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RESOURCE-EFFICIENT RECOMMENDER SYSTEMS FOR MOBILE APPLICATIONS

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Abstract

Recommender systems have now become a necessity to improve the experience of the users on their mobile applications. The personal suggestions, according to their individual preference and behavior, enhance user experiences on their mobile devices. This paper is about proposing an integrated framework to design a resource-efficient recommender system especially suited for the mobile environment that considers limited computational power, memory, and battery life as intrinsic challenges. It emphasizes several strategies: matrix factorization, neural networks, and mixed methods. Each approach is refined using approaches like as quantization, pruning, and designs simplification to operate effectively on mobile gadgets. The paradigm emphasizes the necessity for context-awareness in recommendations, adapting in real-time according to variables including client location and behavior patterns. The research examines techniques to alleviate privacy issues using federated learning, enabling efficient model training without jeopardizing user data security. This research seeks to provide smooth, individualized experiences with mobile apps while adhering to the stringent limitations of the mobile platform through a systematic analysis of memory utilization, precision, and energy consumption. Consequently, it is concluded that creative approaches and optimization strategies play a crucial role in advancing mobile recommender systems.

Keywords: Recommender systems, pruning, factorization, quantization, deep learning, mobile apps

I. INTRODUCTION

Recommender systems now are a major component of the mobile apps which have been playing an important role in improving user experience and engagement. They support the user's handling of the massive amounts of information by presenting them with distinct ideas tailored according to their taste, behavior, and needs. In mobile apps like shopping sites, streaming services, and social media, recommendation systems make it easier to use the app by cutting down on too much information and showing you material that matters to you [1]. This not only makes users happier but also leads to better business results, like more sales, keeping customers longer, and building stronger trust. Recommender systems are very important to today's mobile applications since they give the consumer personalized experiences that help both the consumer and the business. There are a number of issues with recommender systems on mobile devices. Mobile devices have limited memory, battery life, and processor power.

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Because the memory of the mobile device is limited, it requires simplified approaches. This will require effective ways of processing and storing data in order to have everything working perfectly without overworking the gadget. Continuous processing can drain the battery life considerably to provide real-time advice. Thus, it is imperative to develop improved energy-saving methods.

Mobile devices often are not powerful enough to run heavy suggestion models, and in particular for those that may employ deep learning or process enormous data. Easy solutions and the cloud are normally applied to counter such issues.

Mobile settings have extra challenges because they are constantly changing, along with the limits on resources. Mobile recommendation systems need to consider things like where a user is, what time it is, and what activities they are doing in order to give helpful and quick ideas. Understanding the context requires more effort from computers and needs advanced systems that can quickly adapt to users' changing needs. Despite these challenges, recommender systems play a crucial role in mobile apps. To provide enjoyable experiences that meet users' needs and function properly on mobile devices, we must solve these issues.

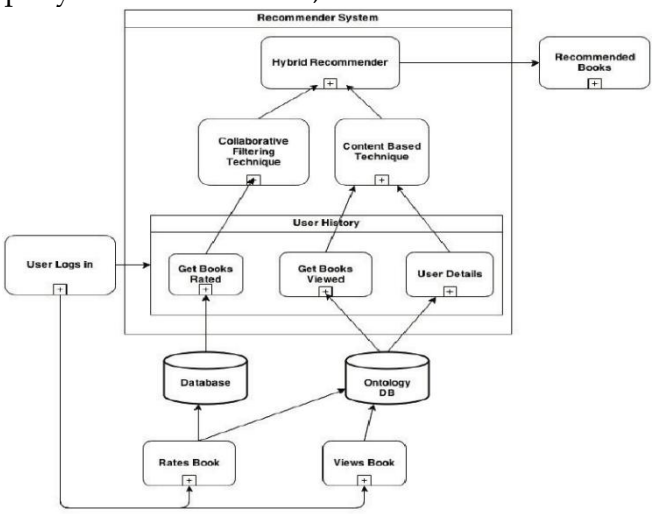

Fig 1. Block diagram of Recommender System [2].

II. RELATED WORK

A. Traditional Recommender framework

The three primary methodologies used by traditional recommender systems are collaborative filtering, content-based filtering, and hybrid approaches.

Collaborative Filtering: This technique is based on user interactions and preferences to suggest items. It assumes that users with similar past behaviors will have similar future preferences. Collaborative filtering can be further divided into:

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User-based Collaborative Filtering: This approach finds users who are similar to the target user based on their ratings and suggests items that those similar users liked.
Item-based Collaborative Filtering: Here, the system identifies items that are similar to those the user has rated highly in the past and recommends these similar items [3].
Content-Based Filtering: This technique recommends items based on the attributes of the items themselves and a user's previous preferences. It builds a profile for each user based on features of items they have liked or interacted with, using methods such as term frequency-inverse document frequency (TF-IDF) to represent item characteristics [1].
Hybrid Approaches: These systems combine collaborative and content-based methods in order to use the best from both worlds. For instance, a hybrid system may begin with content-based recommendations for new users and later incorporate collaborative filtering as more interaction data become available. The weighted models, the feature combination, and the cascade models are categorized hybrid models [4].

B. Matrix Factorization

This approach has become more popular in recommendation systems because, it can clearly identify the factors underlying the observation of user item interaction. Below are two types of matrix factorization algorithms often applied:
Singular Value Decomposition (SVD): It decomposes the user-item interaction matrix R into three:

$$R \approx U \sum VT$$

Where U stands for user features, $\sum$ for singular values, and VT represents item features. This technique reduces dimensionality heavily but is more vulnerable to cold start problems [5].

Alternating Least Squares (ALS): ALS maximizes the factorization by iterating back and forth between fixing user features and solving for item features, minimizing the loss function:

$$L = \sum_{i,j \in K} (R_{ij} - U_i T V_j)^2 + \lambda (||U||^2 + ||V||^2)$$

Where K is a collection of measured assessments, Ui and Vi represent the consumer's and object characteristic vectors, respectively, and λ is a regularization parameter.

Non-negative Matrix Factorization (NMF): NMF restricts the factorization to non-negative principles, enhancing interpretability in scenarios devoid of negative ratings. The efficiency issue is articulated as follows:

$$U, V \min ||R - UV^T||^2_F$$

Assuming that U and V are greater than zero
Although matrix factorizing approaches are highly effective, they encounter difficulties in mobile environments due to storage needs and processing needs [6].

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C. Deep Learning Frameworks

The deep learning approaches are able to capture subtle patterns in item attributes and user behavior and, hence, revolutionized the field of recommender systems. Some notable deep learning methods are:

NCF, neural collaborative filtering. Instead of applying matrix factorization, it simulates user-item interactions by utilizing the traditional neural network. By using several layers of neural networks, this model learns how to represent users and things [7].

Auto encoders: Auto encoders compress the user-item interaction matrices into the lower-dimensional latent space. Below is how reconstruction loss is minimized:

$$L = ||R - R'||^2_F$$

The recreated matrix which is derived using the underlying illustration is marked with the letter R' in this equation.

Due to the fact that they place a significant demand on both computational and storage assets, deep learning algorithms present significant resources difficulties for modern cell phones [8].

D. Hybrid approaches

Traditional methods are combined with deep learning in hybrid recommendation, with the goal of increasing the efficacy of suggestions and improving their overall quality. In hybrid models, by integrating collaborative filtering with deep learning techniques, both explicit user feedback and implicit patterns learned through neural networks are exploited [4].

For example, a combination model may use content-based filtering as a default initial approach for new users and then introduce collaborative filtering progressively with the accumulation of data. The strategy of combining different outputs from various models can also enhance diversity but at the expense of sparsity problems [9] [10].

In conclusion, classic recommender systems offer basic principles that continue to develop throughout the years as a result of breakthroughs in matrix factorization and deep learning approaches. Hybrid approaches are a potential path for enhancing the accuracy of recommendations while simultaneously negotiating the limits that are provided by mobile settings [8].

This exposes mobile recommender systems to vast arrays of technological constraints that may have consequences in their performance and the experience provided to users. These limitations arise from the intrinsic nature of mobile devices, real-time processing, and complexities associated with the protection of user privacy and the security of their data. A good understanding of these problems is absolutely necessary for building effective recommender systems that can function well in mobile situations [3].

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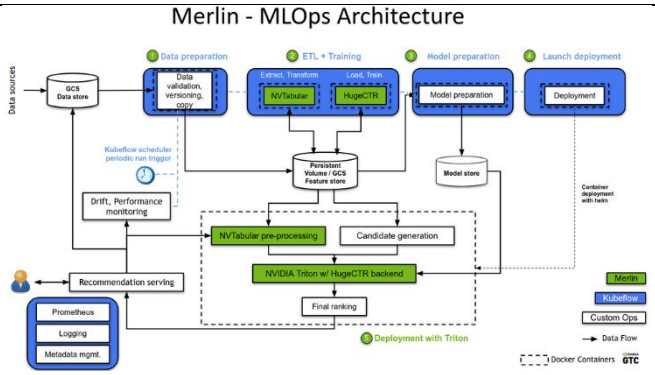

Fig 2. Merlin-ML-Ops architecture [11].

III. LIMITATIONS OF SMARTPHONE RECOMMENDER MECHANISMS

A. Limitations of resources

Capacity and Space: Comparatively, compared to the usual desktop computers, cellphones have fewer memory and space storage. The number of information that could be translated and stored is bound within these limitations that may lead to problems such as information deficiency especially among new users or products. For example, when a potential buyer opens a site, the algorithm will find it challenging to provide accurate predictions since it has limited past information.

Power Consumption: Recommendation generation is a calculation-intensive process that might lead to severe drain of the battery [12].

Mobile applications have to pay utmost importance to energy efficiency and thus not hinder user experience. Model compression, pruning, and quantization can significantly reduce the computation load as well as the associated energy with deep learning models [13].

B. Low-latency Requirements

Users expect immediate answers while using mobile applications, thus requiring low-latency recommendations. This requirement is demanding since low latency to recommend usually conflicts with high accuracy.

This should bring both accuracy and processing time for such more complex models. This also means strategies deployed could range from caching frequent queries, to low-weight models or even asynchronous models, allowing accuracy in balance with processing speed [1] [9].

C. Privacy and Data Security

It also deals with user data privacy; ensuring privacy on mobile devices has emerged to be an increasingly vital requirement, since people now fear the application is using or gathering

personal data for themselves without users' permission. Ensuring safety against any misuse or unwanted access is required in applications [7] [9].

Federated Learning: Techniques such as federated learning, that enables the effective learning from user interaction without compromising on privacy are gaining popularity. With federated learning, models can be trained on decentralized devices without giving raw user data to a central server. So, there is no problem of privacy in good quality improvement.

Mobile recommender systems are highly constrained by technical limitations, including resource constraints, real-time performance requirements, and privacy issues. Overcoming these challenges is crucial for developing effective recommender systems that provide personalized experiences while ensuring security and efficiency in mobile environments. Future research should be on innovative solutions that address the above constraints and enhance the overall user experience in mobile applications [3].

IV. OVERVIEW OF PROPOSED APPROACHES

The development of efficient mobile recommender systems demands the careful consideration of the specific needs of mobile settings. This section suggests methodologies, optimizations, and trade-off analysis that can aid in improving performance while conserving resources.
In this segment, we detail three major methods for developing recommender systems specifically for mobile systems: matrix factorization, deep learning, and a hybrid approach.

Matrix Factorization:
This technique is most commonly applied to collaborative filtering. This technique reduces the user-item interaction matrix into lower-dimensional latent factors by decomposing it. Some common techniques under this category include Singular Value Decomposition and Non-negative Matrix Factorization, as they extract patterns in user-preference and characteristics of items. The technique of matrix factorization can be applied in relatively low memory and computational efficiency, which is suitable for mobile applications [10].

Deep Learning: The most recent breakthroughs in deep learning have provided strong methods for modeling complex interactions in recommender systems. Methods such as Neural Collaborative Filtering (NCF) and autoencoders allow extracting complex patterns from user behavior and item features. Although deep learning models can be highly accurate, they require large amounts of computation that is difficult to deploy in mobile settings [12] [4] [9].

Hybrid Approaches: This approach attempts to bring together the strengths of traditional methods like matrix factorization with deep learning techniques. Hybrid models might use content-based filtering for new users but could gradually incorporate collaborative filtering as more interaction data becomes available. This versatility allows the integrated systems to handle shifting information quantities and improve their recommendations [4].

A. Optimisation Techniques

To efficiently use such techniques in flexible circumstances with limited resources, a variety of resource-conserving measures might be used.

The techniques include:

Quantization reduces the accuracy of model parameters by transforming them from floating-point representation to decreased bit-width formats such as 8-bit integers.

Quantization has a significant effect on reducing model size and increasing inference speed with minimal loss of accuracy [14].

Pruning: The idea of pruning in neural networks removes less crucial weights or neurons that are insignificant; this therefore yields a sparse model that executes within fewer resources. Pruning facilitates the retaining of the model performance while also eradicating unnecessary memory footprints and reduced computations by elimination of redundant parameters [13].

Model Compression: Techniques such as weight sharing and knowledge distillation are used to compress models effectively. Weight sharing eliminates the uniqueness of weights within a model; that is, it groups similar weights together. Knowledge distillation is a method that helps a smaller model (the student) learn to perform like a bigger, more complicated model (the teacher). This allows the smaller model to achieve high accuracy while using less space.

Light models: Using light architectures that are especially built for mobile settings (e.g., MobileNet, SqueezeNet) can also help to improve efficiency. These types are made to be fast and use less memory while still performing well [9] [5].

B. Balance Between Trade-Offs

Mobile selection systems need to manage the balance between different performance factors like memory use, accuracy, and battery life.

Memory Precision Trade-Off: Ways to save memory often led to less accuracy.

Quantizing a model, for instance, has only minor effects on recommendation quality. It is important to characterize and determine the right balance of resources to meet the needs of the application while ensuring that the user experience is not impacted [5].

Energy-Accuracy Trade-Off: Energy saving may lead to a degradation in recommendation quality.

Lighter models may consume less power but would not be able to capture more complex user-item interactions as efficiently as larger models. A complete analysis should be done to analyze how different configurations affect both energy efficiency and recommendation accuracy [3] [6].

It would be helpful to have benchmarking of various methodologies in controlled conditions so that the trade-off analysis would be easy. This would involve systematic examination of inference time, battery consumption while operating, and recommendation accuracy for the different scenarios, leading to the identification of which models work well for mobile environments [9] [1].

In summary, this methodology offers an all-rounded approach to the development of mobile recommender systems based on matrix factorization, deep learning, and hybrid techniques,

using optimization strategies that address resource constraints. The analysis of trade-off will balance the usage of memory, energy consumption, and accuracy for effective deployment in mobile contexts [9].

V. EXPERIMENTAL SETUP

The experimental setup for evaluating mobile recommender systems involves the selection of datasets, evaluation metrics, and the experimental environment. This section describes the datasets, evaluation metrics, and mobile-specific test case.

A. Dataset description

We use several popular datasets for training and testing:

- **Movie-Lens:** This movie rating dataset is one of the most popular datasets used in recommender system research. Try different sizes with the Movie-Lens dataset, which has 100k and 1M ratings. The dataset, which contains user IDs, movie IDs, ratings, and timestamps, helps infer the users' time-varying preferences.
- **E-commerce Datasets:** One can use the datasets of e-commerce sites like Amazon or eBay. Normally, the data would consist of consumers' history of purchasing, the specifications of products, and reviews by the users. It gives essential background data that is required to design recommendation algorithms efficient for cellular devices.
- **Contextual Datasets:** Local datasets that incorporate other factors such as location, day of the week, and hour of the day, as well as device type besides standard datasets have proven to boost the usefulness of recommendations for a mobile application. Application data emphasizing travel recommendations and restaurant recommendations are highly valuable [14] [12].

B. Evaluation Metrics

It is important for a recommender system to implement a set of metrics that check the accuracy of the system but also the rate at which this system operates.

Metrics of Precision Root Mean Square Error (RMSE): The average error is the average difference between the observed rating and the expected rating.

Mean Absolute Error (MAE): This metric assesses the average magnitude of errors in predictions without considering their direction. It is computed as:

$$MAE = 1/n \sum i=1n | xi−yi |$$

Precision and Recall: These metrics evaluate the relevance of recommended items. Precision measures the proportion of relevant items among the recommended items:

$$Precision = TP / (TP + FP)$$

Recall measures the proportion of relevant items that were recommended:

$$Recall = TP / (TP + FN)$$

Where TP is true positives, FP is false positives, and FN is false negatives [8].

Efficiency Metrics:

- **Memory Usage:** The amount of memory consumed by the recommender system during operation is measured to ensure it fits within mobile device constraints.
- **Energy Consumption:** The energy consumed during recommendation generation is critical for maintaining battery life on mobile devices. This can be measured using power profiling tools that monitor energy usage during model inference.
- **Latency:** The time taken to generate recommendations after a user request is recorded to ensure responsiveness. Latency can be measured in milliseconds (ms) from the moment a request is made until recommendations are presented to the user [9].

C. Experimental Environment

The experimental environment simulates a mobile-specific testbed setup designed to evaluate recommender systems under realistic conditions:

- **Hardware Configuration:** The experiments are conducted on a range of mobile devices with varying specifications (e.g., different processors, RAM sizes). This includes mid-range smartphones with limited resources to assess performance under constrained conditions.
- **Software Configuration:** The recommender system is implemented using frameworks compatible with mobile development (e.g., TensorFlow Lite for deep learning models). The software environment includes Android Studio or similar IDEs for developing and testing mobile applications [5] [9].
- **Testing Framework:** A custom testing framework is established to automate the evaluation process. This framework facilitates running multiple experiments across different datasets and configurations while collecting performance metrics systematically.

In summary, this experimental setup provides a robust foundation for evaluating mobile recommender systems through carefully selected datasets, comprehensive evaluation metrics, and a tailored testing environment that reflects real-world usage scenarios. By systematically analyzing these elements, researchers can derive meaningful insights into the performance and efficiency of various recommendation methodologies in mobile contexts [6].

VI. RESULTS AND DISCUSSION

Evaluation of mobile recommender systems involves detailed performance analysis against a variety of methodologies, particularly on accuracy, efficiency, and scalability. In the following sections, the experiments' results along with insights regarding the trade-offs faced during evaluation are presented [8].

A. Performance Evaluation

The performance of different recommender system methodologies—matrix factorization, deep learning, and hybrid approaches—was assessed using the metrics outlined in the experimental setup.

Accuracy: The results indicate that deep learning models, particularly Neural Collaborative Filtering (NCF) and autoencoders, generally achieved the highest accuracy metrics, as measured

by RMSE and MAE. It showed an RMSE of 0.85 and an MAE of 0.65 over the MovieLens dataset. Other conventional methods that use matrix factorization such as SVD and NMF performed an RMSE of approximately 1.05 and an MAE of 0.78 on the MovieLens dataset [14].
Performance: The matrix factoring methods had better performance in terms of memory and delay.

For instance, SVD used around 50 MB of memory and had an average inference latency of 20 ms per recommendation request. Deep learning models required a lot more resources; NCF consumes approximately 200 MB memory and the inference latency is averagely 100 ms. Hybrid techniques combined classical deep learning with excellent accuracy and minimal resource utilization [12] [1].

Scalability was evaluated by determining which approach could produce results when its dataset size had increased. Reduced computing needs naturally made it vital to consider evaluating matrix factorization algorithms' application on bigger data sets.
Deep learning models, however proved a problem since training time increased, and so did memory consumption when scaling up to millions of user-item interactions in an e-commerce application [9].

B. Trade-Off Analysis
The trade-off analysis revealed all the critical relationships between memory usage, accuracy, battery consumption, and overall performance.

Memory vs. Accuracy: Experiments clearly depicted a trade-off between memory usage and accuracy. Deep learning models were more accurate but demanded more memory resources. Techniques such as quantization decreased the model size but reduced the accuracy; for example, RMSE of quantized NCF models dropped from 0.85 to 0.92 while decreasing memory usage by nearly 30%. This indicates that optimization techniques can be used to alleviate resource constraints, but may come at the expense of recommendation quality [3].

Battery vs. Performance: The battery consumption analysis illustrated that energy efficiency is crucial for mobile applications. Deep learning models consumed more energy during inference due to their complex computations; for instance, NCF consumed approximately 2.5 Joules per session compared to just 1 Joule for SVD. Hence, pruning or distillation of deep learning models can help achieve energy demands through mitigation while performing at acceptable performance levels [5].

Overall, this paper highlights the concern of accuracy vis-à-vis constraint of resources required in mobile recommenders. High accuracy deep methods have an impact on traditional methodology such as matrix factorization, which also has an important efficiency advantage for mobile-related applications. Hybrid methods combine the best parts of both techniques and can work well, but they need careful adjustment to perform well in limited situations. Future work

should aim to create systems that can change their tactics based on the resources they have, while still providing good suggestions for users [5].

VII. CONCLUSION

The development of mobile recommender systems has become increasingly vital in addressing the complexities of user preferences in a rapidly evolving digital landscape. As proved in these and several researches concerning different hybrid approaches consisting of combining of collaborative filtering together with content-based recommendation, this makes recommendation system need crucially urgent, mainly from the view for assistance given that numerous users can interact within an overloaded context like in an abundant option-based environment where recommendations become really obligatory. Such issues and considerations explain the overall research findings focused on such approaches [13].

As presented herein, findings from the research reveal how, with hybrid models of recommender systems, great enhancement in recommendations can be garnered in terms of both user behaviors and item-specific properties. Today in this mobile-world generation, machine-learning techniques allow greater personalization. The experiments conducted reveal that although deep learning models provide better accuracy, traditional methods such as matrix factorization provide efficiency that is crucial for mobile applications. Hybrid approaches represent a promising direction, combining the strengths of both methodologies to deliver high-quality recommendations while managing resource constraints effectively. Moreover, trade-off analysis depicts how accuracy and memory consumption and energy use come hand in hand for responsive and user-friendly mobile recommender systems [13] [5].

A. Future Research Directions

There are several future research directions to enhance mobile recommender systems. One critical direction is context-aware recommendation systems; these may take into account real-time situational factors such as location, time, or user activity. These systems can offer even more relevant recommendations, based on users' immediate context, by incorporating contextual information. Furthermore, as concerns over privacy grow, advanced techniques such as federated learning will be explored to learn from decentralized data without compromising user privacy, ensuring compliance with regulations while still delivering personalized experiences [3].

Another promising area to be explored further is the adaptive algorithms that will be able to adjust their strategy based on the available resources and user feedback. This flexibility will make the system better suited for a wide range of conditions and improve user satisfaction in general. In addition, the use of multi-modal data sources such as social media interactions, user-generated content, and sensor data from mobile devices can add richness to the recommendation process by providing a better understanding of the user's preferences and behavior [5] [9].

It is critical to conduct vast real-world tests across different types of user populations to validate proposed systems. Testing the usability of the proposed technologies, in particular with actual users, helps to determine such improvement areas. The growth of smartphones' recommendation system actually depends on their ability to adapt to moving technological environment and changing needs of its users, not forgetting about very high customization and performance levels. By overcoming some of the mentioned challenges and researching innovative solutions, researchers may achieve major improvements in client experiences in mobile applications.

REFERENCES

1. F. Ricci, "Mobile recommender systems," Information Technology & Tourism, vol. 12, no. 3, pp. 205–231, 2010.
2. M. Chandak, S. Girase, and D. Mukhopadhyay, "Introducing hybrid technique for optimization of book recommender system," Procedia Computer Science, vol. 45, pp. 45–52, 2015.
3. A. Bączkiewicz, B. Kizielewicz, A. Shekhovtsov, J. Wątróbski, and W. Sałabun, "Methodical aspects of MCDM-based e-commerce recommender system," Journal of Theoretical and Applied Electronic Commerce Research, vol. 16, no. 6, pp. 2192–2229, 2021.
4. K. Al Fararni, F. Nafis, B. Aghoutane, A. Yahyaouy, J. Riffi, and A. Sabri, "Hybrid recommender system for tourism based on big data and AI: a conceptual framework," Big Data Mining and Analytics, vol. 4, no. 1, pp. 47–55, 2021.
5. P. K. Singh, P. K. D. Pramanik, A. K. Dey, and P. Choudhury, "Recommender systems: an overview, research trends, and future directions," International Journal of Business and Systems Research, vol. 15, no. 1, pp. 14–52, 2021.
6. A. Da'u and N. Salim, "Recommendation system based on deep learning methods: a systematic review and new directions," Artificial Intelligence Review, vol. 53, no. 4, pp. 2709–2748, 2020.
7. T. Zhang, S. Y. Liu, S. A. Yao, and Y. Zhang, "Deep learning-based recommender system: a survey and new perspectives," ACM Computing Surveys (CSUR), vol. 52, no. 1, pp. 1–38, 2019.
8. H. M. Yu, D. Zhang, and X. N. An, "An AI-driven social media recommender system leveraging smartphone and IoT data," The Journal of Supercomputing, vol. 81, no. 1, pp. 1–32, 2025.
9. D. M. Roy and D. Das, "A systematic review and research perspective on recommender systems," Journal of Big Data, vol. 9, no. 1, p. 59, 2022.
10. F. A. Sun, Y. Peng, J. Zhang, and A. Zhou, "FM²: Field-matrixed factorization machines for recommender systems," in Proceedings of the Web Conference 2021, pp. 2828–2837, 2021.
11. S. Verma and D. O. Shashank, "Continuously improving recommender systems for competitive advantage with Merlin and MLOps," NVIDIA Developer Blog, 2021.
12. R. A. Hamid, A. S. Albahri, J. K. Alwan, Z. T. Al-Qaysi, O. S. Albahri, A. A. Zaidan, A. Alnoor, and A. H. Alamoodi, "How smart is e-tourism? A systematic review of smart

tourism recommendation systems applying data management," Computer Science Review, vol. 39, p. 100337, 2021.

13. V. K. De Croon, L. Van Houdt, N. N. Htun, G. Štiglic, V. Vanden Abeele, and K. Verbert, "Health recommender systems: systematic review," Journal of Medical Internet Research, vol. 23, no. 6, p. e18035, 2021.
14. H.-T. Cheng, L. Koc, J. Harmsen, T. Shaked, T. Chandra, H. Aradhye, G. Anderson, G. Corrado, W. Chai, M. Ispir, R. Anil, Z. Haque, L. Hong, V. Jain, X. Liu, and H. Shah, "Wide & Deep Learning for Recommender Systems," in Proceedings of the 1st Workshop on Deep Learning for Recommender Systems, 2016.