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Digital Sensor-Aware Recommendation Systems: A Progressive Framework Using Agentic AI and Explainable Hybrid Techniques †

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Abstract

In the current scenario, the recommendation system is challenging to maintain due to three key requirements: the need for real-time user behavior analysis, the inability to explain why recommendations are made, and struggles to handle new users/items. In this article, our objective is to develop a hybrid recommendation system that solves the challenges of traditional approaaches. Our framework combined real-time learning, agentic rules, as well as sensor compatibility in a dynamic environment. We develop a novel framework called SAFIRE (Sensor-Aware Framework for Intelligent Recommendations and Explainable Hybrid Techniques), where the 8 traditional algorithms (User-Based CF, Item-Based CF, KNNWithMeans, KNNBaseline, SVD, SVD++, NMF, BaselineOnly), a Hybrid ensemble, and Explainable AI are used to recommend it. From our experimental work, it reveals that the accuracy of BaselineOnly provides an RMSE score of 5-fold RMSE of 0.5156, and MAE is 0.34055. Similarly, 10-fold CV of RMSE is 0.51558, and MAE is 0.34069. The lowest MAE of the 5-fold is 0.29913. For 10-fold, NMF MAE is 0.30144. This study also conducted the statistical test and found that Memory-Based CF (KNN variants, UserCF, ItemCF), having 10-fold CV, performs slightly better than 5-fold., p-values are significant.NMF, the mean difference is −0.00248 very small improvement in 10-fold CV, and p-values < 0.05, which is significant. Model-based techniques like BaselineOnly, NMF, and SVD show little variation (mean difference < 0.003) and hold up well during CV folds.

Keywords: progressive recommender systems; digital behavioral sensors; traditional algorithms; digital sensor analytics; unsupervised machine learning; filtering approach

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1. Introduction

In today's digital market, Product Recommender systems have a pivotal function in delivering customized suggestions to users on the basis of their preferences and browsing history. Traditional recommendation systems are based on some filtering techniques, such as collaborative filtering and content-based filtering, for suggesting preferred products to users. Though these methods function effectively with good results, they still have some limitations cold-start problem, a lack of personalization, and a lack of transparency during recommendations of the products. To overcome the above issues, hybrid recommendation systems came into existence, where a combination of multiple recommendation techniques, such as collaborative, content-based, and ARM (association rule mining), is implemented. But, with an increase in users' experience and engagement in e-business, users' demand for transparency and understanding of why a particular product is recommended increased, where trust and decision-making play a crucial role. To meet the above challenges, Explainable Hybrid Recommendation Systems came into existence with the combination of ARM, filtering algorithms, and explainable Artificial Intelligence (XAI) not only enhances user trust and transparency and understanding of why a particular product is recommended but also increases the user satisfaction and acceptance of recommendations.

Major Contribution

1. This study utilizes an 8 collaborative filtering approach for a product recommendation system.
2. This study uses statistical significance testing (*t*-test, Wilcoxon signed-rank test) to confirm reported improvements are not random. This study uses statistical significance testing (*t*-test, Wilcoxon signed-rank test) to confirm that reported improvements are not random.
3. Developed an approach that uses error measures (MAE, RMSE) and hypothesis testing to assist people in choosing the best recommendation algorithm.
4. In this paper, we have developed a framework (Digital Sensor-Aware Recommendation Systems) that improves e-commerce decision-making by giving accurate results and statistically supported recommendations.

This study consists of a 4-section study, and our objective was to recommend the product. Section 1 presents the introductory concept of the product recommendation, digital sensors, explainability, etc., as well as discusses the motivation of product recommendation. Section 2 presents the state-of-the-art of product recommendation through the various techniques. Section 3 discusses the material and methods for product recommendation. Section 4 presents the results and discussion, followed by a conclusion.

2. Materials and Methods

Perumal, B., et al. [1] The authors proposed the recommendation system as well as used the XAI technique. Though the existing explainable recommendation system is popular in e-commerce many times, it affects user satisfaction and trust due to a lack of explanations in the product recommendation. To achieve this goal, it contributes to some visibility, trustworthiness, effectiveness, and customer satisfaction of recommendation systems. Hashmi, E., & Yayilgan, S. Y. (2024) [2] sentiment analysis is employed using three distinct embedding methods, including TF-IDF, Word2Vec, and FastText. It results in the FastXCatStack model, which achieved accuracy scores of 0.93, 0.93, and 0.94 on mobile electronics, major appliances, and personal care appliances datasets, respectively, and linear SVM showed an accuracy score of 0.91 on software reviews when combined with FastText.Zhang, Y., et al., [3] the author focused much on recommendation categorization and discussed 5 "WH" words, such as how recommendation is possible, where recommendation is possible, etc. Chaudhary, M., et al., [4] Based on the challenge of understanding and explaining the outcomes generated by AI algorithms that affect the trustworthiness of the user, the Explainable AI (XAI) is introduced, which focuses more comprehensible to users. These systems aim to provide instant justifications, filling the gap left by current technologies that struggle to offer thorough explanations of the decision-making process behind AI-generated results or recommendations. Vultureanu-Albişi, A.,et al., [5] In this paper, we introduce a model that generates high-quality recommendations, proposing to develop intuitive and trustworthy explanations. The problem that the explainable recommendation wants to solve is to let people understand why certain elements, rather than others, are recommended by the system. This ur work contributes to understanding the concept of explainable recommendation and what it should accomplish to increase its acceptability and to enable its accurate evaluation.

Sanjammagari, H. S. G., et al., [6] the adaptive XAI framework is used to explain the fitness of user-level expertise by classifying users into novice, intermediate, expert, and advanced users with domain-specific knowledge. Our approach strengthens user trust, promotes digital literacy, and improves the user experience generally. Here, BERT transformers were also implemented on a recommendation dataset and have achieved better scores (above 0.9) between input user queries and recommendations. Chen, C., et al. [7] the authors demonstrate that the presence of post hoc explanations increases interpretability perceptions, which in turn fosters positive consumer responses (e.g., trust, purchase intention, and click-through) to AI recommendations. Sreelakshmi, A., et al. [8] presented how the hybrid algorithms help us to make effective decisions for product recommendation. The author explores the different rules and discovers the effective one for recommendation. Their objective was to use the apriori and FP-Growth algorithm individually, as well as make them a hybrid to see the efficient rules. Padhy, N., et al. [9], the authors used the association rule mining algorithms (Apriori, FP-Growth) and collaborative filtering algorithms such as SVD, SVD+, ALS for product recommendation. Along with this, the author used the item-based filtering (KNNBasic) to recommend the E-Commerce products.

3. Results and Discussion

Proposed Model for Digital Sensor-Aware Recommendation Systems

The following Figure 1 discusses how the product recommendation is possible through collaborative approaches. This model comprises the 4 phases altogether to recommend the product as well as interpret the model prediction.

Phase 1: Data Acquisition (Sensor-Aware Layer): In this phase, we have done the data prepossessing where the data sources were Opt devices, wearable trackers, and smart devices. The dataset consists of different features, which consist of timestamp,visitor_id, event,item_id, and transaction_id. These are the features that are there in this dataset. The above structure helps with recommendation logs. The feature time_stamp is created during purchasing any product, Visitor_id is the unique ID of the users, and it is an important feature for user-based collaborative filtering and personalization purposes we used. What type of interaction is done, either view, cart, or purchase, this information is available in the event feature, and item_id is used for item-based similarity computation purposes. Phase 2—Data Preprocessing & Feature Engineering: In this phase, we have cleaned the dataset. During this process, we removed the null entries, duplicate logs, as well as incomplete entries. Finally, we prepared the Structured user-item matrix. Phase 3 –Model Layer. In this phase, we used the 8 recommendation algorithms in parallel, and these are as follows:-User-Based CF: this algorithm is used to identify similar users based on the historical interactions. Item-Based CF: This algorithm is used to find the co-occurrence of patterns to recommend them. KNNWithMeans: It is used when you compute for similar users/items. KNNBaseline: This algorithm is suitable when we need to increase the accuracy (user baseline ratings). SVD and SVD++: This algorithm is suitable for matrix factorization purposes as well as increasing the SVD with feedback signals. NMF: It is used for generating the interaction matrix. BaselineOnly: This algorithm is used to predict the ratings. Our objective was to generate a ranked list of the recommended products for the user. The hybrid ensemble layer is created to see how best the recommendation can be possible. Phase 4—Explainable AI (XAI) Layer: In this phase, we have interpreted the product recommendation algorithms. We used three different methods to achieve such as SHAP and LIME. Our objective was to provide a transparent recommendation system. We have evaluated the items preferred by similar visitors. Items similar to what the visitor has already interacted with, and a ranked list of item_id values for each visitor_id.

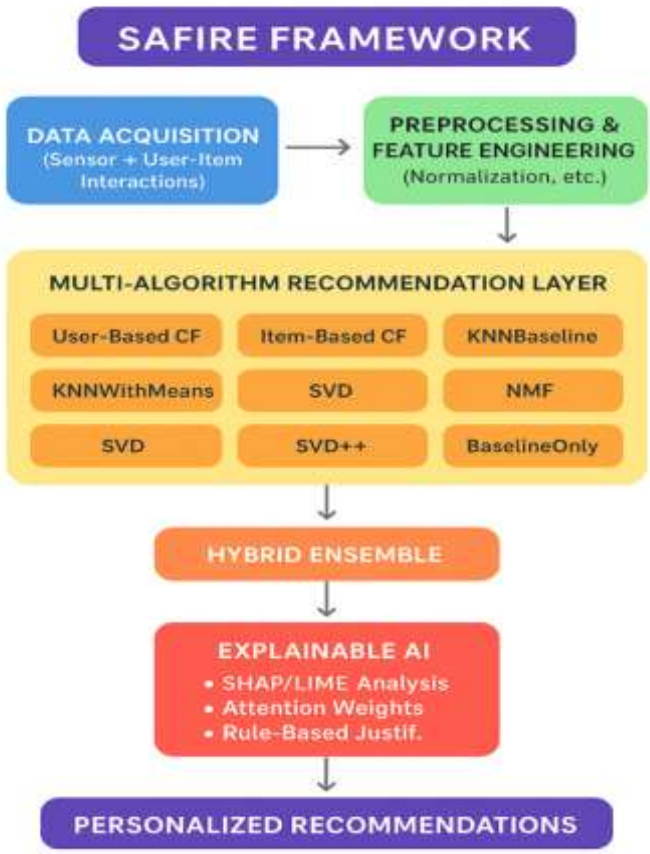

Figure 1. Proposed model for a product recommendation system using a collaborative filtering approach.

Given a target user (visitor_id), SAFIRE employs eight collaborative filtering algorithms, a hybrid ensemble, and XAI to offer a prioritized list of item_ids with which the person is most likely to interact or purchase next.

Table 1 discusses the performance metrics. Here, we used 5 5-fold cross-validation with 8 collaboration filtering techniques for product recommendation. The performance metric RMSE was considered to recommend the product. The CXF model, like Baseline Only, obtained the lowest RMSE (0.5156) score, and the MAE is 0.34055. The matrix factorization method obtained SVD (RMSE: 0.52695, MAE: 0.34235) and SVD++ (RMSE: 0.52733, MAE: 0.34205) of the relationship between the product and the users. Overall, these findings show that matrix factorization and baseline-enhanced models are more suited for accurate product rating predictions, resulting in more reliable personalized recommendations than typical neighborhood-based collaborative filtering.

Table 1. 5-Fold Cross-Validation Performance Metrics**.**

Algorithm	RMSE	MAE
BaselineOnly	0.5156	0.34055
SVD	0.52695	0.34235
SVD++	0.52733	0.34205
KNNBaseline	0.54874	0.34948
Item-Based-CF (KNNWithMeans)	0.56062	0.34646
NMF	0.56173	0.29913
User-Based-CF (KNNWithMeans)	0.56252	0.35977
KNNWithMeans (default)	0.56617	0.36609

Table 2 discusses the 0-fold cross-validation technique for a product recommendation system. It has been observed that the BaselineOnly model gives the best RMSE (0.5156) and MAE (0.3407) performance. The factorization method VD (RMSE 0.5267, MAE 0.3423) and SVD++ (RMSE 0.5272, MAE 0.3422) stabilized in 10-fold cross-validation.

Table 2. 10-Fold Cross-Validation Performance Metrics.

Algorithm	RMSE	MAE
BaselineOnly	0.51558	0.34069
SVD	0.52665	0.34231
SVD++	0.52722	0.3422
KNNBaseline	0.53726	0.34685
Item-Based CF (KNNWithMeans)	0.54965	0.34492
User-Based CF (KNNWithMeans)	0.5516	0.35408
KNNWithMeans (default)	0.55418	0.36002
NMF	0.56018	0.30144

Table 3 presents the comparison between 5-fold CV and 10-fold CV. It has been observed that the factorization method provides good results. Memory-based techniques benefited from the higher training portion in a 10-fold CV, with RMSE reductions ranging from 0.0109 to 0.0120 and MAE improvements reaching 0.0061.

Table 3. Comparison of 5-Fold and 10-Fold Cross-Validation Results.

No.	Algorithm	RMSE (5-Fold)	MAE (5-Fold)	RMSE (10-Fold)	MAE (10-Fold)	ΔRMSE (10–5)	ΔMAE (10–5)
1	BaselineOnly	0.5156	0.34055	0.515579	0.340685	−0.00002	0.000131
2	SVD	0.52695	0.34235	0.52665	0.342311	−0.0003	-3.6×10^{-5}
3	SVD++	0.52733	0.34205	0.527224	0.342195	−0.0001	0.000146
4	KNNBaseline	0.54874	0.34948	0.537263	0.346854	−0.01147	−0.00262
5	Item-Based CF (KNNWithMeans)	0.56062	0.34646	0.549647	0.344923	−0.01097	−0.00153
6	User-Based CF (KNNWithMeans)	0.56252	0.35977	0.551603	0.354075	−0.01091	−0.0057
7	KNNWithMeans (default)	0.56617	0.36609	0.554182	0.360023	−0.01198	−0.00607
8	NMF	0.56173	0.29913	0.56018	0.301441	−0.00155	0.002311

The mentioned Tables 4 and 5 are meant for the RMSE score of 5-fold vs 10-fold cross-validation. The baseline-only algorithm is the best because it obtained a consistently lower RMSE score (0.515879 for 5-fold, 0.515715 for 10-fold). The difference is negligible, and it is with (mean difference = –0.00016, and Cohen's d = –1.833, which is negligible. We also conducted the paired *t*-test and obtained the t-value is t = –5.796, $p = 0.000261$. The model SVD++ and SVD obtained a higher RMSE score and its mean (≈0.527), (SVD: $p = 0.3666$) or marginally significant (SVD++: $p = 0.0250$). But the CF algorithm memory-based (KNNBaseline, User-CF, Item-CF, KNNWithMeans) showed a marginal improvement when it shifted from 5-fold to 10-fold CV. The mean RMSE between them is –0.01053 and –0.01135, and $p < 0.001$. Baseline: Only provide the best performer as a comparison to the other collaborative filtering algorithms because of the lowest RMSE.It doesn't lower RMSE, but also improves statistical stability and consistent performer for product recommendation.

Table 4. Detailed Statistical Results.

Algorithm	RMSE (5-Fold) Mean	RMSE (5-Fold) Std	RMSE (10-Fold) Mean	RMSE (10-Fold) Std	Mean Diff (10–5)	SD Diff	Cohen's D
KNNBaseline	0.54832	0.00069	0.537218	0.000212	−0.0111	0.000541	−20.525
User-CF (KNNWithMeans)	0.56258	0.000952	0.552052	0.000764	−0.01053	0.000632	−16.664
Item-CF (KNNWithMeans)	0.561638	0.000793	0.550315	0.000655	−0.01132	0.000699	−16.189
KNNWithMeans (default)	0.565748	0.001012	0.554403	0.000674	−0.01135	0.000736	−15.417
NMF	0.56133	0.000592	0.55885	0.000916	−0.00248	0.000968	−2.56
BaselineOnly	0.515879	0.000212	0.515715	0.000182	−0.00016	0.00009	−1.833
SVD++	0.527289	0.000466	0.527018	0.000402	−0.00027	0.000319	−0.849
SVD	0.527568	0.000703	0.527408	0.000489	−0.00016	0.000534	−0.301

Table 5. Detailed Statistical Results with testing hypothesis.

T-Stat	*p*-Value (t)	Wilcoxon W	*p*-Value (W)	CI Low	CI High	Significant @ 0.05
−64.906	0	0	0.001953	−0.01149	−0.01072	YES
−52.697	0	0	0.001953	−0.01098	−0.01008	YES
−51.193	0	0	0.001953	−0.01182	−0.01082	YES
−48.754	0	0	0.001953	−0.01187	−0.01082	YES
−8.096	0.00002	0	0.001953	−0.00317	−0.00179	YES
−5.796	0.000261	1	0.003906	−0.00023	−0.0001	YES
−2.685	0.025006	8	0.048828	−0.0005	-4.3×10^{-5}	YES
−0.951	0.366602	19	0.431641	−0.00054	0.000221	NO

Table 6. Hypothesis Test Summary.

Algorithm	Mean Diff (10–5)	*p*-Value (*t*-Test)	*p*-Value (Wilcoxon)	Significant @ 0.05
KNNBaseline	−0.0111	0	0.001953	YES
User-CF (KNNWithMeans)	−0.01053	0	0.001953	YES
Item-CF (KNNWithMeans)	−0.01132	0	0.001953	YES
KNNWithMeans (default)	−0.01135	0	0.001953	YES
NMF	−0.00248	0.00002	0.001953	YES
BaselineOnly	−0.00016	0.000261	0.003906	YES
SVD++	−0.00027	0.025006	0.048828	YES
SVD	−0.00016	0.366602	0.431641	NO

In Figure 2, we have done a comparison of collaborative filtering algorithms for product recommendation. The statistical significance of the different folds has been estimated for different CF algorithms. We observed that the CF models, such as KNNBaseline, User-CF (KNNWithMeans), Item-CF (KNNWithMeans), and KNNWithMeans (default), perform a highly significant improvement with $p < 0.001$ in RMSE under the 10-fold CV. But SVD doesn't statistically significant difference and $p > 0.05$. This figure demonstrates that neighborhood-based CF is more sensitive to the folds. But we observed the matrix factorization method relatively unaffected. All the models found that significant difference in RMSE except SVD.

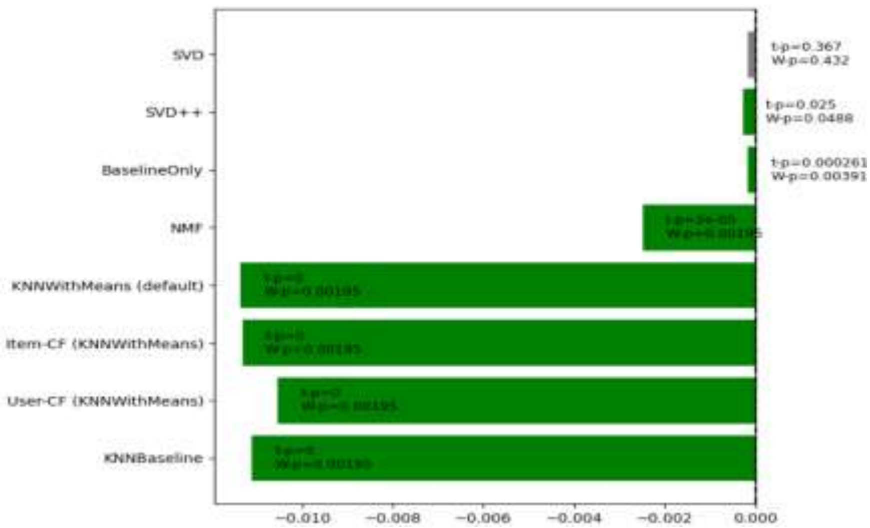

Figure 2. Comparison of collaborative filtering algorithms for product recommendations using a statistical test.

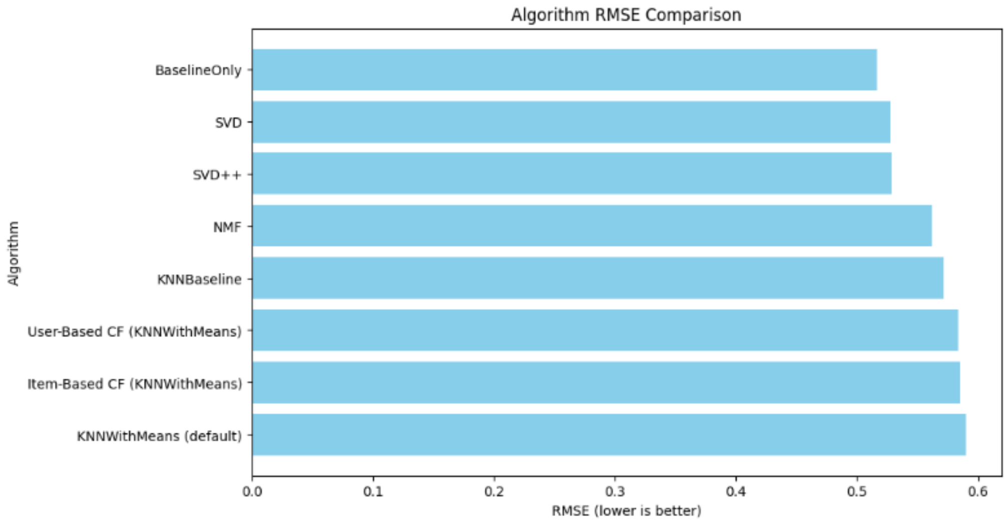

Figure 3. RMSE comparison of different collaborative filtering approaches.

The above-mentioned Figure 2 presents the RMSE comparison of 8 collaborative filtering algorithms. This figure reveals that the CF models, such as BaselineOnly, SVD, and SVD++, obtained a lower RMSE score (≈0.51). It means the model is performing well. Again, the CF model, like NMF and KNNBaseline RMSE score that is a little bit higher (~0.55). These findings show that matrix factorization techniques (SVD, SVD++) and baseline-adjusted methods are better at reducing prediction mistakes than traditional neighborhood-based collaborative filtering. This shows how well they can find hidden patterns of how users interact with items.

Figure 4 discusses the mean RMSE of the 5-fold as well as 10-fold cross-validation. In this case, we have estimated the 5 and 10-fold cross-validation scores and present them in the bar graph to represent which cross-validation is the best choice for product recommendation. It has been observed that 5 5-fold CV represents the blue and 10-fold CV is for orange. The 10-fold CV constantly gives a lower RMSE score as comparison to the 5-fold CV. That means when we increase the number of folds, the performance increases. Especially observed in the case of neighborhood-based collaborative filtering methods.

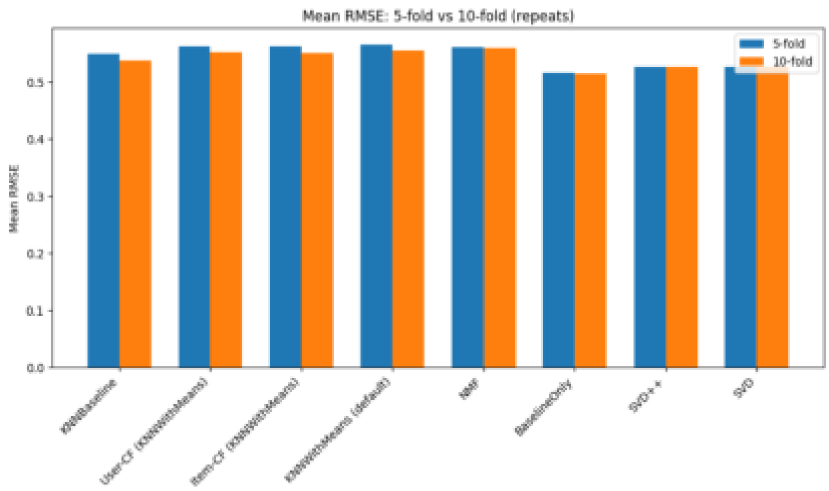

Figure 4. Comparison of Mean RMSE between 5-fold and 10-fold.

The above-mentioned Figure 5 demonstrates the difference between the 10-fold CV and 5-fold CV of different algorithms along with 95% confidence intervals. We obtained the negative value, which means the performance is improved with a 10-fold CV. It has been observed that the lower RMSE is a better choice. NMF performance is not good, but we observed a significant improvement in the RMSE.NMF also shows a modest but significant improvement. On the other hand, BaselineOnly, SVD++, and SVD show differences that are very close to zero, with SVD's interval crossing zero to show that there was no statistically significant change. These results show that adding more folds is good for most algorithms, especially those that use neighborhood-based joint filtering. However, matrix factorisation methods like SVD aren't affected.

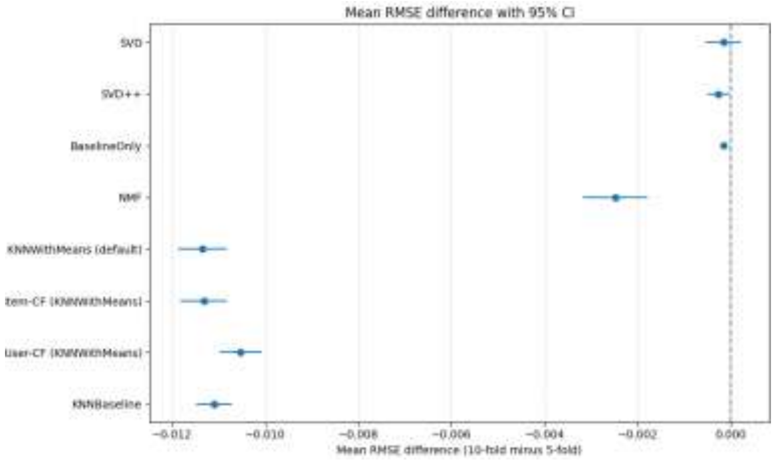

Figure 5. Mean RMSE difference (10-fold minus 5-fold).

The above-mentioned Figure 5 presents the RMSE comparison between 5-fold nd 10-fold CV. We have considered the 8 collaborative filtering approaches to see whether 5-fold or 10-fold CV is best for product recommendation. It has been observed that there is a marginal difference between these two folds. The difference occurred in the 3rd decimal place. Memory-based methods, like User-Based CF and KNNWithMeans (default), have slightly lower RMSE in the 10-fold setup. This suggests that adding a little more training data per iteration might lead to small improvements in performance.

The above-mentioned Figure 6 presents the MAE comparison between 5-fold and 10-fold cross-validation. We used the 8-recommendation algorithm. We observed that the MAE score is almost the same for the validation strategies. Some approaches exhibit a little bit of improvement. Such as memory-based (User-Based CF (KNNWithMeans) and KNNWithMeans (default)). Between the 5-fold CV and 10-fold CV, the 10-fold CV performed well with marginal improvement for the collaborative filtering method.

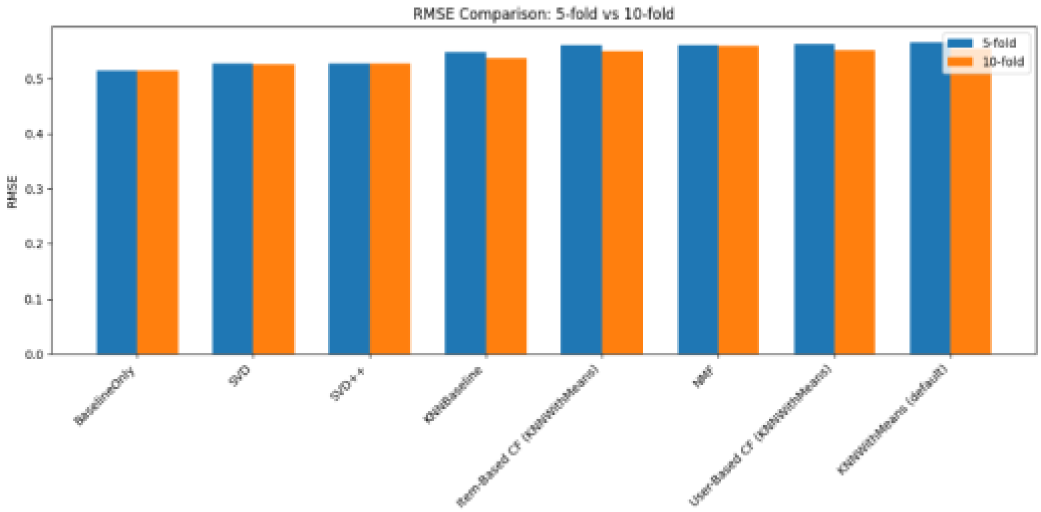

Figure 6. Comparison of RMSE between 5-fold and 10-fold.

Figure 7 discusses for transition from 5-fold to 10-fold cross-validation of product recommendation. We utilized the 8 CF algorithm to accomplish the task, where RMSE is considered one of the performance metrics. The X-axis represents the difference between 10-fold and 5-fold, and the negative numbers suggest an improvement in accuracy with tenfold cross-validation. The Y-axis represents the CF algorithms.

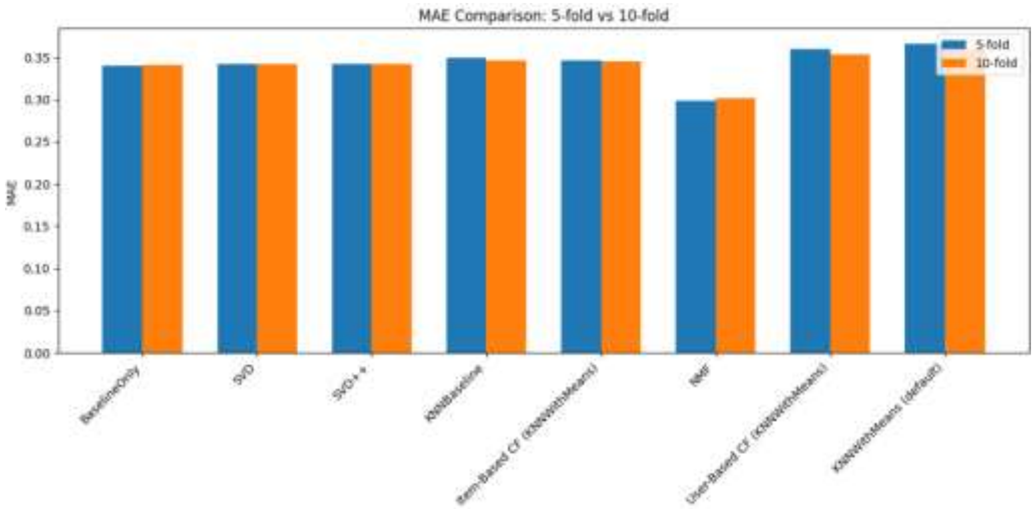

Figure 7. Comparison of 5-fold vs 10-fold towards MAE.

The above-mentioned Figure 8 discusses the XAI for a product recommendation system. It has been observed that KNNBaseline performs well and its score is 1.50 as comparisons to other models. This model has a strong impact direction. KNNBaseline had the most positive influence, with high SHAP values indicating a significant contribution to accurate suggestions.

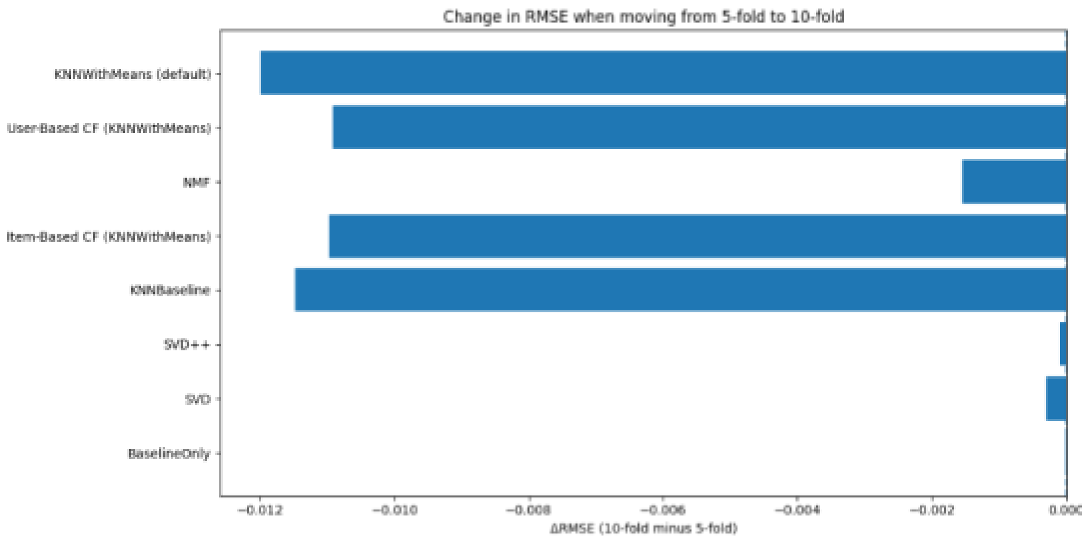

Figure 8. Change in RMSE when moving from 10-fold to 5-fold CV.

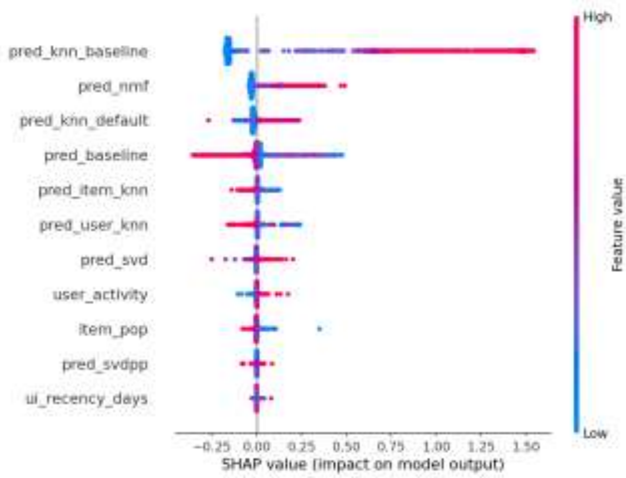

Figure 9. Distribution of SHAP value for recommendation algorithms in SAFIRES hybrid ensemble model.

Figure 10 presents the SHAP values and their prediction score. How the SHAP values impact the models and represent their score. Through this score, we can interpret the model's prediction.

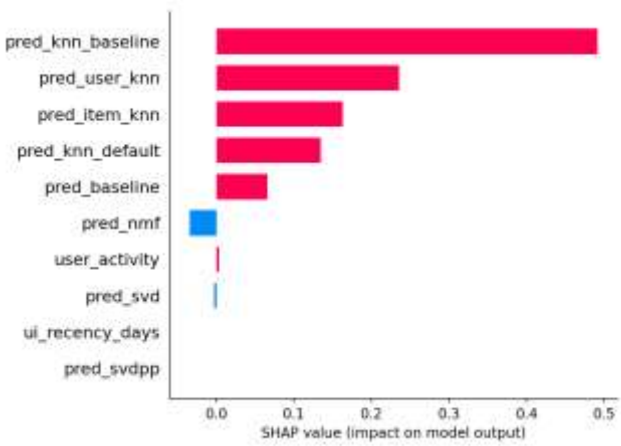

Figure 10. presents an analysis of SHAP contribution in SAFIRE.

4. Conclusions

This study discusses the product recommendation system using collaborative filtering techniques. In this paper, the 8 CF algorithms utilized are:-BaselineOnly, SVD, SVD++, KNNBaseline, Item-Based-CF (KNNWithMeans), NMF, User-Based-CF (KNNWithMeans), and KNNWithMeans (default). The 5-fold cross-validation and 10-fold cross-validation techniques are used for a product recommendation system. The BaselineOnly model exhibits well. Its RMSE score is 0.51558 and MAE is 0.34069. Similarly, for 5-Fold Cross-Validation Performance Metrics, the RMSE is 0.5156, MAE is 0.34055. We also obtained the difference between the 5-fold and 10-fold cross-validation technique and found that ΔRMSE-0.00002 and ΔMAE (10–5)

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