is comprised of the aspects: information representation model, approaches to learning, and logical techniques. Using Fuzzy Cognitive Maps, they developed one intelligent recommendation system based on this architecture (FCMs). The knowledge model for this Intelligent Recommender System (IRS) is clearly specified and takes into account knowledge about the users, things, domain, context, and criticisms. Then, in order to increase its performance, IRS makes use of the information about users that was acquired by the learning approach.

Yassine et al.[14] combined a collaborative filtering (CF) and the well-known unsupervised machine learning algorithm *k*-means clustering in a new intelligent recommender system. Additionally, in order to construct segmented user profiles, some user demographic characteristics were taken into account, such as gender and age. Strong recommendations that effectively increase the accuracy and performance of movie recommendations are made using Principal Component Analysis (PCA) extraction of features and Singular value decomposition (SVD) collaborative filtering.

Zhou et al.[15] addressed the cold-start recommendation issues in edge environments with sparse data and developed an intelligent service recommendation approach termed Inverse CF Rec. The indirect friend induction rule of the Social Balance Theory is used by this recommender to first look for the adverse users (i.e., rivals) of the client targeted before looking for their friends. Eventually, based on the user target's deduced friends, appropriate services are suggested to the user targeted. Through trials on real-world datasets, the recommendations' accuracy and effectiveness were assessed.

Sadeghi et al.[16] proposed IMVGRS, an improved multi-view group recommender system that relies at personal preferences (ranking) and socialization (trust). The multi-view group recommender system's clustering was enhanced using the singular value decomposition and complete coupling approaches. Complete linkage is more accurate than other clustering algorithms like *k*-means since it prevents chaining and creates compacted clusters.

Ghodsad and Chatur[17] proposed a mechanism for recommending products on social networking websites that takes into account members of the group's opinions. By using a group recommender model, they attempted to address the issue of cold starts. In this model, the machine will eventually identify a set of users who share a common interest and preferences. Following group development, each group member's interests will be determined, and items will be recommended to the group based on those interests. The system uses the extended recommendation model, and it will provide recommendations in two different ways: individually and collectively.

Iqbal et al.[18] offered Kernel Context Recommender System, a revolutionary algorithm that detects the value of context and includes contextual data using kernel function when drawing conclusions. It is a versatile, quick, and accurate kernel mapping framework. They discovered that taking into account contextual information can improve system performance and produce more accurate, pertinent, and significant findings for various evaluation metrics. Context is a crucial factor in suggestions.

Hasan et al.[19] proposed an item-based recommendation system based on clustering algorithms having basic purpose of finding a likeness and resemblance amongst items. Researchers analyzed the user-item rating matrix with the help of item-based clustering algorithm to find the relationship between different items.

Wang et al.[20] addressed the serendipity issue of recommendation and an innovator based Collaborative Filtering algorithm to prescribe cold items to users is suggested. They introduced the innovators concept who discovers cold items and solves the cold start issue which also led to saving of cost of communication and computing resources.

Guo et al.[21] suggested a mobile e-commerce recommendation system to examine and scrutinize requirement of consumers makes use of multi-source information to suggest the most required and mandatory information to the consumers at the most suitable time, also to make their shopping experience comfier and more easeful. Also, the suggested approach is superior in respect of recommendation simplicity, accuracy, coverage rate and recall rate.

Guo et al.[22] In order to produce a better suggestion and in order to evaluate item similarity from the standpoint of the probability scoring distribution, a Hellinger distance (HD) driven item similarity is provided. In order to successfully draw attention to variations within a group of items and the HD matching algorithm additionally takes a function that is sigmoid into account to highlight the significance of co-rated elements.

Lee and Lee[23] proposed a model based on neural network for collaborative filtering. Suggested model or method used supervised learning, a technique of machine learning, different from other collaborative filtering technique which are based upon deep learning techniques. For providing input in neural network, item-rating vector and normalized user-rating vector were used. Also, normalization technique is used to speed up the training and avoid overstating.

Goel et al.[24] suggested a recommendation system which predicts the best recommendation for books and their prices over various portals of e-commerce. They extracted the significant data from various e-portals and applied both collaborative and content-filtering in hybrid filtering approach and proposed a dynamic recommendation model for books recommendation. This model used cosine similarity rule, a user-based collaborative filtering approach and improvised with the bee algorithm and after that natural language processing is applied over review for refinement. They also tried to solve the cold start issue.

Wei et al.[25] used deep learning neural network and combined with the tightly coupled collaborative filtering approach framework and suggested two models of recommendation, one is to provide a solution of complete cold start and the other to solve the incomplete cold start problem in recommendations. They used SDAE architecture a deep learning approach and time SVD++, a collaborative filtering model.

Zarzour et al.[26] proposed RecDNNing, a unique strategy for enhancing recommendation quality. It integrates user and item data with deep neural networks. RecDNNing works in 2 parts, firstly to create input vector by using item and user embedding and secondly using deep neural network to recommend.

Liu and Guo[27] used deep learning framework in grid environment to optimize the recommendation algorithm which improved the recommendation accuracy.

Zhou[28] suggested a deep neural network-based recommender system that dynamically augments the original recommendation systems with product and user information and also suggests target material to new members. Keeping the compressed interaction networks (CIN) and deep neural networks (DNN) structures, the associations can be added before and after of sequences. Also, the new information can be added dynamically while keeping the computing cost low.

Hawashin et al.[29] proposed machine learning techniques can be used to connect patterns combining user profile information and user extracted interests, which enhanced the accuracy. It has also been stated that latent user interests can be used to tackle the problem of cold start. Various classifiers of machine learning are used to find out the solution in terms of accuracy.

Mana and Sasipraba[30] used various machine learning algorithms used to make a banking service recommendation system and hybrid recommendation algo to make a movie recommendation system. And concluded that machine learning algorithms are ready to be implemented in recommendation.

Oshnoudi et al.[31] advised users clustering for better improved recommendations. Dimension expansion has been proposed, Dimension expansion lowers the item-rates matrix and can handle the sparsity issue also. To enhance clustering, they applied k-nearest neighbors (KNN) techniques and the Auto Multilayer Perceptron (MLP) machine learning algorithm.

Almaghrabi and Chetty[32] suggested models that capture the subtle and unseen interactions between individuals and products to enhance the recommendation system. These models are based on collaborative filtering recommendation and deep learning-based augmentation framework.

Wu et al.[33] suggested a Deep Latent Factor Model (DLFM) which resolved the cold start and sparsity problems by constructing a deep-structured RS on a HiDS matrix. Instead of using multilayered neural networks, a deep structured design is built by connecting numerous latent factor (LF) models successively using an activation function that is nonlinear.

Guo et al.[34] introduce the Balanced Partitioning (BaPa) methodology, which simplified the distribution of load by separately adjusting both columns and rows and causing assessments to be spread equally throughout sections. By examining the variance in scoring counts between section, it was possible to demonstrate its viability. Its high performance was then experimentally demonstrated by using it with two common parallel matrix factorization algorithms.

Ahmed et al.[35] proposed TCrossDNMF, a framework for trust-aware cross-domain recommendations, models linear and nonlinear interactions through matrix factorization and perceptrons with multiple layers in cross-domain situations of "User Overlap". It also forecasts an item's rating for users who are engaged and addresses the user cold start problem. In order to increase the precision of recommendations, the concept of trustworthiness level among trustors and trustees was also introduced. The aforementioned trust level was constructed in the TCrossDNMF model.

Bai et al.[36] proposed DLTSR, a deep learning framework, to handle the long-tail web service recommendations, a gradually emerging problem in the web service economy.

Used the deep learning model SDAE as the fundamental building block to learn reliable and efficient representations to address the issue of poor quality of explanation provided by service developers and mashup inquiries. Researchers forced the hot service utilization data as a regularization on the encoding output of SDAE to improve the performance of long-tail service recommendations.

Fernández-Garcíaa et al.[37] used methods of intelligent data analysis and suggested a recommender system to solve the problem of prediction of best item for any user and at any moment. They used algorithms and techniques of machine learning and applied over dataset gathered after interaction with the data to deliver better predictions and make a good recommendation model.

Many things were considered like contextual information, usage of application over different machines and devices with different pattern and scheme of interaction and also the time passage (addition and removing of components over time) was taken into account. Various algorithms of machine learning[38–40] were used with the help of techniques from feature engineering methods and feature selection to address the issue of converting the real dataset toward an actual component-based application to an optimized dataset.

3. Proposed model: LSTM CNN based attention model (LCNA)

Recommender systems are a type of technology for information filtering that tries to provide users with information that is most likely to be beneficial to them. The system encounters the cold start issue when it is incapable of establishing any connections between users and objects about which it lacks sufficient data. In recommendation system mainly 2 types of cold start.

User cold-start issues: These issues occur if there is often no data available about the user.

Product cold-start issues: The product cold-start issue appears when there is basically nothing data available about the product.

3.1. Why LCNA and working of LCNA with block diagram

Cold start problem exists due to Systematic Bootstrapping when system starts and no information is available, Low Interaction when new items are added to the catalogue no interaction occurs between users-items which happens particularly in collaborative filtering and New User added to the system and recommender system has no user's previous interactions. This problem is due to a lack of user and product interaction information.

There are many solutions available, like matrix factorization, but they predict linear interaction and ignore other possibilities.

Authors improved performance by using a CNN-based approach with non-linear mapping and the drop feature to generalize the relation.

Authors also hybridize this approach by using semantic LSTM-RNN. These both improve the generalization of relations with semantic information and drop features (using the activation function).

In this research, the recommendation problem that is being explored is estimating the RMSE, MAE and Accuracy for the electronics dataset from the Amazon dataset.

These issues are recovered by introducing semantic ranking and attention layer which provide priority. Proposed model works into following way:

1) First, User-Item matrix of input data is divided into item latent factor matrix and user latent factor matrix and then merged into interaction map matrix.
2) Now interaction matrix is mapped non linearly in Convolution Neural Network and user rating matrix is generated.
3) Parallelly, Same training data is provided to Recurrent Neural Network (RNN). In proposed model RNN uses LSTM. LSTM provides a short-term memory for RNN, i.e., due to this feature it processes entire sequences of data and then has semantic ranking of input training data.
4) After CNN based ranking, it is fed to deep attention layer. Attention layers are deep learning layers that evoke the idea of attention. Deep Attention layer can help any neural network to handle the large sequences of data by memorizing it. If we are providing huge dataset, deep attention layer improves the performance and in proposed model deep attention layer uses cosine similarity and is termed as X is a refined rating.
5) In proposed approach, focus is given on refine rating and it is done by Cosine similarity function which further enhance the rating by comparing the ratings achieved from deep attention layer and semantic rating.
6) Cosine similarity is calculated by following equation:
7) Cosine Similarity = ΣAiBi/(√ΣAi2√ΣBi2) And then decision is taken by recommendation system.

The proposed model for intelligent recommender system is shown in **Figure 2**.

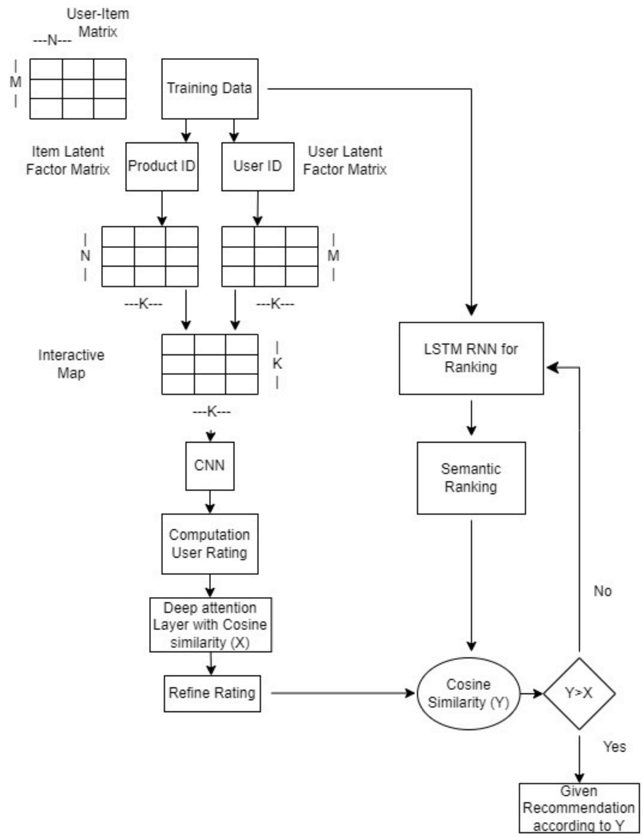

Figure 2. Block diagram of LCNA model for intelligent recommender system.

3.2. Algorithm of LCNA

Algorithm 1 described the process of converting dataset into desired format for the model.

Algorithm 1 LCNA1-Converting Dataset into Desired Format

Item Embedding
Input: $S = \{S_1, S_2, , \dots \dots . . S_n\}$
L = Labels
Output:
Vl = vector of Item
U = matrix corresponding to user
For each i ε [0, n−1] do
Input S_i into item 2 Vl C

$$\frac{1}{N}\sum_{y \neq i}^{M} logp\left(I_{y\propto}|I_x\right) \quad (1)$$

end for
for each i ε [0, n−J] do
$Vl_J = \overline{Vl_J} + l_J;$
end for
return $S_i = \{Vl_1\ Vl_2, , \dots \dots . . Vl_n\}$

Algorithm 2 describes recommendation model.

Algorithm 2 LCNA1-Converting Dataset into Desired Format

User preference Learning
Input:
$S_i = \{Vl_1\ Vl_2, , \dots \dots . . Vl_n\}$. The first J − 1 item set.
ω_i = Input Weight
Output:
$\overline{R_\iota}$= Recommendation of K list
For each J_i [0, m−1] do
$P_J = V_J$ and a_i input deep LSTM-RNN by Equation (2)
If J < length − 1
Apply CNN by Equation (3)
Else if J = length − 1 then
Apply Attention by Similarity, error by Equation (4)
Else return V_J
MAE optimize parameters by Equation (1)
Sort items according to MAE
for each i ε [0, k−1]
for each j ε [0, n−1]
Sim = $\overline{P_\iota} i V_J$
end for
sort items
end for
return Top k-elements

$$h_t = \mathrm{f}(Ah_t + Bh_{t1} + Z) \quad (2)$$

h_t←item at time
A←user vector
$\overline{B}$←Bias weight
Z←return learning

$$\mathrm{A} = \mathrm{Softmax}\ (I_z W (I_d)^T) \quad (3)$$

I_z←Learning
W←Layered weight
I_d←Unit vector

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{M}\left(V_i - \hat{V}_i\right)^2 \quad (4)$$

3.3. Flow chart of LCNA

Flow chart and working flow for LCNA model for intelligent recommender systems is shown in **Figure 3**. Proposed framework primarily functions in stages, starting with the creation of interactive map matrices, then improving ranking using CNN, LSTM, and deep attention layer, and concluding with the framework's prediction of three key metrics: mean absolute error (MAE), root MSE (RMSE), and accuracy.

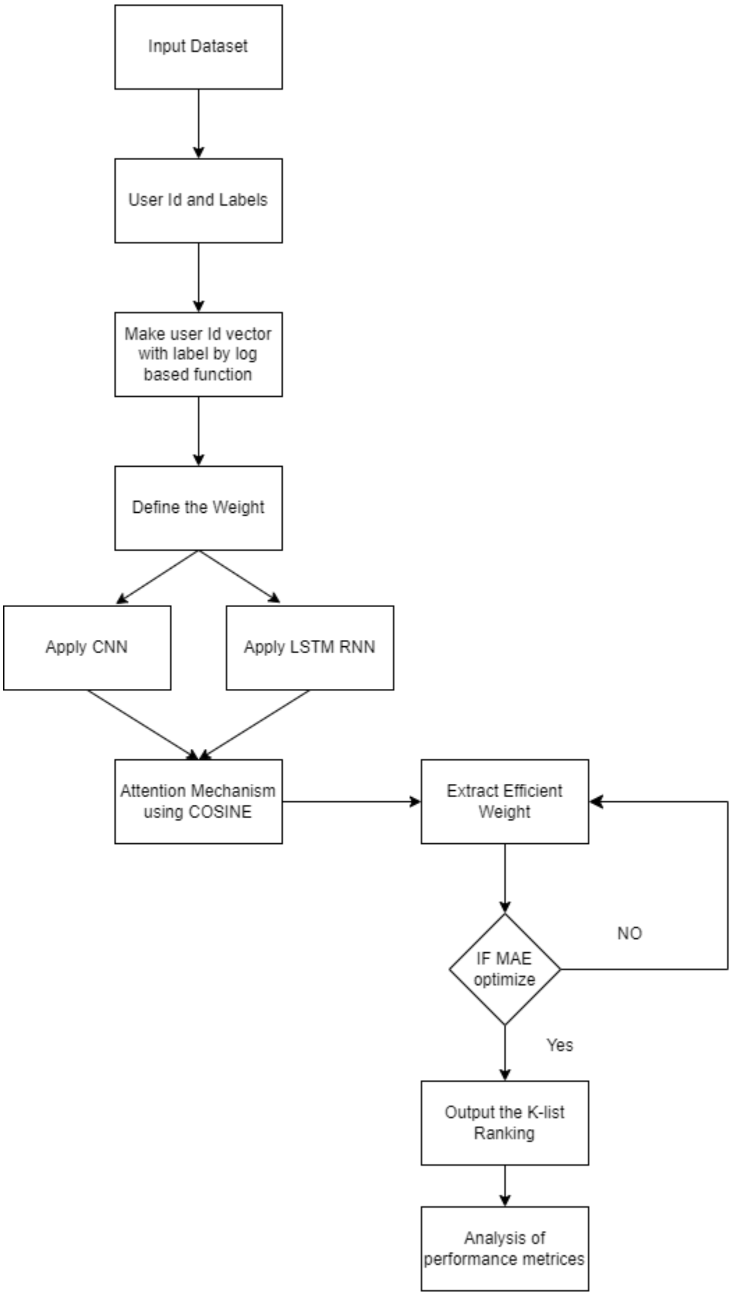

Figure 3. Flow chart for LCNA model.

4. Dataset description

Researchers will use the electronics dataset from the Amazon Review dataset for this study, which is a commonly used resource obtained from the Amazon Dataset[41]. These data were crawled from Amazon.com which is freely available for everyone. Amazon dataset contains both users' ratings and products' reviews. For this dataset, between May 1996 and July 2014, 14,280 crores assessments on Amazon products were collected, together with user information and item details. Reviews in this dataset comprise textual, ratings, relevance scores, and goods characteristics, such as a product description, category information, pricing, branding, and image attributes. This dataset also includes links which contains also viewed and also bought graphs.

5. Results and analysis

The effectiveness of the suggested models for the cold start problem is assessed in this part. Results for the suggested models are compared to other benchmark recommendation models and assessed in terms of

RMSE, MAE, and accuracy. To gauge the importance of mistake rate in recommendations, RMSE and MAE are used. Usually, MAE and RMSE are used for statistical accuracy metrics.

5.1. Mean absolute error (MAE)

Mean Absolute Error (MAE), which calculates the mean of the significant disparity between the ratings' forecasts and actual outcomes, is the metric that is most frequently used in CF study literature. It serves as a gauge for how far a suggestion strays from a user's particular value. The computation will be done as equation (4):

$$MAE = \frac{1}{N}\sum_{i=1}^{M}\left(V_i - \hat{V}_i\right)^2 \tag{4}$$

where N is the number of datapoints, V_i is the i-th measurement and $\hat{V}_i$ is the corresponding prediction. The recommendation engine anticipates with better fidelity as MAE decreases. From **Figure 4**, it can be seen that the MAE get better in for our proposed model, validating our model or hypothesis and can lead to a better recommender system.

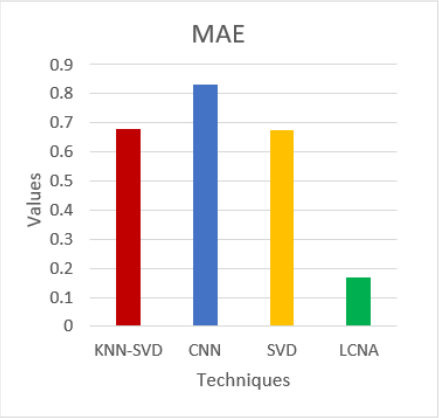

Figure 4. MAE comparison of KNN-SVD, CNN, SVD and LCNA.

5.2. Root means square error (RMSE)

One of the most crucial metrics for testing the models is the Root Mean Square Error (RMSE). Many statistical metrics have used the root mean square error (RMSE) to assess the success of models in various fields. Greater absolute error is given more weight by RMSE, and the suggestions seem to be more appropriate the relatively low the RMSE. It is the average of the squared differences between the precise measurement and the prediction. From **Figure 5**, we can see RMSE improvement highly in our proposed model.

$$RMSE = \sqrt{\frac{\left\|\sum_{i=1}^{N} V_i - \hat{V}_i\right\|}{N}}^{2} \tag{5}$$

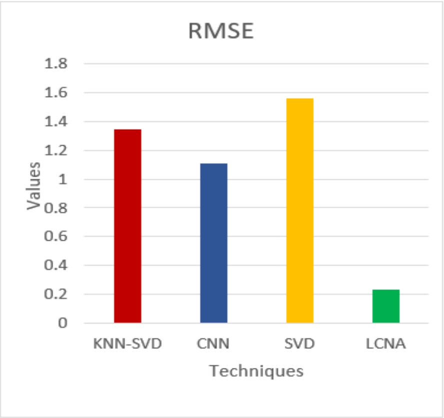

Figure 5. RMSE comparison of KNN-SVD, CNN, SVD and LCNA.

5.3. Accuracy

Figure 6 displays the accuracy-based efficacy of various models. In the Amazon Electronics dataset, the accuracy of the recommender system using our proposed model increased from 16.7% to 83.3%, demonstrating the outstanding accuracy of the model. Accuracy is calculated as

$$Accuracy = 1 - MAE \tag{6}$$

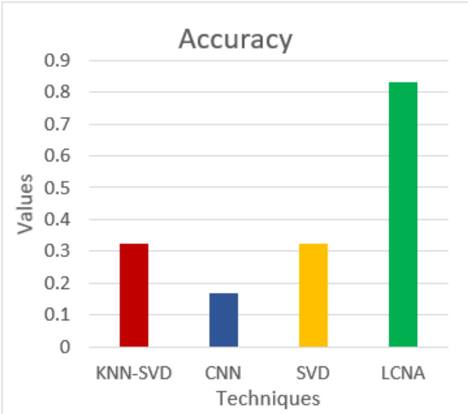

Figure 6. Accuracy comparison of KNN-SVD, CNN, SVD and LCNA.

5.4. Comparison of LCNA with KNN-SVD, CNN and SVD

Table 1 shows the overall comparison of RMSE, MAE and Accuracy for KNN-SVD, CNN, SVD with our proposed model and it is clearly proved that LCNA has given the better results in all fields.

Table 1. Overall comparison of KNN-SVD, CNN, SVD and LCNA.

Algorithm	RMSE	MAE	Accuracy
KNN-SVD	1.342	0.678	0.322
CNN	1.11	0.833	0.167
SVD	1.56	0.675	0.325
LCNA	0.234	0.167	0.833

Figure 7 shows the graphical comparison of RMSE, MAE and Accuracy for KNN-SVD, CNN, SVD with LCNA.

Furthermore, the outcome demonstrates that the suggested strategy is better and improves RMSE by 12%–18%, MAE by 20%–22% and accuracy by 18%–20% compared to many state-of-the-art methods.

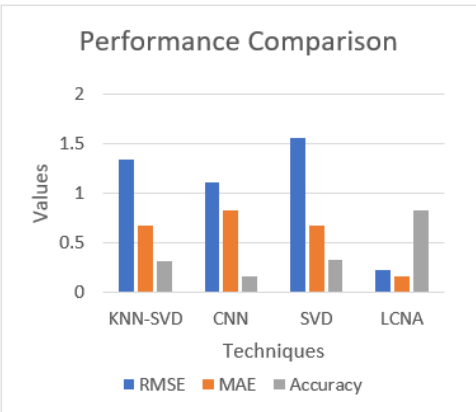

Figure 7. Performance comparison of KNN-SVD, CNN, SVD and LCNA.

5.5. Performance of LCNA on different epochs

To verify the efficiency of our model and for better justification authors have implemented LCNA on different epochs which are shown in **Table 2** and it is concluded that as the number of epochs is increased, RMSE and MAE values decreases with better accuracy. The optimized values for RMSE, MAE and accuracy are obtained at epoch (50).

Table 2. LCNA Metrices at various epochs.

Epochs	RMSE	MAE	Accuracy
20	0.345	0.234	0.766
30	0.3023	0.2432	0.7568
40	0.234	0.1755	0.8245
50	0.2345	0.167	0.833
60	0.2534	0.182	0.818
80	0.264	0.178	0.822
100	0.2533	0.18	0.82

Figure 8 shows the graphical representation of RMSE, MAE and Accuracy for LCNA at various epochs.

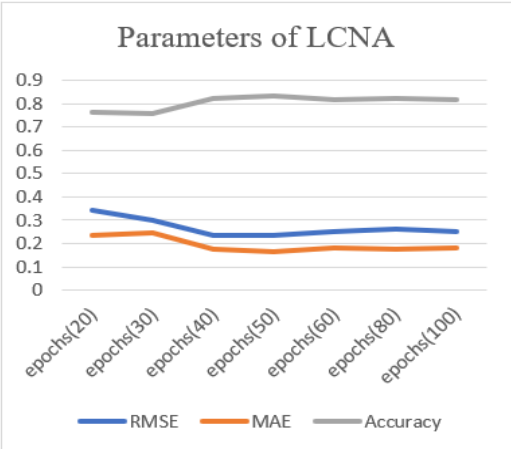

Figure 8. Graphical representation of LCNA Metrices at various epochs.

5.6. Comparison of LCNA with other existing systems

Table 3 shows that proposed model LCNA have better performance as compared to different research work models used to solve cold start problem. RMSE and MAE values decrease by nearly 0.4 as compared to these models.

In the study of Mondal and Bhowmik[42], cold start problem is addressed by introducing deep neural network and named as DeCS. In this research model, “DeCS” framework that has been proposed mainly operates through stages, starting with the creation of vectors and embeddings, then training and forecasting a variety of recommender’s metrics.

During the feature extraction stage, information about present users, items, and their past performance is extracted from these vectors to forecast the rating. The completely linked deep layers are next supplied with these vectors. And the table shows a very good improvement of proposed model LCNA as compared to DeCS.

Sun et al.[43], have focused on anticipating client tastes and drafting feedback. As both are dual in nature. By creating duality between prediction and generating review, researchers propose a probabilistic dual correlation model. Researchers have conducted comprehensive tests on real-life data sets. The research results unequivocally demonstrate the efficacy of our suggested model LCNA in terms of RMSE, which performs better than the dual approach.

In the studies of Lin et al.[44], Han et al.[45] and Lin et al.[46], researchers learned the significance of evaluations and the importance for each word according to deep neural networks (DNN) and deep learning technique. Researchers developed hybrid prediction structures, MAHR and MulAttRec by integrating Factorization Machine (FM) and DNN which emphasizes the relationship among high-order and low-order traits. LCNA performs better as compared to MAHR, ADLFM and MulAttRec system when it is compared in terms of RMSE.

Recommender systems have been the subject of numerous research. Several methods have been put forth in the past to increase the efficiency of recommender systems.

In the study of Chen et al.[47], an explicable recommendation framework for co-attentive multitask learning is put forth in this article. Through completely utilising the connections among the suggestions and the clarification tasks, the model increases both predictability and the explainability of recommendations. Researchers created an encoder-selector-decoder architecture that is motivated by the cognitive psychology model of how humans handle information. To successfully model the cross-knowledge transferred for both tasks, a hierarchical co-attentive selector is used.

The research article of Chen et al.[48],creates free-text explanations in natural language for individualized recommendations. A HSS, hierarchical sequence-to-sequence paradigm is suggested by researchers for the generation of customized explanations.

In this research article researchers introduced LCNA which is far better than existing systems. As latest research issue is addressed and popular machine learning approaches are used. Researchers have compared RMSE values, which is well diagrammatically explained in **Figure 9**.

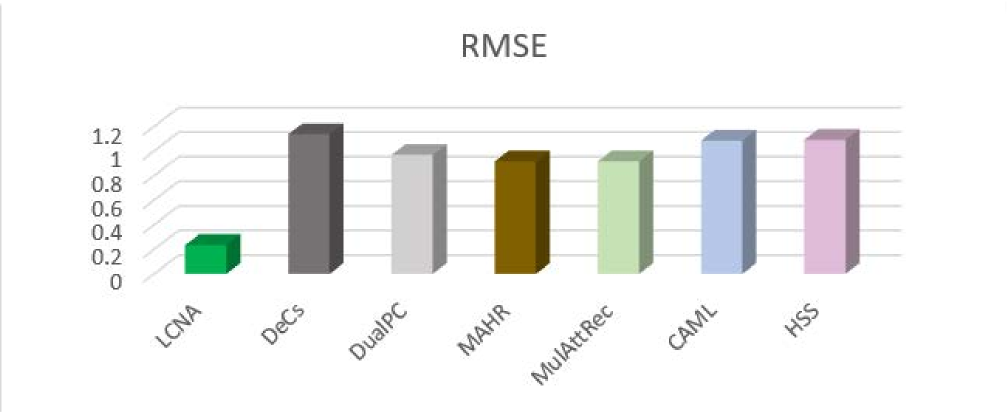

Figure 9. Graphical representation of LCNA comparison with other studies.

Table 3. Comparison of LCNA with other systems.

Recommender system (Year)	Machine learning approach	Issue addressed	Dataset	Performance parameters		
				RMSE	MAE	Accuracy
LCNA (2023)	LSTM-RNN, CNN, Deep Attention	Cold Start	Amazon (Electronics)	0.234	0.167	0.833
DeCS (2022)[42]	DNN	Cold Start	Amazon (Electronics)	1.1362	0.8745	NA
DualPC (2020)[43]	Probabilistic dual correlation	User preference prediction and review generation	Amazon (Electronics)	0.9672	-	-

Table 3. (*Continued*).

Recommender system (Year)	Machine learning approach	Issue addressed	Dataset	Performance parameters		
				RMSE	MAE	Accuracy
MAHR (2019)[44]	Factorization Machine (FM) and DNN	User–item interaction	Amazon (Electronics)	0.915	-	-
ADLFM (2020)[45]	Deep learning technique with LFM (Latent Factor Model)	Sparsity and Individual Diversity	Amazon (Electronics)	-	0.942	-
MulAttRec (2018)[46]	Deep Neural Network and Matrix factorization	User preferences and items reviews relation	Amazon (Electronics)	0.915	-	-
CAML (2019)[47]	Co-attentive multitask learning model	Enhances prediction accuracy	Amazon (Electronics)	1.085	-	-
HSS (2021)[48]	Deep Learning framework	recommendation accuracy	Amazon (Electronics)	1.090	-	-

6. Conclusion and future scope

Ecommerce system has lots of technical issues which are resolved efficiently by recommendation system. But recommendation system also faces different challenges i.e., cold start, scalability, and sparse datasets and same recommendation system perform differently on different datasets. Proposed framework LCNA targets these challenges and researchers propose an intelligent recommendation system to make better marketing strategies on e-commerce.

Proposed LCNA system is based on CNN and LSTM RNN for semantic ranking, for collaborative filtering which will solve the cold start issue for a new user. The LCNA model proposed in this study also used deep attention layer with cosine similarity and after testing the model for various metrices like MAE, RMSE and Accuracy on electronics dataset from Amazon dataset, results shows that the proposed LCNA model improves above mentioned metrics.

In future authors will try to resolve privacy or trust issue which is another major issue in recommendation system as users might experience a trust issue whenever the system learns a lot regarding themselves because the information, the system gathers generally involves personally identifiable data that individuals desire to keep hidden.

Author contributions

Conceptualization, VS and RK; methodology, VS and RK; software, VS and SM; validation, VS, RK and SM; formal analysis, VS and RK; investigation, VS, RK, SM, ABG, SN and SR; resources, VS; data curation, VS; writing—original draft preparation, VS; writing—review and editing, VS, RK, SM, ABG, SN and SR; visualization, VS and RK; supervision, RK and SM; project administration, VS and RK. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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