International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2s
DOI: https://doi.org/10.17762/ijritcc.v11i2s.6043
***Article Received**: 22 November 2022 **Revised**: 24 December 2022 **Accepted**: 02 January 2023*

A VOS analysis of LSTM Learners Classification for Recommendation System

[1]M. Jahir Pasha , [2]Channapragada Rama Seshagiri Rao, [3]A. Geetha, [4]Terrance Frederick Fernandez, [5] Y. Krishna Bhargavi

[1]Associate Professor, Department of CSE, G. Pullaiah College of Engineering and Technology, Kurnool
[2]Department of CSE ,Professor & Principal ,Vignana Bharathi Engineering College Chintapalliguda(v) Ibrahimpatnam
Email: crsgrao@gmail.com
[3]Assistant Professor, Department:-CSIT ,-CVR College Of Engineering, MangalPalli,Hyderabad
Email: songagitaabothu@gmail.com
[4]Professor ,Institute of CSE ,Saveetha school of Engineering, SIMATS
Email: frederick@pec.edu
[5]Associate Professor, Department of CSE ,Gokaraju Rangaraju Institute of Engineering and Technology, Hyderabad, India.
Email: krishnabhargavi.griet@gmail.com

Abstract

In response to the growing popularity of social web apps, much research has gone into analyzing and developing an AI-based responsive suggestion system. Machine learning and neural networks come in many forms that help online students choose the best texts for their studies. However, when training recommendation models to deal with massive amounts of data, traditional machine learning approaches require additional training models. As a result, they are deemed inappropriate for the personalized recommender generation of learning systems. In this paper, we examine LSTM-based strategies in order to make useful recommendations for future research.

Keywords: LSTM; Deep Learning; Artificial Intelligence; Machine Learning; recommendation system; VOS Software.

I. INTRODUCTION

Due to the ever-growing popularity of social Web apps, there has been a rise in the number of people looking for information online. This type of content website attracts users because of its convenience, ease of use, and ability to provide suggestions based on the user’s preferences. Companies that use business intelligence to create an individual recommendation system might propose reading materials, like books or scholarly papers, to students according to their interests [1]. Customers and businesses benefit from recommendation systems used in the education, entertainment, and retail sectors. A lot of time and effort has been put into studying and creating a customized suggestion system to anticipate the learner’s interest based on their search activity. These algorithms consider users’ reviews, comments, and search histories to make personalized recommendations [2] .

Effective recommender systems are in high demand because of the growing need for accurate and personalized student suggestions. But it’s tough to provide consumers with accurate and useful recommendations. Most websites these days employ AI-powered search engines to help students find content relevant to their needs on the web. Using traditional ML, creating recommendation models for processing massive amounts of data necessitates using extra training models. Therefore, suggestions are made using DL models. However, issues arise with these systems due to a lack of relevant data, shifting user preferences, and unpredictable content updates. This encourages the team to devote more time and energy to fixing these issues and making the recommendation system more effective. There are several recommendation system options available, but each has its limitations. The biggest problems stem from the sentiment categorization data itself. The recommendation process often involves extracting and using summary data from online users or learners, and the usage of irrelevant data might negatively impact the model’s accuracy[3] .An additional issue is that the categorization model relies too heavily on only three possible feelings (happy, sad, or neutral) and may make inappropriate suggestions. Accuracy might suffer if unneeded inputs, including irrelevant characteristics or emotions, are included. These limitations must be overcome, and the social media data extraction process should center on various emotional qualities gleaned via a mix of sentiment analysis and ontology. Incorporating deep learning techniques, which can increase the recommendation models’ accuracy, would assist in boosting the performance of recommendation systems [4].

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2s
DOI: https://doi.org/10.17762/ijritcc.v11i2s.6043
***Article Received**: 22 November 2022 **Revised**: 24 December 2022 **Accepted**: 02 January 2023*

This study examines the existing literature on online customer recommendation systems that employ cognitive intelligence or learner-driven categorization. This study aims to combine deep learning-based models with existing recommendation system models. Effective deep learning methods, such as Long-short term memory (LSTM), are combined in the learner models. We'll put the suggested model through its paces to see how well it can recommend relevant information online using what we're calling the LSTM technique.

The remainder of the paper is organized as follows: chapter 2 provides background literature, section 3 provides methodology, section 4 provides research findings and results, and section 5 provides a conclusion.

II. LITERATURE BACKGROUND

The field of machine learning, known as "recommendation engines," focuses on rating and ranking items and consumers. A recommender system is a system that, in a broad sense, anticipates the ratings a user may give to a given item. A ranked list of these forecasts will then be sent back to the user. Google, Instagram, Spotify, Amazon, Reddit, Netflix, and many more well-known websites often employ them to boost user and community interaction [5]. To keep you listening to music on Spotify, the service will suggest more tracks like ones you've recently listened to or enjoyed [6]. Amazon's recommendation feature makes product suggestions to consumers based on previous purchases and other personal information [7]. In the eyes of many, recommender systems are a mysterious "black box," as the models developed by major corporations are difficult to decipher [8]. User suggestions for items they need or desire but didn't know they needed until they saw the recommendation to the results list. This part will review the current literature on tailored suggestions and the various recommender systems.

As online systems have improved, so has an interest in recommender systems that use those improvements to provide suggestions about what other online material users would like. One of the most talked-about issues in today's internet systems, this concept was studied for years and implemented several times with great success. The recommendation systems aim to help consumers find the services they need by providing them with tailored suggestions for relevant material and products to peruse online[9] . In this phase, recommender systems try to tailor their suggestions to the individual tastes of a student. Several recommender systems have been presented to address specific issues with learning by different groups of researchers. Learning-related aspects are commonly included in recommender systems' design; these systems use the learner's behavior data to produce product suggestions[10]. Based on their guiding principles and the methods they employ when making recommendations, these systems can be broken down into four distinct classes: collaborative filtering systems, content-based recommender systems, demographic recommender systems, Knowledge-based recommender systems, and context-aware recommender systems. By including user ratings in the suggestion process, recommender systems based on collaborative filtering (CF) can better serve their users [11]. Memory-based approaches and model-based methods are two subsets of CF-based systems. Content-based (CB) recommender systems use data characteristics and include various data sources to provide suggestions. The CB-based systems connect users with the information they'll like based on what they've already viewed [12]. Demographic recommender systems use the user's profile data to tailor recommendations to each individual's interests and preferences [13]. Knowledge-based recommender systems analyze the learner's habits and tastes to make suggestions for reading materials like books or articles [14].

Implicit and explicit knowledge-related data will be collected from the user's preference data. On the other hand, context-aware recommender systems take operational context into account for various aggregate types of user data, such as the learner's current activity, location, and availability [15]. Collaborative filtering is frequently utilized in the construction of recommender systems, but it is inefficient when making real-time recommendations that consider each learner's unique qualities [16]. Further, data sparsity is a problem in these setups. Researchers have advocated using learner categorization and cognitive intelligence to provide instantaneous suggestions and solve these issues.

The proposed effort focuses on reviewing cognitive intelligence to develop effective deep learning-based recommendation systems for suggesting material. Multiple papers have suggested using AI in recommendation systems. The recommender system is built on cognitive intelligence models that evaluate user preferences, track preferences over time, and predict the user's likely interests [17] . According to the suggested study and review analyses for a banking system, traditional recommendation models do not contain any domain-related information to adapt to new circumstances, and they cannot forecast the preferences of the user based on the ratings for a certain product. Additionally, this investigation suggested that no preexisting models supported data collecting and analytics revolving around customers' cognitive activities. Several researchers described new methods for integrating cognitive models into current recommender systems. According to the suggested

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2s
DOI: https://doi.org/10.17762/ijritcc.v11i2s.6043
***Article Received**: 22 November 2022 **Revised**: 24 December 2022 **Accepted**: 02 January 2023*

analysis, all possible cognitive elements that account for the user's behavior should be designed and evaluated before making any suggestions. For example, if a student's intelligence test results indicate that they might benefit from a certain piece of material or a particular product, the framework for making these suggestions should detail the reasons for making these selections. Emerging developments like artificial intelligence and machine learning play a significant part in the recommendation services offered to users, directly correlated with the cognitive intelligence of recommender systems [18] .Previous research has demonstrated that machine learning strategies improve the efficiency of personalized recommendation systems.

III. METHODOLOGY

The study's primary objective is to educate researchers and academics about the existing body of knowledge on the subject and its current global connections. As an added benefit, this research might aid in coordinating international, multi-author, and multi-university research networks. This article employs a relational method for bibliometric research to achieve this goal. The relational approach establishes connections between papers in the same study field using a variety of studies, including but not limited to co-citation analysis, bibliographic coupling analysis, co-authorship analysis, and co-word analysis. Bibliometric analysis and science mapping are the best ways to describe the scientific landscape of a study area, either regionally or internationally. The method was used to compile findings from 495 studies published between 2016 and the beginning of 2023. The LSTM learner recommendation model was mapped by analyzing the VOS viewer program's bibliographic references to this research. Through bibliometric analysis, we were able to compile a large body of literature on the learners' recommendation model and related topics and then use that data to conclude the nature of the connections between different areas of study and how those areas are structured. In comparison to traditional reviews, such as those employing critical or narrative synthesis or meta-analysis, this method was able to synthesize a greater body of data. The rest of the study is based on the following research aims:

1. To survey the state of research on LSTM.
2. The second goal is to examine submissions according to authorship, citations, and location.
3. Find out whom the most cited and widely worked.
4. To assess how the LSTM Learners' recommending models have changed over time.

A growing field's volume and growing trend in literature may be determined by bibliometric analysis, a quantitative research strategy. It provides a historical perspective on the research outputs in a certain area of study. Performance analysis and science mapping were two methods used in the research. Publication output by country, author, affiliated institution, and annual growth rates were all factors considered in the performance evaluation. By analyzing the links between publications and the organization and development of the subject of study, bibliometric or scientific mapping analysis is another related method. Co-authorship analysis, co-word analysis, and topic development analysis were all carried out for this study. Utilizing citation data, co-citation analysis sheds light on the leading journals and authors in a certain field of study. To foresee how their profession will change over time, researchers do an evolution study.

3.1. Data Collection

Scopus's primary database served as the basis for the research. Scopus is widely recognized as a premier international scientific citation index. In addition to its focus on the recommendation model, research on the LSTM learner has found its way into machine learning, AI, deep learning, and cognitive decision-making. In the field labeled "Topic," we looked for "Long Short-term Memory," "LSTM," and similar terms. A burst of activity in this study area began in 2016, the same year that most of these papers made their debut. Figure 1 depicts the steps involved in the article-searching process and additional analysis. After a Boolean subject search, 493 documents were chosen for further review. Articles (n = 198), conferences (289), book reviews, and chapters (6 total) made up the bulk of the publications, while editorial reviews and proceeding papers (both = 5) accounted for less than 5%. All 493 papers had full data exported, including abstracts and referenced references, author and address details, publication year, Journal, title, topic categories, and other relevant information. All the information collected in the first stage was used in the second when bibliometric analysis and data visualization were performed.

We further analyzed and visualized the connections between authors, nations, journals, co-citations, and phrases using the free bibliometric analytic program VOSviewer (Visualization of Similarities). VOSviewer's engaging visual user interface allows for speedy analysis of such maps, which is especially useful given the difficulty of detecting clusters and deriving themes from them. This research also used Bibliometrix, a tool created by Massimo Aria and Corrado Cuccurullo. Bibliometrics for VOS has a built-in tool for non-coders with a graphical interface,

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2s
DOI: https://doi.org/10.17762/ijritcc.v11i2s.6043
***Article Received**: 22 November 2022 **Revised**: 24 December 2022 **Accepted**: 02 January 2023*

allowing for in-depth analysis and enhanced plot display. It uses various bibliometric techniques, such as the analysis of co-words and co-citation networks, the development of cooperation networks, and the presentation of findings in a time-series graph, to reveal the evolution of a field of study.

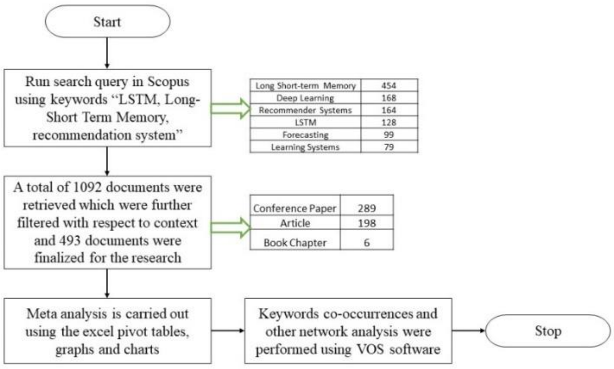

Figure 1: Data Collection and Filtering

IV. FINDING OF RESEARCH AND RESULTS

A specific form of recurrent neural network called a Long-Short-Term-Memory (LSTM) network can pick up on the importance of sequence order when learning to solve sequence prediction challenges. This trait is necessary for solving difficult problems in machine translation, speech recognition, and others. Long short-term memories (LSTMs) are a difficult subfield in deep learning. Understanding LSTMs and the connections between concepts like bidirectional and sequence-to-sequence can be challenging. The specialists who created LSTMs are among the best communicators because they can explain the technology's potential and operation in simple terms. In this research, we conduct a bibliometric study of LSTMs and their variants and a bibliometric meta-analysis of related topics.

4.1. Quantity And Development of Published Works

Figure 2 shows the evolution of the scientific field as depicted by yearly publications. The annual number of publications on the topic has increased exponentially from the idea's debut in 2016, with 2019 having the most (80) articles. In addition, the most influential authors, nations, affiliations, and keywords throughout all 493 papers included in this research were required to be viewed to grasp the overall direction. Table 1 shows the frequency of terms by country, and figure 3 shows how the top 10 countries, sources, authors, affiliations, and keywords are distributed throughout these categories. A keyword co-occurrence analysis can reveal how often a specific word was used as a keyword in the 493 documents under consideration.

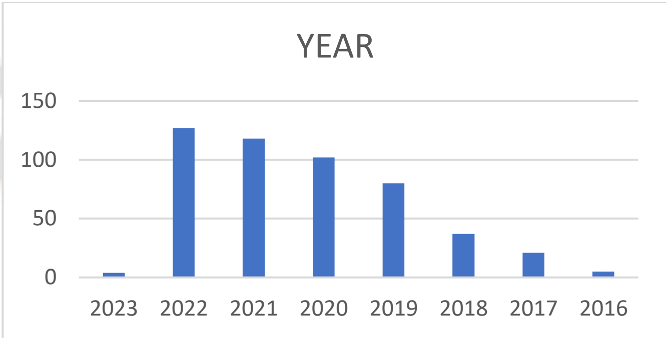

Figure 2: Yearly publication Distribution

The highest number of authors researching LSTM are from China (243), followed by India (85) and then the United States (57). The detailed author participation distribution is shown in the table 1.

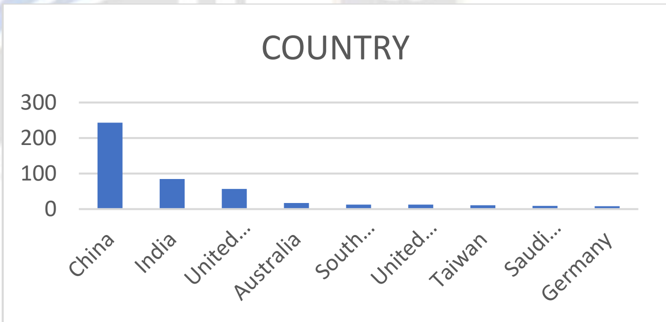

Figure 3: Top Publication Countries

Table 1: Author Country Participations

COUNTRY	COUNT	COUNTRY	COUNT	COUNTRY	COUNT
China	243	Czech Republic	4	Sweden	2
India	85	Hong Kong	4	Turkey	2
United States	57	Indonesia	4	Belgium	1
Australia	17	Iran	4	Croatia	1
South Korea	13	Japan	4	Cuba	1
United Kingdom	13	Netherlands	4	Denmark	1
Taiwan	11	Thailand	4	Egypt	1
Saudi Arabia	9	United Arab Emirates	4	Estonia	1

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2s
DOI: https://doi.org/10.17762/ijritcc.v11i2s.6043
***Article Received**: 22 November 2022 **Revised**: 24 December 2022 **Accepted**: 02 January 2023*

Germany	8	Algeria	3	Ethiopia	1
Malaysia	8	Austria	3	Luxembourg	1
Pakistan	8	Brazil	3	Mexico	1
Canada	7	France	3	Nepal	1
Greece	7	Italy	3	Peru	1
Undefined	7	Morocco	3	Romania	1
Bangladesh	6	Poland	3		
Russian Federation	6	Tunisia	3		
Singapore	6	Colombia	2		
Jordan	5	Ecuador	2		
Spain	5	Nigeria	2		
Sri Lanka	5	Norway	2		
Viet Nam	5	Qatar	2		

Figure 4 illustrates the distribution of sources of the titles from highly indexed journals named "Lecture Notes in Computer Science Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics (40)"; "IEEE Access (66)"; "ACM International Conference Proceeding Series (19)" are the top publishers. The source categories are as follows Conference Proceeding (225), Journal (201), and Book Series (68). Figure 5 illustrates the network of overlay visualization with average publication per year vs. the countries. From early 2016 to 2019 United States, Australia, Canada, and Singapore have published, extending to the United Kingdom. Saudi Arabia, India, and others have started extending their research between 2020 and 2023. Smaller countries like Jordan and Bangladesh have also entered into the LSTM research.

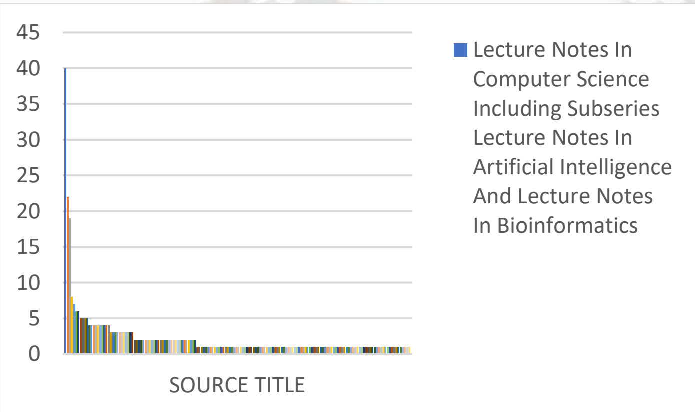

Figure 4: Source Titles

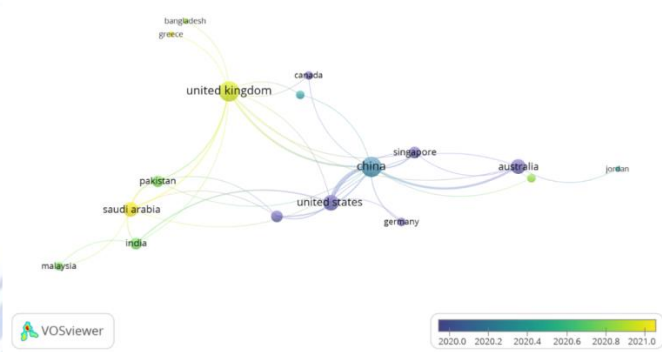

Figure 5: Average Publication per country

4.2. Authorship And Publication Mapping

When doing an authorship analysis, many authors serve as the unit of analysis. Fractional authorship, in which credit is distributed proportionally among writers, was used, and the basic analytical unit was a pair of authors. Figure 6 illustrates the distribution of the frequency of authors publishing their articles on the given topic. Top 10 authors publishing the area of Deep Learning, LSTM, and AI given as Dai, T. (n=4), Chen, Y.C. (n=3), Deepak, G. (n=3), Huang, J.L.(n=3), Lu, Y.S. (n=3), Pal, S. (n=3), Pradhan, T. (n=3), Qiu, G.(n=3), Xu, X. (n=3), Zhu, L. (n=3). Figure 8 illustrates the author's network connecting with their source institutions from China connected to the United Kingdom, Australia, and the United Nations of America. The authors from India are connected and collaboration with authors from Saudi Arabia, Pakistan, and Malaysia.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2s
DOI: https://doi.org/10.17762/ijritcc.v11i2s.6043
Article Received: 22 November 2022 Revised: 24 December 2022 Accepted: 02 January 2023

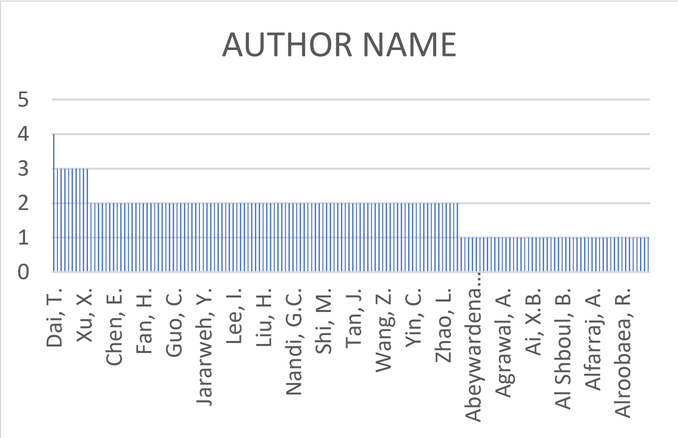

Figure 6: Authors' Publication stats

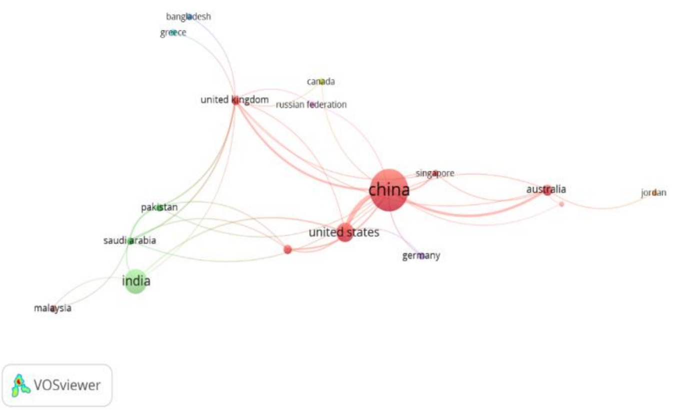

Figure 7: Author Country Affiliation

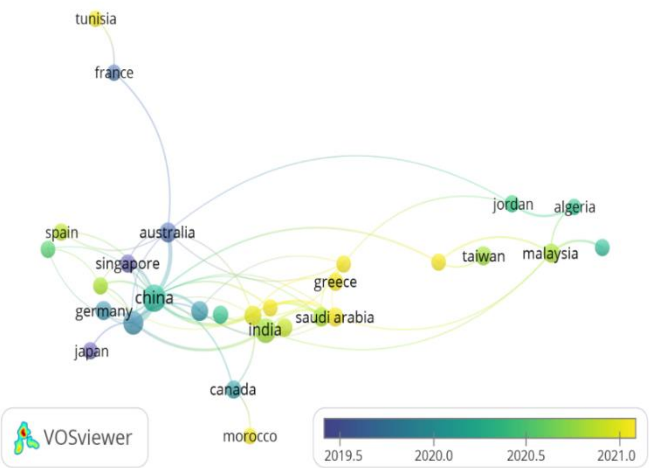

Figure 8: Average Publication Per Year

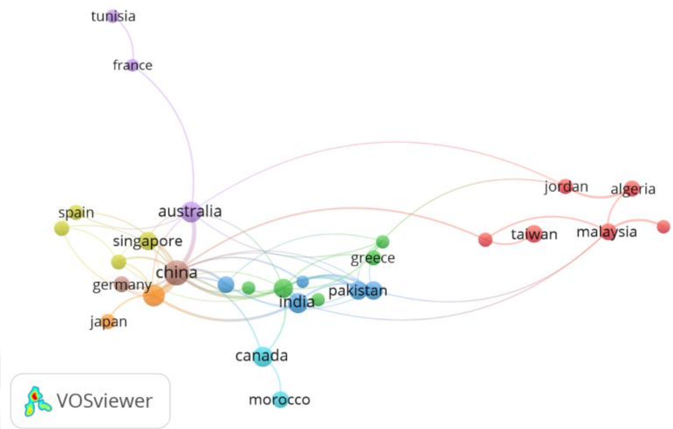

Figure 9: Average Citation Mapping Country wise

In Figure 7, the colure balls stand in for 8 collaborating clusters, with the 44 arrows denoting cooperation whose combined strength is 54.00. These clusters help reveal the authors' nationalities by weighing documents and averaging the year of publication that received the lowest possible score. Figure 8 shows that the United States of America, the United Kingdom, China, and Germany are among the nations with the strongest links. Not only do "China" and "USA" not have any direct author collaboration, but neither does "India" and "Saudi Arabia," despite their high link-weights. Other countries that helped include Canada, Jordan, Spain, and others. Figure 9 depicts the average publishing year from 2016-2022 with a color gradient from blue to yellow, where the size of the circles reflects the number of citations the document received from each country. Papers published in prior years reveal substantial connections to countries including "Australia," "Singapore," and "Canada," as indicated by the density of the yellow circles, which represents the most highly connected clusters for nations represented in the network research. Countries with whom Germany, the United States of America, and the United Kingdom have worked closely in the past are so depicted in the visualizations. Connections and partnerships have become stronger as international aid has grown. According to the data, the frontiers of knowledge and the scholars who explore them are expanding into other emerging economies, including Spain, Morocco, Taiwan, France, and Tunesia. This enhancement helps to widen the scope for potential future research contributions and author collaborations in the areas under consideration.

4.3. Co-occurrence of Keywords Analysis

Figure 10 demonstrates the frequency of use of several keywords by displaying their occurrences as larger or smaller-sized circles. The greater the circle's diameter, the more frequently that search term appears in the candidate papers. Figure 10 shows that the keywords “LSTM” (purple), “deep learning” (blue), and “recommendation system” (red) are the strongest of all items because they are connected only with “LSTM,” “Forecasting,” and “Learning Systems,” and also with “Collaborative Filtering,” “Attention Mechanisms,” “Deep Neural Networks,” and “Semantics.” Figure 11 shows the publications’ average citation scores and co-keyword link weights, with the lowest average score in dark blue and the greatest in light green (yellow). Somewhat surprisingly, publications with a high average citation score had keywords that occurred less frequently than those in low-scoring papers, while low-scoring publications had keywords that occurred more frequently than those in high-scoring publications. As a result, citing connected papers may not affect the co-occurrence of terms. The number of times a term was detected as a keyword in the 493 papers examined is revealed using keyword co-occurrence analysis.

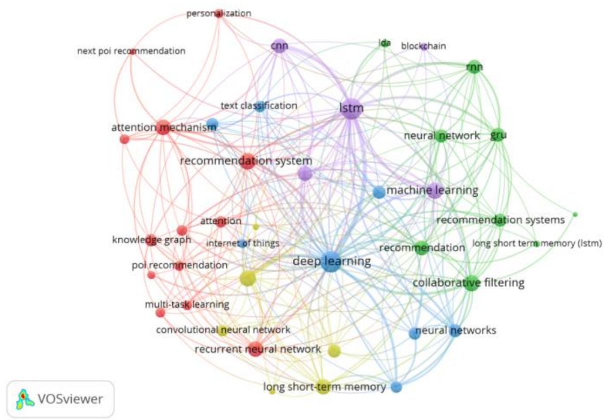

Figure 10: Keyword Mapping Associations

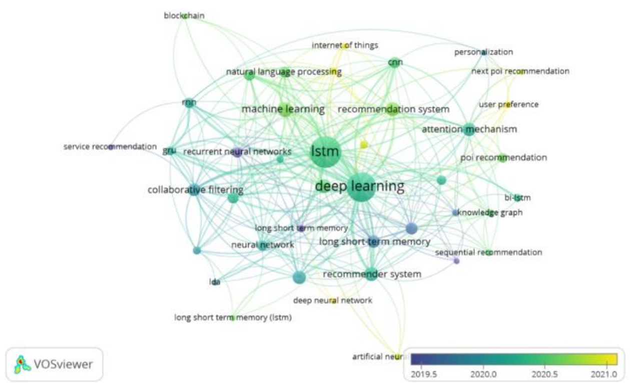

Figure 11: Keyword Mapping Citation

4.3.1. LSTM Model

The basic RNN solution LSTM, developed by Sepp Hochreiter and Jürgen Schmidhuber in 1997, can address the vanishing and expanding gradient issues. Rather than using the term “neural,” the terms “memory” and “complexity” are used to characterize LSTM’s size and complexity[19] . Compared to RNNs, the memory cells, memory blocks, or cells in LSTM networks do far more calculations. Each LSTM network consists of three gates: an input block, a memory cell, and an activation function for the output. Computes are performed by each gate in a sophisticated LSTM architecture. The gate that forgets information about a cell. The memory state is updated based on the input gate’s decision about which values will be sent out. The information stored in a memory cell can be revealed or concealed at the LSTM unit’s output, thanks to the output gate. The inputs and outputs of an LSTM block have a cyclical connection. In an LSTM, the input, forget, and output gates all have sigmoid activation functions to ensure that the input is always between 0 and 1 . In most LSTM implementations, Tanh is used for input and output activation functions. The LSTM neural network, like RNN and other neural networks, builds a learning model through iterative forward and backward operations [20] .

LSTM models are applied in several areas of research. The figure illustrates the distribution of the area of application. The application area mentioned in the figure are distributed as Computer Science (n=452); Engineering (n=194); Mathematics (n=121); Decision Sciences (n=111); Materials Science (n=33); Physics and Astronomy (n=32); Social Sciences (n=29); Business, Management and Accounting (n=23); Energy (n=22); Medicine (n=19) and Neuroscience (n=14) are the top application subject areas.

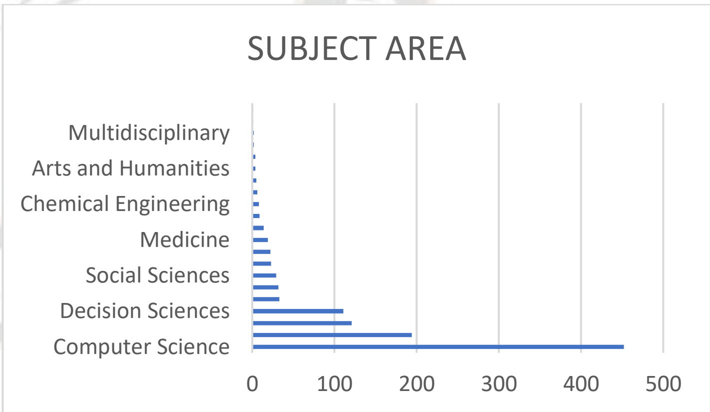

Figure 12: Application Areas of LSTM

The LSTM has revolutionized machine learning and neurocomputing. Multiple online sources attest that this technique has improved the accuracy of voice recognition by Google, machine translation by Google Translate, and Alexa’s responses. This neural system at Facebook performed approximately 4 billion LSTM-based translations daily in 2017. Until the advent of long short-term memory

(LSTM), training for recurrent neural networks was a discrete process. This recurrent network is effective because it avoids the exploding/vanishing gradient problem that arises while training recurrent and deep neural networks. [21] Sequential information is essential for many learning processes. Model sequences are needed for applications like image captioning, speech synthesis, and music composition. Models that can learn from sequences are essential for various applications, including time series prediction, video analysis, and music information retrieval. Both are necessary for tasks like translation, human-robot interaction, and dialogue. A type of connectionist model, recurrent neural networks (RNNs), can capture sequence dynamics through iterative node connections. Contrary to feedforward neural networks, recurrent neural networks may use information from any context window to represent such information. Large-scale learning with recurrent neural networks is now feasible because of recent advances in network topologies, optimization, and parallel processing. In recent years, LSTM and BRNN-based systems have achieved remarkable results in image captioning, language translation, and handwriting recognition[22]. We conducted a bibliometric review and synthesis of the research that developed and deployed LSTM learning models during the previous five years.

V. CONCLUSION

Due to the exponential increase of digital data, innovative hardware and software are required to store, manage, display, and analyze this data for maximum user benefit. Information discovery is simplified with recommender systems based on recurrent neural networks. RNN-based recommender systems have the potential to automatically train user and item feature vectors using deep learning techniques, resulting in improved recommendation accuracy, a more accurate depiction of the user base's various interests, and a fusion of heterogeneous multi-source data. In the analysis, LSTM is precisely put under Deep Learning technology, combining Artificial Intelligence, Machine Learning, and cognitive learning models. The future scope of the paper is to carry out extensive research in the less explored areas of the applications.

References

[1]. Antonopoulos, I., Robu, V., Couraud, B., Kirli, D., Norbu, S., Kiprakis, A., . . . Wattam, S. (2020). Artificial intelligence and machine learning approaches to energy demand-side response: A systematic review. Renewable and Sustainable Energy Reviews, 130, 109899. https://doi.org/10.1016/j.rser.2020.109899

[2]. Batmaz, Z., Yurekli, A., Bilge, A., & Kaleli, C. (2018). A review on deep learning for recommender systems: challenges and remedies. Artificial Intelligence Review, 52(1), 1–37. https://doi.org/10.1007/s10462-018-9654-y

[3]. Beheshti, A., Yakhchi, S., Mousaeirad, S., Ghafari, S. M., Goluguri, S. R., & Edrisi, M. A. (2020). Towards Cognitive Recommender Systems. Algorithms, 13(8), 176. https://doi.org/10.3390/a13080176

[4]. B.Nagesh, Ch.Harika(2015) .Recommendation System for Find Friend on Social Networks. International Journal of Computer Engineering In Research Trends,2(12).1188-1191.

[5]. Habeebunissa Begum, G.S.S Rao(2017). Associating Social Media to e-Merchandise - A Cold Start Commodity Recommendation. International Journal of Computer Engineering In Research Trends,4(10).378-382.

[6]. N.SATISH KUMAR, SUJAN BABU VADDE (2015). Typicality Based Content-Boosted Collaborative Filtering Recommendation Framework. International Journal of Computer Engineering In Research Trends,2(11).809-813.

[7]. Telaprolu Swamulu, P.Sujatha(2015). Social Network Based "FndSearch" Recommender Framework. International Journal of Computer Engineering In Research Trends,2(10).847-852.

[8]. Huang, Y., Obada-Obieh, B., & Beznosov, K. (2020). Amazon vs. my brother: How users of shared smart speakers perceive and cope with privacy risks. Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, 1-13.

[9]. Javed, U., Shaukat, K., Hameed, I. A., & Iqbal, F. (2021). A review of content-based and context-based recommendation systems. International Journal of Emerging Technologies in Learning (iJET), 16(3), 274-306.

[10]. Antonopoulos, I., Robu, V., Couraud, B., & Kirli, D. (2020). Artificial intelligence and machine learning approaches to energy demand-side response: A systematic review. Renewable and Sustainable Energy Reviews.

[11]. Batmaz, Z., Yurekli, A., Bilge, A., & Kaleli, C. (2019). A review on deep learning for recommender systems: challenges and remedies. Artificial Intelligence Review, 52(1), 1-37.

[12]. Beheshti, A., Yakhchi, S., Mousaeirad, S., & Ghafari. (2020). Towards cognitive recommender systems. Algorithms, 13(8), 176.

[13]. Deldjoo, Y., Noia, T. D., & Merra, F. A. (2021). A survey on adversarial recommender systems: from attack/defense strategies to generative adversarial networks. ACM Computing Surveys (CSUR), 54(2), 1-38.

[14]. Fan, C., Wang, J., Gang, W., & Li, S. (2019). Assessment of deep recurrent neural network-based strategies for short-term building energy predictions. Applied energy, 700-710.

[15]. Feng, C., Liang, J., Song, P., & Wang, Z. (2020). A fusion collaborative filtering method for sparse data in

recommender systems. Information Sciences, 521, 365-379.
[16]. González, A., Ortega, F., Pérez-López, D., & Alons. (2022). Bias and Unfairness of Collaborative Filtering Based Recommender Systems in MovieLens Dataset. IEEE Access, 10, 68429-68439.
[17]. Huang, Y., Obada-Obieh, B., & Beznosov, K. (2020). Amazon vs. my brother: How users of shared smart speakers perceive and cope with privacy risks. Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, 1-13.
[18]. Javed, U., Shaukat, K., Hameed, I. A., & Iqbal, F. (2021). A review of content-based and context-based recommendation systems. International Journal of Emerging Technologies in Learning (iJET), 16(3), 274-306.
[19]. Khanal, S. S., Prasad, P. W., & Alsadoon, A. (2020). A systematic review: machine learning based recommendation systems for e-learning. Education and Information Technologies, 25(4), 2635-2664.
[20]. Lüders, M. (2021). Pushing music: People’s continued will to archive versus Spotify’s will to make them explore. European Journal of Cultural Studies, 24(4), 952-969.
[21]. Mohamed, M. H., Khafagy, M. H., & Ibrahim, M. H. (2019). Recommender systems challenges and solutions survey. 2019 International Conference on Innovative Trends in Computer Engineering (ITCE), IEEE, 149-155.
[22]. Monsalve-Pulido, J., Aguilar, J., & Montoya, E. (2020). Autonomous recommender system architecture for virtual learning environments. Applied Computing and Informatics.