

Deep learning for Context-Aware Recommender Systems: A Systematic Literature Review

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ABSTRACT

Due to innovative advancements and an increasing amount of digital information over internet, recommendation systems (RS) are gaining more attention to find relevant information in a short instance. Currently, context-aware recommendation systems (CARS) are making a significant contribution to item recommendations based on user context. The addition of context in RS is a challenging task that not only broadens its dimensionality but also creates more sparsity. Recently, the field of deep learning (DL) has gained more focus due to its revolutionary improved efficiency in various domains. Nowadays, due to the efficient functionality of DL, Rs used it to produce high-quality recommendations. The DL based CARS facilitate improved ways to capture user preferences, items and user interaction histories and item features. In this systematic literature review (SLR), a review of studies relevant to deep learning-based context-aware recommender systems is presented in a systematic manner. The current work synthesises the recent studies that cover the advancement in the field of context-aware recommender systems based on diverse variants of deep learning techniques. The SLR also discusses the application domains where DL based CARS perform significant contribution. The SLR concluded by discussion, based on research questions that highlighted twenty-two DL techniques which can be integrated in CARS to improve recommendation accuracy. The results have discovered nine domains where DL is used in CARS to provide higher efficiency. Finally, the study presented some future suggestions on the basis of current scenarios of DL utilization in CARS.

Introduction

In recent years, recommender systems (RSs) become a key part of most web applications like music streaming, movie streaming, e-commerce, e-education applications and others. The rapid increase in the amount of digital data on the web is due to the increasing number of web-based applications and users. The importance of

existing recommendation systems lies in saving the time and effort of users and increasing the profit for service providers. Currently, due to the rapid growth of web applications and services, the construction of recommender systems is a hot area of research that can provide suggestions to users according to their needs and preferences.

One of the most popular algorithms for recommendation is the content-based (CB) algorithm that was implemented by traditional recommendation systems to make recommendations based on the contents of the items. The main challenge for CB is spamming (as the contents can be modified easily by the users).

Another common recommendation algorithm is collaborative filtering (CF). CF is an algorithm that depends on users' histories. CF has classified into three categories. Firstly, item-based CF that recommends items to the users similar to items in their histories. The second one, user-based CF, makes item recommendations on the basis of histories of similar users. Lastly, the model-based CF uses data mining and machine learning algorithms to model the user-item interaction. The similarity depends on the ranks of the items that have been given by the users. Utilization of CF in RS has two main challenges: cold-start and data sparsity. To overcome the stated issues, a hybrid approach is used that combines the features of CB and CF.

In recent years, the RSs started to be directed to personalization that focuses on the user, named as user-centered (UC) recommendation systems. In order to achieve some level of personalization, UC utilizes user characteristics such as location, time, device, emotions, situations and others. With user data, the user surrounding acts as a context that facilitates attaining more accurate recommendations. Using contextual data in recommendation systems has provided promising results.

Many machine learning techniques analyze and extract patterns from contextual data to enhance the recommendation results. Deep learning (DL) is one of the most successful machine learning algorithms that shows significant performance in various domains such as computer vision, multimedia, HCI, natural language processing (NLP), social networks and others. DL used representations of data as opposed to algorithms specific to task-specific. DL models automatically perform feature extraction and transformation based on connected non-linear processing units (neurons) that contain multi-layered orientation. Numerous algorithms are used in deep learning to analyze user's pattern. Due to the success of deep neural networks, researchers have also applied deep models in RS. Empirical evidences demonstrate DL based RS can enhance the accuracy of the recommendations.

In this paper, we conducted a Systematic Literature Review (SLR) according to the guidelines of Kitchenham (Kitchenham et al.2004) to recognize, assess, understand and synthesize the available literature to address particular research questions on the context-aware recommender systems (CARS) based on DL.SLR is used to ascertain the state of evidence with in detail analysis.

The proposed SLR is based on studies published from 2016 to 2025. To perform SLR, we have used a pre-defined review protocol (discussed in Section 2). According to our knowledge till now, no existing work has attempted to address the literature review on explanations in DL based context aware RS through a systematic way. In the literature, some survey studies exist, but they only focused on the selection of papers that can target certain aspects of the research topic. Often, the main objective of

survey papers is to summarize the existing work without considering trends and developments in the research area over time.

The rest of the paper is structured as follows. Section 2 presents the SLR methodology used to conduct the review. The results of the quality assessment (QA) with papers overview are discussed in Section 3. Afterward the detailed analysis of review and research questions is discussed based on selected studies. Finally, in Section 4, the work is concluded with some future suggestions.

Methodology

An SLR provides a way to discover, assess and understand the existing work related to the research field. The main objective of an SLR is to provide authenticate evidences that acts as a base for conclusions (Kitchenham et al.2004).

To perform this SLR, we have followed the review protocol and guidelines proposed by Kitchenham and Charters (Kitchenham et al.2004). According to the guidelines, the process of SLR comprises numerous activities (see Fig 1) that assemble in three main stages: review planning, conduction and reporting. The main three stages future consists of many steps such as: i) recognition systematic review need; ii) review question formulation; iii) an ample and thorough searching for primary studies; iv) quality evaluation of selected studies; v) selection of the data needed to address the research question; vi) extraction of related data; vii) synthesis of study results; viii) results analysis; and ix) reporting results.

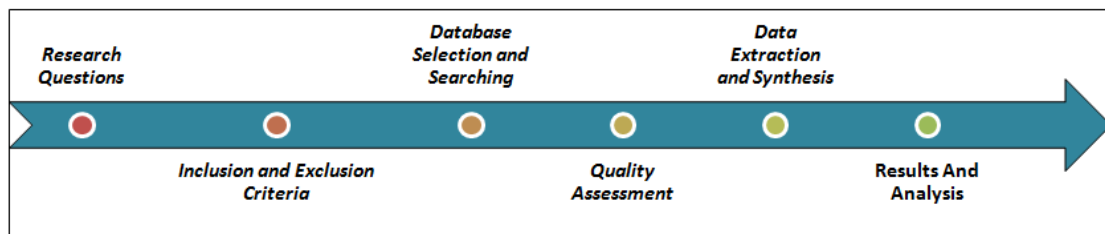


Fig 1. Review Methodology

Research Questions

Our review's aim is to interpret the existing techniques related to DL based CARSS and discover how this concept is being applied in various fields. Thus, to achieve our aim, we intend to address our two main research questions (RQs):

RQ1: What techniques exist to implement context-aware recommender systems based on Deep learning?

RQ2: In what areas can deep learning based context aware systems be used?

Inclusion and Exclusion Criteria

The purpose of the inclusion criteria is to identify those studies that help to collect direct evidence related to the research questions. However, exclusion criteria facilitate the exclusion of irrelevant studies. Table 1 provides the details of the inclusion and exclusion criteria defined according to our SLR.

Table 1. Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
Papers related to research questions (RQ1 and RQ2)	Thesis and posters
Full Access papers	Articles providing unclear results or findings
Peer-reviewed articles	Papers not written in English language
Articles published in 2016 to 2025	Papers that discuss RS but not directly related to our topic

Database Selection and Searching

We have used only those digital databases which was validate by experts on recommender systems. We have selected search terms according to our main research objective and use Boolean operators to make our query string from these search terms. The resultant search query is as follows:

("Deep learning" OR "Deep Neural Network" OR "Deep structured learning" OR "Hierarchical learning") AND ("Context" OR "Contextual") AND ("Awareness" OR "Aware") AND ("Recommendation" OR "Recommender" OR "Recommendations") AND ("System" OR "Technique" OR "Approach" OR "Software" OR "Engine" OR "Technology")

By using a search query string, we have performed automatic searching in IEEE Xplore, SpringerLink, Science Direct and Web of Science databases.

Quality Assessment

The selected papers were evaluated on the basis of quality assessment (QA) by a scoring mechanism that validates their reliability, completeness and relevancy. The selected studies were appraised against a set of 4 quality criteria given in Table 2. QA questions were designed in accordance with the research scope and RQs of this SLR. The questions' scoring mechanism was determined through two grade scaling either Yes or No. The Yes is interpreted as 1 point for the candidate study; otherwise, No receives 0 points.

Table 2. Quality Assessment Criteria

QA#	Question
QA1	Is the proposed technique clearly demonstrated?
QA2	Is the application of the proposed technique clearly stated?
QA3	Is there a clear statement of limitations and contributions?
QA4	Is there any validation of the proposed method or approach?

The computation of the QA score for the selected study is calculated by taking the summation of all its 4 scores achieved in each question. Those papers are selected in the proposed SLR that attained at least 50% score in QA. Each selected study was evaluated by all authors independently. At last, the discrepancies found in the scores were discussed by all authors. In case of any disagreement, the study was re-evaluated

with the intention of getting a consensus.

Data Extraction and Synthesis

After the searching and the selection processes, the relevant data is extracted by examining the introduction, full-text and conclusion screening of each selected paper. The data extraction procedure was adapted according to the guidelines provided by Kitchenham (Kitchenham et al.2004). From each of the 19 papers selected for this SLR, the data were extracted according to a designed data extraction form (Table 3) that contains fundamental information about the studies (i.e. study identity, authors' details, publication year, article type, application domain, research methodology and QA scores. The form was designed to get a detailed full record of the articles under review and to address our research questions.

Table 3. Extraction Form

Sr #	Study Data	Description
1	Identity	Unique identity for the study
2	Bibliographic reference	Authors, Publication Year, Title and Source of publication
3	Article Type	Journal, Conference
4	Attribute related to RQ1	Techniques related to Deep learning based context aware RS
5	Attribute related to RQ2	Areas where Deep learning based context aware RS used
6	Findings/Contribution	Indicate findings and contribution of study

Results and Analysis

The data to answer derived RQs were extracted from 19 papers that fulfill inclusion criteria and qualify the QA questions. Firstly, the results of QA are presented for each study, and then the detailed analysis and outcomes based on RQs are reported.

Studies Quality Assessment

The quality assessment mechanism on selected studies increases the accuracy and reliability of data extraction outcomes. The results of QA based study evaluation facilitate establishing the validity of the synthesis of results.

The results of QA are presented in the right pane of Table 4 as scored points against each question described in Table 3.

Overview of the Papers

Table 4 presents fundamental characteristics of the selected papers extracted through our designed data extraction form. The details of compiled information are as follows:

Table 4. List of Studies with their General Information and Quality Assessment Scores

ID	Author	Year	Publication Type	Application Domain	Validation Method	QA1	QA2	QA3	QA4
S1	Bartomiej Twardowski	2016	Conference	Social media	Controlled Experiment	Yes	Yes	Yes	Yes
S2	De Maio et al.	2017	Journal	Social media	Controlled Experiment	Yes	Yes	Yes	Yes
S3	Travis Ebesu et al.	2017	Conference	Academic	Controlled Experiment, Qualitative & Quantitative Analysis	Yes	Yes	No	Yes
S4	Donghyun Kim et al.	2016	Conference	Academic	Controlled Experiment, Qualitative Analysis	Yes	Yes	Yes	Yes
S5	Gabriel de Souza Pereira Moreira et al.	2018	Conference	Social media	Controlled Experiment	Yes	Yes	Yes	Yes
S6	Yogesh Singh Rawat et al.	2016	Conference	Multimedia	Controlled Experiment	Yes	Yes	No	Yes
S7	Daniel Shapiro et al.	2017	Conference	HCI	Controlled Experiment	Yes	Yes	Yes	Yes
S8	Elena Smirnova et al.	2017	Conference	Ecommerce	Controlled Experiment	Yes	Yes	Yes	Yes
S9	A. Tripathi et al.	2018	Conference	Multimedia	Controlled Experiment	Yes	Yes	Yes	Yes
S10	Moshe Unger et al.	2016	Journal	POI	Controlled Experiment, Qualitative Analysis	Yes	Yes	Yes	Yes
S11	H. Ye et al.	2017	Conference	Academic	Controlled Experiment	Yes	Yes	Yes	Yes
S12	Heng-Tze Cheng et al.	2016	Conference	POI	Controlled Experiment	Yes	Yes	Yes	Yes
S13	J. Liu et al.	2024	Conference	Generic	Controlled Experiment,	Yes	Yes	No	Yes
S14	Xie et al.,	2019	Journal	Generic	Qualitative & Quantitative Analysis	Yes	Yes	No	Yes
S15	Aftab et al.,	2023	Journal	Generic	Controlled	Yes	Yes	No	Yes

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					Experiment				
S16	Casillo et al.,	2025	Journal	Tourism	Qualitative & Quantitative Analysis	Yes	Yes	Yes	Yes
S17	Wu et al.,	2022	Journal	Generic	Controlled Experiment, Qualitative & Quantitative Analysis	Yes	Yes	No	Yes
S18	Patel et al.,	2025	Journal	E-Commerce/ multi-Domain	Controlled Experiment	Yes	Yes	Yes	Yes
S19	Sohafi-Bonab et al.,	2023	Journal	User Interaction	Controlled Experiment, Qualitative & Quantitative Analysis	Yes	Yes	Yes	Yes

Publication Year

The papers included in our review were published between 2016 and 2025. From Fig 2, a temporal view of publications is observed since 2016. The percentage of publication in year 2016 (26%), 2017(26%), 2018 (11%), 2019(5%), 2020 (0%), 2021 (0%), 2022 (5%), 2023 (11%), 2024 (5%) and 2025 (11%) shows prominent research on intended topic in years 2016 and 2017. After that, other techniques gain more attention than simplified deep learning for CARS.

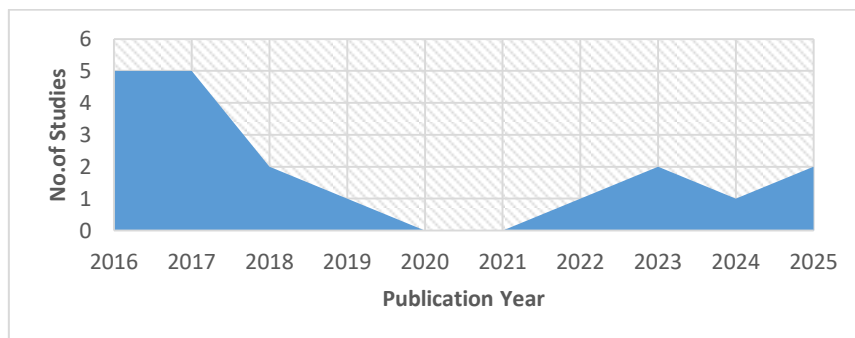


Fig 2. Temporal view of Selected Studies

Publication Type

The papers selected for our SLR are either a journal article or a conference publication. The majority of selected papers are conference publications (57.89%; 11 papers), whereas less from journal publications (42.11%; 8 papers)

Validation Methodology

As from the selected studies, the papers are classified in two categories: i) Controlled

experiment, and ii) Controlled experiment with Qualitative and Quantitative Analysis, on the basis of validation methodology.

Application Domain

The analysis of selected studies has identified nine domains (Social Media, Academic, Multimedia, HCI, Ecommerce, Tourism, Application across domain, User Interaction, and POI) where the DL based CARS are used. The majority of studies (25%; 3 papers each) are from the social media and academic domains. Further, in the domain of multimedia and POI, the next higher rate of studies is discovered (16.7%; 2 papers each). However less percentage of studies have been investigated in the domain of HCI, E-commerce, Tourism, and Applications across domains (8.3%; 1 paper each)

What techniques exist to implement context-aware recommender systems based on Deep learning?

Rawat et al. (2016) proposed a convolutional deep neural network (CNN) based context-aware tag recommender system named ConTagNet. To predict a list of user tags, CNN performs multi-label classification by integrating context with image corresponding labels and pixel values through a unified model. The system identified the significance of image labelling (assigned by the user) in context awareness.

CNN learned image from end to end to understand the contents of the image along with the context in which the image was taken. A fully connected feed-forward neural network that consists of two layers (i.e. CNN and NN) is used to process context representations. The first layer CNN mines visual knowledge from image pixels. However, the second layer NN deals with user context. The outputs generated by two neural networks are concatenated and input to a softmax function that predicts the probability of user tags. The proposed model evaluates predicated tags on three measures: recall, precision and accuracy. The validation is performed on a test dataset (YFCC100M) provided by Yahoo-Flickr (Thomee et al.2016). The test dataset provides meta information related to the image, such as image capturing time and location. To represent user context, the model utilizes this Meta information that specifies when and where the candidate image was taken. The experimental results demonstrate that the integration of context notably improves the tag prediction accuracy.

Ebsesu et al. (2017) proposed a neural citation network (NCN) for citation recommendation based on context awareness. The proposed architecture incorporates author metadata for recommendations. NCN integrates two networks, CNNs and RNNs, in an encoder-decoder framework with the attention mechanism for citation recommendation. The context of citation encoder (CNNs) captures the enduring dependencies. The decoder (RNNs) learns the probability of a word from the cited paper's titles. The learning was performed from the representation achieved by CNNs with all previous words. Using author metadata, NCN construct contextual information from citation contexts and the corresponding title. To achieve significant performance, NCN utilize only the author's name of cited literature as each writer has their own writing technique, grammatical composition, word practice and citation choice. Furthermore, the NCN model can generalize to new papers that were not

included in the training set. The validation of the proposed system is performed on CiteSeer dataset.

Experimental results present a considerable improvement of NCN over baseline methods in terms of Recall, Mean Reciprocal Rank, Mean Average Precision and Normalized Discounted Cumulative Gain. Additionally, quantitative results support significant improvement of NCN over viable baselines. Moreover, the results of qualitative analysis reveal the effectiveness of the proposed citation neural network.

Kim et al. (2016) proposed a novel context-aware document recommendation model. The model is based on the convolutional matrix factorization (ConvMF) technique that incorporates a convolutional neural network (CNN) into probabilistic matrix factorization (PMF), which is generally used for recommendation activities. CNN supports capturing the confined characteristics of documents or images through shared weights, corresponding fields and subsampling (Lecun et al.1998). Thus, CNN enhances a deeper understanding of documents and produces an improved latent model over existing approaches, particularly for items that prefer to choose their description documents due to the absence of ratings. To attain an in-depth understanding of description documents related to an item, CNN take benefit from Glove (Pennington et al.2014), one of the already trained word embedding models. Recommendation is a regression task that aims to accurately estimate user ratings on items, whereas the existing CNNs only address the classification problem. Thus, the proposed ConvMF employs both collaborative and contextual information to achieve the intended recommendation. Consequently, ConvMF precisely envisages unidentified ratings even in scenarios when the data of ratings is tremendously sparse. The proposed model is evaluated through a root mean squared error (RMSE) measure that is particularly used for conventional rating predication models. The evolution is validated through an experiment on three real-world datasets. Experimental results reveal the significant performance of the proposed model over numerous datasets that have sparse rating information. Additionally, qualitative analysis shows the effectiveness of ConvMF as it efficiently captures fine contextual variations of a word in a document

Shapiro et al. (2017) proposed an architecture based on deep learning recommender system for personal computer users. The proposed model presents an unsupervised learning technique for training a virtual assistant recommender system called Automated Virtual Recommendation Agent (AVRA). The action recommendations created by proposed system are produced in real time and personalized to the user. The proposed unsupervised learning uses context and keyword to partition all images space and words into sub regions. Two clustering mechanism are used for partitioning; i) Keyword clustering and ii) image clustering. The unsupervised learning technique is supported in AVRA through addition of clustering of keywords sets and labels of images. AVRA decipher the sequence of user interested events through histories of browser and screen content. AVRA learns new information unforeseen by its developers once it watches users and sketch fundamental associations from user actions. The proposed system interprets computer screen image to learn new keywords. To generate action recommendations for user, the system learned new contexts from linked keywords in a fully unsupervised way. The validation of the proposed model is done through testing of 3 dataset: i) Extending an

existing context of Eclipse IDE, ii) A new context through keywords of a cake recipe, and iii) From two small sets of related keywords classified according to new entities in Java program. Experimental results demonstrate that without any integration of assistant in individual programs executing on computer, the action recommendations can be produced for any user for their personalized usage. The suggested recommendations can be acknowledged with a user single mouse click.

C. D. Maio et al. (2017) proposed a method to re-rank the tweets for tweets recommendation system. The proposed method used the multi-layers perceptron feedforward neural network based on the concept of the comparative neural network (cmpNN). This ranking method takes two tweets, the user and the time as inputs. The output of the cmpNN is two values, 0 or 1, where 0 indicates the user's interest in the first tweet, and 1 indicates the user's interest in the second tweet. The tweets and users feature that cmpNN takes into consideration during the comparative process are: The tweet topics, the quality and popularity of the tweets, the publisher's authority and social relations. To evaluate cmpNN tweet ranking method, a Twitter dataset was collected by choosing two users and then extracting their network of followers and followee, the first 5000 users' data where used. The efficiency of cmpNN tweets ranking method was measured by using NDCG and Map. A good precision was achieved for both metrics in the morning and night time periods, while the metrics provide a discrete result for evening and afternoon periods.

In E. Smirnova et al. (2017) a developed version of recurrent neural network algorithm (RNN) is proposed called contextual recurrent neural network (CRNN). The difference between RNN and CRNN that RNN uses the items that the users interact with in the past while CRNN uses in addition to users' history, the time of the day that the interaction occurs in, the period between two interactions and the associated information of the interactions such as the items. CRNN was tested using two e-commerce datasets (YooChoose and Internal dataset from multiple e-commerce systems) to check its efficiency in predicting the next item. The Recall metric was the evaluation metric, and CRNN improved the recommendation results for both datasets. Another work on RNN was proposed by G. Pereira et al. (2018). The work proposed a method for next-article recommendation in a news recommendation system. The proposed method is formed by two modules. Firstly, the article content representation (ACR) and secondly, the next-article recommendation (NAR). The convolutional neural network (CNN) was used in the ACR module to extract features from the textual content and metadata of the articles, in addition to the embedded content (text distribution representation). As for the NAR module, the long-short-term memory neural network is used (LSTM). The inputs for NAR are the results of the ACR module of the last viewed article in the active session, the contextual data of the article (recency, popularity) and the user (location, time, and device). The proposed method was tested on the Globo.com dataset. By using cross validation method, two experiments were applied. The first one, applying the training and evaluating processes every 5 hours in a time period of 15 days. The second one, applying the training and evaluating processes every 1 hour on the next day. MRR and HR metrics were used to measure the efficiency of the method. The method improved the next-article recommendation, and it provides a higher accuracy than the benchmark methods.

M. Unger et al. (2016) proposed a method to use deep learning and principal component analysis (PCA) to extract the user's hidden contextual patterns (latent patterns) from the mobile sensors' raw data. The extracted latent patterns are used along with the user-item traditional data and explicit context data to make the recommendations. As using all the previously mentioned data results in a high-dimensional dataset, the PCA and auto-encoder deep neural network techniques are used for context patterns and feature extraction, thereby decreasing the dimensions.

In order to test the method, self-collected data in addition to the Foursquare API were used. They tested 3 models, matrix factorizing model (MF) (without context data), explicit context model (EC) and latent context model (LCM). Accuracy and qualitative measures were used to measure the efficiency of the method and test the previously mentioned models. For accuracy measures, RMSE and Hit@K measures were used. For measuring the performance, two metrics were used: NDCG (normalized discounted cumulative gain) and simple average. The latent context model using PCA outperforms the other models in terms of accuracy, where it improved the accuracy by 25%. In terms of performance, negative and positive feedback were taken into consideration, and the latent context deep learning patterns outperform the other models.

Heng-Tze Cheng et al. (2016) provided an integration between wide linear models and deep neural networks to collect their advantages in the Wide & Deep learning framework, by introducing the concept of memorization and generalization. Memorization is learning repetitive co-occurrence of elements or attributes and exploiting the link available in historical data. In addition, generalization explores new combinations of features that have never or barely occurred. The strategy of the proposed system is to find the related items in a database and then rank the items based on specific objectives, such as clicks or purchases. The input is a group of users and contextual information, and the output is a ranked list of items. Live online experiments have been conducted on Google Play to evaluate the framework for three weeks. A group of users are selected randomly and conducted the evaluation on the Wide & Deep mode and the previous systems, which are the wide-only model and deep-only model. As a result, using a Wide & Deep learning recommender system led to greatly increasing applications acquired in contrast with using wide only and deep only.

H. Ye et al. (2017) presented a novel context-aware recommendation system named Long Short Term matrix decomposition (LstmMF) that combines the Long Short Term neural network (LSTM) into the probability matrix factor (PMF) to gain the contextual information from the review document and further enhance rating prediction accuracy. The performance of LstmMF was evaluated on the actual dataset, and thorough experimental results showed that LstmMF significantly outperforms other advanced models. which means that LstmMF can deal with dispersed problems of the recommendations system

A. Tripathi et al. (2108) provided an original hybrid technique for context-aware video recommendation by emotional intelligence through combining the advantages of Reinforcement Learning (RL) and Recurrent Neural Networks (RNN). Where the intensity of emotional response to users is captured towards the video recommended by analysing users' facial expressions and system interactions. To evaluate the

proposed system, two datasets were selected and then tested on five real users. To train the system, 20 videos were generated with more emotions and intensities and enhancements were done by RL on streaming data. After certain repetitions, the proposed system recorded enough data to train DBRNN on it. After that, DBRNN generated Context-aware sequences and fed them to RL for optimisation. In addition, user feedback was recorded from multiple sessions to know how much the prediction is enhanced to attain more accuracy and a lower miss rate. Initially, when the users start to interact with no previous knowledge, the proposed system faced the cold start problem. However, when the number of sessions and the user are collected, the system presented less errors. Finally, the results provide evidence that the proposed approach is greatly better than state-of-the-art methods.

B. Twardowski (2016) provided a Session-Aware Recommender System in which the user information is not required. The Session-Aware Recommender System is considered a kind of context-aware recommender system. The problem with a session-aware recommender is that when the recommender items are impermanent, for example, news, internet auctions. The recommendation process depends only on the definition of one session of the user as a set of consecutive events. This paper provided two methods for a session-aware recommender system. The first method is explicit context modelling, which is a version of Factorization Machines. The second method used two types of neural networks, which are the Recurrent Neural Network (RNN) and Feed Forward Neural Network (FFNN). To evaluate the methods, two real-life datasets were used. Only sessions with more than two events are selected, and events connected with other items with more than 10 clicks. As a result, both methods based on sessions from a particular life system presented the best recommendations.

J. Liu et al. (2024) proposed an innovative self-adaptive module named “self-adaptive attention module (SAM)” that not only captures the textual information but also the contextual information to adjust the selection bias that influences the textual representation. The proposed module is incorporated in recommender systems to enable the system’s components to perform learning from this module. The results collected over three real-world datasets show the effectiveness of the proposed approach over the existing one.

Xie et al. (2019) proposed a unique paragraph vector matrix factorization (P2VMF) context-aware recommendation system that embeds an unsupervised learning of paragraph implants into probabilistic matrix factorization (PMF). The anticipated work improves the rating’s prediction accuracy by capturing the contextual information of the paragraph in contrast to existing text-based analysis systems. The results depict the improvement in rating prediction, particularly where ratings are sparse.

Aftab et al. (2023) introduced a novel contextual grid triplet network approach for context-aware recommendation. The proposed work captures the semantic information from data, items, and users by constructing a contextual grid topology. The learning process consists of the fusion of CNN with a triplet network. On the basis of a triplet network, the anticipated strategy uses a variant of the hinge loss function that boosts the quality of recommendations and improves performance.

Wu et al. (2022) presented an enhanced CARS via integration of a graph convolution

strategy in context-aware recommendations. The study proposed a Graph Convolution Machine (GCM) that consists of three major modules: encoder that create an embedded vector which reflects users, items, and contexts; graph convolution layer uses the context aware graph convolutions to refine users and items in a user-item graph; and a decoder that predict the scoring on the basis of interaction among items, users and embedded context. The experimental results over three prominent datasets from Amazon and Yelp demonstrated the efficiency of the proposed approach and its effectiveness.

Sohafi-Bonab et al. (2023) proposed an innovative deep context-aware recommendation system (DCARS). The anticipated approach incorporates and catches the dynamicity of user preferences that occurs during the recommendation procedure. The recommendations are generated using a combination of the user's long-term and short-term preferences collected from their history of interaction. DCARS utilized underlying representations of user interaction sessions. The experimental results show the efficiency of the proposed approach over other state-of-the-art existing systems.

In what areas can deep learning based context aware recommender systems be used?

In the field of social media, users share images with others and like to tag captured images before sharing. The image tags mechanism acts as a context that significantly helps other users to easily search for and discover the desired image. Inspired by this, Rawat et al. (2016) proposed a technique that explores the role of context in multi-label user-tag prophecy based on a deep neural network in the field of social media.

The growing number of items and users in the field of e-commerce enhances the sparseness of user rating data for items. To address the stated issue, Kim et al. (2016) proposed a document context-aware recommendation model, ConvMF, that captures contextual information of items from item description documents through CNN. The CNN-based technique further improves the accuracy of rating prophecy. H. Ye et al. (2017) presented a contribution in the document recommendation system through a novel context-aware recommendation system named Long Short Term matrix decomposition (LstmMF) to gain the contextual information from the review document that further enhances rating prediction accuracy.

The growing rate of scientific publications makes it complicated to locate related work or relevant citations. Through analysis of a short passage of text, Context-aware citation recommendation resolves this issue by producing a particular list of high-quality candidates. Ebseu et al. (2017) proposed an encoder and decoder architecture, called NCN, consist of CNNs and RNNs. The model integrates a strong depiction of the citation context with an NN that additionally improves with author relationships and an attention mechanism. The RNN decoder takes output from the encoder as input to provide the best possible paper for recommendation that is exclusively based on the document title.

Shapiro et al. (2017) proposed an architecture for personal computer users based on a deep learning recommender system. Action recommendations are generated in real time that are personalized to the user.

Moreover, recently in the field of point of interest (POI), DL based RS has been a hot area of research. In this area, Unger et al. (2016) proposed a method to use PCA and auto-encoder neural networks to extract and analyse users' hidden context patterns (latent patterns) and to decrease the data dimensions. Using latent patterns has proven to significantly outperform the other techniques in terms of accuracy and performance. Heng-Tze Cheng et al. (2016) provided a contribution in the POI field by integrating wide linear models and deep neural networks to collect their advantages in the Wide & Deep learning framework.

B.Twardowski (2016) provided a Session-Aware Recommender System in the field of multimedia, in which the user information is not required. By considering the same domain, Pereira et al. (2018) proposed a method to recommend the next article to the users in a news recommendation system. The method was applied using two types of deep neural networks, the CNN for extracting the features and patterns from the text contents and LSTM using the results of CNN, article contexts and users' context to make the recommendation. This method was proven to increase the accuracy of the recommendations in the same active session. Another major contribution is recorded by A. Tripathi et al. (2018), who presented a hybrid technique for contextual aware video recommendation by emotional intelligence that combines the advantages of Reinforcement Learning (RL) and Recurrent Neural Networks (RNN).

Casillo et al. (2025) proposed a personalized cultural context-aware recommender system based on cultural contextual situations. The proposed framework utilized two archaeological locations of Pompeii and Paestum for development and testing purposes. The evaluation of the anticipated system is performed in two phases. In the first phase, the accuracy and reliability are assessed using 972 user ratings gathered from Pompeii visitors. Whereas in the second phase, the user satisfaction is measured through real time cultural setting (in-situation evaluation) within the park by direct interactions. The results demonstrate the 90% improvement in user satisfaction over the existing personalized recommender systems.

Patel et al. (2025) presented a novel recommender system that overcomes the issues of existing recommender systems, such as cold start and sparsity. The proposed work combined the two innovative features, contextual awareness with time and cross-domain recommendation, to improve personalized recommendations. The recommendation is computed on the basis of a weighted similarity metric. However, the experimental results of the proposed system demonstrate the improvement in the user personalized recommendations over existing systems.

Discussion

After addressing the proposed RQs, the study has performed a detailed analysis of the whole review data and provided a summary. A thorough analysis has identified 22 DL algorithms that are incorporated in CARS to perform efficient recommendations. However, on the basis of RQ2 results, DL based CARS are classified in nine domains where they are applicable and show improved outcomes. A summary of the study findings is provided in Table 5.

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Table 5. A Summary of Review Analysis

Application Domain	ID	Year	DL Algorithm	Strategy	Context	Result
Social Media	S1	2016	FM, RNN, FFNN	Session-Aware Recommender System approach	User's clicks (search, view, watch/cart add/remove)	Improved session-aware recommendation system
Social Media	S2	2017	cmpNN	Comparing two tweets to decide the tweet of user interest	Time, date	Improving the tweets ranking especially in morning and evening time periods
Education	S3	2017	NCN (CNN+RNN)	Encoder-decoder framework with the attention mechanism	Article citations	Context-aware citation recommendation
Education	S4	2016	CoNN+MF	Item review, description and abstract	Documents Features	Improve the rating prediction accuracy of ConvMF
Multimedia	S5	2018	CNN+LSTM	A framework to recommend next-article in news recommendation using content and contextual data	Article context (recency and population), users' context(location, time, device)	Improved the next-article recommendation
POI	S6	2016	FFNN+ wide linear model	A framework to recommend next list of apps in Google Play	Input as user and contextual information, and ranked list of items is output	Increasing applications acquiring in with using wide only and deep only technology
HCI	S7	2017	AVRA	Unsupervised learning based on context and keyword	Computer Screen Features	Improved action recommendation for personalized use
E-commerce	S8	2017	CRNN	New version of RNN using more contextual data to predict next-item	Users' purchasing history, time of the events, the time gap between the events	Improved the next-item recommendation
Multimedia	S9	2018	CNN	Extracts visual information from image pixels and models user-context	Image Tags	Improves the tag prediction accuracy
POI	S10	2016	Auto-Encoder Neural Networks +PCA	Extract hidden context patterns from the raw data of mobile sensors using two ways: deep learning and PCA	Hidden context from mobile sensors data (GPS, Wi-Fi, microphone, etc), explicit context (weather, location etc)	Significantly improved the recommendation accuracy and performance
Education	S11	2017	PMF+ LSTM	Provide a novel	context information	Significantly

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			+ LstmMF	context-aware recommendation (LstmMF) by combining(LSTM) into the (PMF)	from project review documents	outperform and can deal with dispersed problems of the recommendations system
POI	S12	2018	RL+ DBRNN	Combining the strengths of RL and DBRNN to present video recommender system	users' facial expressions	Improved video suggestion results approach than state-of-the-art methods.
Generic	S13	2024	Deep Neural Module	A combined attention mechanism with self-adaptive deep neural module	User and Item contextual information	Prominent improvement in context-aware recommendation
Generic	S14	2019	Unsupervised deep representation learning (UDRL)	An unsupervised deep representation learning with embedded paragraph	paragraph-embedded user/item descriptions	Improved text-aware recommendation efficiency
Generic	S15	2023	Contextual Grid network modeling	A triple loss network with Deep metric learning and contextual grid network	Time, Location or situation, User condition and state, Item's contextual attributes	Significantly improvement in contextual similarity learning
Tourism	S16	2025	Personalized deep learning	Personalized deep learning	Cultural preference context, User place, and visit interval	Improved personalized cultural experience recommendation
Generic	S17	2022	GCN + graph convolution	A graph convolution based Graph Neural Networks (GCN) learning	Item and context relational links	Enhanced context-aware relational recommendation
E-Commerce/ Multi-Domain	S18	2025	Dynamic context modeling	A hybrid content based dynamic context modeling	User interaction history	Improved personalization in cross-domain
User Interaction	S19	2023	Deep session-based learning + neural networks	A latent context representation and deep session-based neural network learning	Short and long term user interaction session	Improved session-aware recommendations

Conclusion

In this work, we aimed to understand how deep learning has been utilised in context-aware recommender systems through SLR. More specifically, the main purpose of this SLR was to analyse which deep learning strategies can enhance the efficiency of recommender systems and identify how this concept is being applied to various fields. After analysis of all selected studies, the study concluded that deep learning-based

context-aware recommender systems show improved performance in the context of recommendations.

After conducting this SLR, the findings found that in future, a multi-layer deep learning technique incorporated in context-aware recommender systems can discover deeper user behavior patterns and provide improved recommendations. Additionally, we suggest that a meta-analysis on the same dataset is needed that acts as a benchmark and can compare all DL based CARS models to recommend the best one for generalized scenario.

References

- Cheng, H.-T., Koc, L., Harmsen, J., Shaked, T., Chandra, T., Aradhye, H., Shah, H. (2016). *Wide & Deep Learning for Recommender Systems*. Paper presented at the Proceedings of the 1st Workshop on Deep Learning for Recommender Systems, Boston, MA, USA.
- De Maio, C., Fenza, G., Gallo, M., Loia, V., & Parente, M. (2017). Time-aware adaptive tweets ranking through deep learning. *Future Generation Computer Systems*. doi:<https://doi.org/10.1016/j.future.2017.07.039>
- Ebesu, T., & Fang, Y. (2017). *Neural Citation Network for Context-Aware Citation Recommendation*. Paper presented at the Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval, Shinjuku, Tokyo, Japan.
- Kim, D., Park, C., Oh, J., Lee, S., & Yu, H. (2016). *Convolutional Matrix Factorization for Document Context-Aware Recommendation*. Paper presented at the Proceedings of the 10th ACM Conference on Recommender Systems, Boston, Massachusetts, USA.
- Mahmood, F., Abbas, K., Raza, A., Khan, M.A., & Khan, P.W. (2019). Three Dimensional Agricultural Land Modeling using Unmanned Aerial System (UAS). *International Journal of Advanced Computer Science and Applications (IJACSA)* [p-ISSN : 2158-107X, e-ISSN : 2156-5570], 10(1).
- Kitchenham, B. (2004). *Procedures for Performing Systematic Reviews*. Retrieved from Department of Computer Science, Keele University, UK:
- Khan, U. S., Ishfaq, M., Khan, S. U. R., Xu, F., Chen, L., & Lei, Y. (2024). Comparative analysis of twelve transfer learning models for the prediction and crack detection in concrete dams, based on borehole images. *Frontiers of Structural and Civil Engineering*, 1-17.
- Raza, A., & Meeran, M. T. (2019). Routine of Encryption in Cognitive Radio Network. *Mehran University Research Journal of Engineering and Technology* [p-ISSN: 0254-7821, e-ISSN: 2413-7219], 38(3), 609-618.
- Khan, S. U. R., & Khan, Z. (2025). Detection of Abnormal Cardiac Rhythms Using Feature Fusion Technique with Heart Sound Spectrograms. *Journal of Bionic Engineering*, 1-20.

- HUSSAIN, S., Raza, A., MEERAN, M. T., IJAZ, H. M., & JAMALI, S. (2020). Domain Ontology Based Similarity and Analysis in Higher Education. *IEEEP New Horizons Journal*, 102(1), 11-16.
- Khan, S.U.R., Asif, S., Bilal, O. et al. Lead-cnn: lightweight enhanced dimension reduction convolutional neural network for brain tumor classification. *Int. J. Mach. Learn. & Cyber.* (2025).
- Lecun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11), 2278-2324. doi:10.1109/5.726791
- Khan, U. S., & Khan, S. U. R. (2025). Ethics by Design: A Lifecycle Framework for Trustworthy AI in Medical Imaging From Transparent Data Governance to Clinically Validated Deployment. arXiv preprint arXiv:2507.04249.
- Meeran, M. T., Raza, A., & Din, M. (2018). Advancement in GSM Network to Access Cloud Services. *Pakistan Journal of Engineering, Technology & Science* [ISSN: 2224-2333], 7(1).
- Khan, S.U.R., Zhao, M. & Li, Y. Detection of MRI brain tumor using residual skip block based modified MobileNet model. *Cluster Comput* 28, 248 (2025).
- Moreira, G. d. S. P., Ferreira, F., & Cunha, A. M. d. (2018). *News Session-Based Recommendations using Deep Neural Networks*. Paper presented at the Proceedings of the 3rd Workshop on Deep Learning for Recommender Systems, Vancouver, BC, Canada.
- Khan, S. U. R., Asim, M. N., Vollmer, S., & Dengel, A. (2025). FloraSyntropy-Net: Scalable Deep Learning with Novel FloraSyntropy Archive for Large-Scale Plant Disease Diagnosis. arXiv preprint arXiv:2508.17653.
- Pennington, J., Socher, R., & Manning, C. (2014). *Glove: Global Vectors for Word Representation*. In *Empirical Methods in Natural Language Processing (EMNLP)*, 1532–1543
- S. ur R. Khan, Asif. Raza, Muhammad Tanveer Meeran, and U. Bilhaj, “Enhancing Breast Cancer Detection through Thermal Imaging and Customized 2D CNN Classifiers”, *VFAST trans. softw. eng.*, vol. 11, no. 4, pp. 80–92, Dec. 2023.
- Rawat, Y. S., & Kankanhalli, M. S. (2016). *ConTagNet: Exploiting User Context for Image Tag Recommendation*. Paper presented at the Proceedings of the 24th ACM international conference on Multimedia, Amsterdam, The Netherlands.
- Khan, S. U. R., Rehman, H. U., & Bilal, O. (2025). AI-powered cancer diagnosis: classifying viable (live) vs non-viable (dead) cells using transfer learning. *Signal, Image and Video Processing*, 19(15), 1326.
- Shapiro, D., Qassoud, H., Lemay, M., & Bolic, M. (2017). *Unsupervised Deep Learning Recommender System for Personal Computer Users*. Paper presented at the IARIA, Nice, France. Conference retrieved from

- Khan, S. U. R., Asif, S., Zhao, M., Zou, W., Li, Y., & Li, X. (2025). Optimized deep learning model for comprehensive medical image analysis across multiple modalities. *Neurocomputing*, 619, 129182.
- O. Bilal, Asif Raza, S. ur R. Khan, and Ghazanfar Ali, "A Contemporary Secure Microservices Discovery Architecture with Service Tags for Smart City Infrastructures ", *VFAST trans. softw. eng.*, vol. 12, no. 1, pp. 79–92, Mar. 2024
- Smirnova, E., & Vasile, F. (2017). *Contextual Sequence Modeling for Recommendation with Recurrent Neural Networks*. Paper presented at the Proceedings of the 2nd Workshop on Deep Learning for Recommender Systems, Como, Italy.
- Raza, Asif , Soomro, M. H., Shahzad, I., & Batool, S. (2024). Abstractive Text Summarization for Urdu Language. *Journal of Computing & Biomedical Informatics*, 7(02).
- Khan, S. U. R., Asif, S., Zhao, M., Zou, W., & Li, Y. (2025). Optimize brain tumor multiclass classification with manta ray foraging and improved residual block techniques. *Multimedia Systems*, 31(1), 1-27.
- Thomee, B., Shamma, D. A., Friedland, G., Elizalde, B., Ni, K., Poland, D., Li, L.-J. (2016). YFCC100M: the new data in multimedia research. *Commun. ACM*, 59(2), 64-73. doi:10.1145/2812802
- S. U. R. Khan, A. Raza, I. Shahzad and G. Ali, "Enhancing Concrete and Pavement Crack Prediction through Hierarchical Feature Integration with VGG16 and Triple Classifier Ensemble," 2024 Horizons of Information Technology and Engineering (HITE), Lahore, Pakistan, 2024, pp. 1-6.
- Khan, S. R., Asif Raza, Inzamam Shahzad, & Hafiz Muhammad Ijaz. (2024). Deep transfer CNNs models performance evaluation using unbalanced histopathological breast cancer dataset. *Lahore Garrison University Research Journal of Computer Science and Information Technology*, 8(1).
- Khan, S. U. R., Asif, S., & Bilal, O. (2025). Ensemble Architecture of Vision Transformer and CNNs for Breast Cancer Tumor Detection From Mammograms. *International Journal of Imaging Systems and Technology*, 35(3), e70090.
- Tripathi, A., A, T. S., & Guddeti, R. M. R. (2018, 9-13 July 2018). *A Reinforcement Learning and Recurrent Neural Network Based Dynamic User Modeling System*. Paper presented at the 2018 IEEE 18th International Conference on Advanced Learning Technologies (ICALT).
- Hekmat, A., Zuping, Z., Bilal, O., & Khan, S. U. R. (2025). Differential evolution-driven optimized ensemble network for brain tumor detection. *International Journal of Machine Learning and Cybernetics*, 1-26.

- Khan, Zia, Saif Ur Rehman Khan, Omair Bilal, Asif Raza, and Ghazanfar Ali. "Optimizing Cervical Lesion Detection Using Deep Learning with Particle Swarm Optimization." In 2025 6th International Conference on Advancements in Computational Sciences (ICACS), pp. 1-7. IEEE, 2025.
- Al-Khasawneh, Mahmoud Ahmad, Asif Raza, Saif Ur Rehman Khan, and Zia Khan. "Stock Market Trend Prediction Using Deep Learning Approach." *Computational Economics* (2024): 1-32
- Twardowski, B. (2016). Modelling Contextual Information in Session-Aware Recommender Systems with Neural Networks. Paper presented at the Proceedings of the 10th ACM Conference on Recommender Systems, Boston, Massachusetts, USA.
- Khan, S. R., Asif Raza, Inzamam Shahzad, & Hafiz Muhammad Ijaz. (2024). Deep transfer CNNs models performance evaluation using unbalanced histopathological breast cancer dataset. *Lahore Garrison University Research Journal of Computer Science and Information Technology*, 8(1).
- Asif Raza, Inzamam Shahzad, Ghazanfar Ali, and Muhammad Hanif Soomro. "Use Transfer Learning VGG16, Inception, and Resnet50 to Classify IoT Challenge in Security Domain via Dataset Bench Mark." *Journal of Innovative Computing and Emerging Technologies* 5, no. 1 (2025).
- Unger, M., Bar, A., Shapira, B., & Rokach, L. (2016). Towards latent context-aware recommendation systems. *Know.-Based Syst.*, 104(C), 165-178. doi:10.1016/j.knosys.2016.04.020
- Bilal, O., Hekmat, A., & Khan, S. U. R. (2025). Automated cervical cancer cell diagnosis via grid search-optimized multi-CNN ensemble networks. *Network Modeling Analysis in Health Informatics and Bioinformatics*, 14(1), 67.
- Ye, H., Zheng, X., & Rong, C. (2017, 15-17 Aug. 2017). *Hybridization of PMF and LSTM for Recommendation of Intelligent Resource*. Paper presented at the 2017 International Conference on Green Informatics (ICGI).
- Khan, Saif Ur Rehman, Asif Raza, Inzamam Shahzad, and Shehzad Khan. "Subcellular Structures Classification in Fluorescence Microscopic Images." *International Conference on Computing & Emerging Technologies*, pp. 271-286. Cham: Springer Nature Switzerland, 2023.
- Raza, Asif, Inzamam Shahzad, Muhammad Salahuddin, and Sadia Latif. "Satellite Imagery Employed to Analyze the Extent of Urban Land Transformation in The Punjab District of Pakistan." *Journal of Palestine Ahliya University for Research and Studies* 4, no. 2 (2025): 17-36.
- Bilal, Omair, Arash Hekmat, Inzamam Shahzad, Asif Raza, and Saif Ur Rehman Khan. "Boosting Machine Learning Accuracy for Cardiac Disease Prediction: The Role of Advanced Feature Engineering and Model Optimization." *The Review of Socionetwork Strategies* (2025): 1-30.

- Khan, S. U. R., Asim, M. N., Vollmer, S., & Dengel, A. (2025). Robust & precise knowledge distillation-based novel context-aware predictor for disease detection in brain and gastrointestinal. arXiv preprint arXiv:2505.06381.
- N. Mayumu, D. Xiaoheng, P. Mukala, S. U. R. Khan and M. U. Saeed, "Omni-V2X: A Vision-Language Model for Actionable Insights in Vehicle-to-Everything Systems," 2025 International Joint Conference on Neural Networks (IJCNN), Rome, Italy, 2025, pp. 1-8, doi: 10.1109/IJCNN64981.2025.11228491.
- Aftab, S., Ramampiaro, H., Langseth, H., & Ruocco, M. (2023). Deep Contextual Grid Triplet Network for Context-Aware Recommendation. IEEE Access, 11, 97522-97537. <https://doi.org/10.1109/ACCESS.2023.3310470>
- Casillo, M., Colace, F., Conte, D., Lombardi, M., Santaniello, D., & Valentino, C. (2025). A context-aware recommender system-based framework for improving cultural experiences. User Modeling and User-Adapted Interaction, 36(1), 1. <https://doi.org/10.1007/s11257-025-09437-1>
- Asif Raza, Salahuddin, Ghazanfar Ali, Muhammad Hanif Soomro, Saima Batool, "Analyzing the Impact of Artificial Intelligence on Shaping Consumer Demand in E-Commerce: A Critical Review", International Journal of Information Engineering and Electronic Business(IJIEEB), Vol.17, No.5, pp. 42-61, 2025.
- Liu, J., Wei, Z., Li, Z., Mao, X., Wang, J., Wei, Z., & Zhang, Q. (2024, 14-19 April 2024). SAM: A Self-Adaptive Attention Module for Context-Aware Recommendation System. ICASSP 2024 - 2024 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP),
- Yang, H., Khan, S. U. R., Bilal, O., Chen, C., & Zhao, M. (2025). CEOE-Net: Chaotic Evolution Algorithm-Based Optimized Ensemble Framework Enhanced with Dual-Attention for Alzheimer's Diagnosis. Computer Modeling in Engineering & Sciences, 145(2), 2401.
- S. Ur Rehman Khan, O. Bilal, S. Mistry, N. Deb, M. Mahmud and M. Bhuyan, "KDLight: A Lightweight Knowledge Distillation Framework for Medical Image Classification," 2025 International Joint Conference on Neural Networks (IJCNN), Rome, Italy, 2025, pp. 1-8, doi: 10.1109/IJCNN64981.2025.11228615.
- Patel, J., Kumar, P., Modi, H., Palkhiwala, P., Patel, J., Kapdi, R., & Patel, A. (2025). Enhancing Personalisation Using Dynamic Context-Aware and Content-Based Cross Domain Recommender System. SN Comput. Sci., 6(7), 16. <https://doi.org/10.1007/s42979-025-04303-8>
- Sohafi-Bonab, J., Hosseinzadeh Aghdam, M., & Majidzadeh, K. (2023). DCARS: Deep context-aware recommendation system based on session latent context. Applied Soft Computing, 143, 110416. <https://doi.org/https://doi.org/10.1016/j.asoc.2023.110416>

Online ISSN

3007-3197

Print ISSN

3007-3189

<http://amresearchreview.com/index.php/Journal/about>

- Wu, J., He, X., Wang, X., Wang, Q., Chen, W., Lian, J., & Xie, X. (2022). Graph convolution machine for context-aware recommender system. *Frontiers of Computer Science*, 16(6), 166614. <https://doi.org/10.1007/s11704-021-0261-8>
- Xie, J., Zhu, F., Huang, M., Xiong, N., Huang, S., & Xiong, W. (2019). Unsupervised Learning of Paragraph Embeddings for Context-Aware Recommendation. *IEEE Access*, 7, 43100-43109. <https://doi.org/10.1109/ACCESS.2019.2906659>