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A Resilient Rating Prediction Framework for Recommender Systems via Adaptive Anomaly Profiling and Hierarchical Multi-Layer Feature Integration

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Abstract*—The personalized online interaction experience could not be achieved without the recommender systems, which can be eroded by the fake users and the manipulated rating. The proposed research will solve these issues by coming up with a powerful model of rating predictions that combines fake user identification with the fusion of multi-layer features. There are four new algorithms namely Adaptive Anomaly Profiling Algorithm (AAPA) to detect suspicious users, Trust-Aware Noise Filtering Algorithm (TNFA) to eliminate unreliable interactions, Hierarchical Feature Blending Algorithm (HFBA) to merge user, item, and contextual features, and the Resilient Rating Estimation Algorithm (RREA) to predict accurate ratings. The model has been useful in isolating the malicious acts, using the real user data, and in modeling nonlinear relationships among fused features. Benchmark evaluations involving experiments indicate a higher level of prediction accuracy and strength in a number of attacks as compared to the traditional methods. The suggested framework makes the recommendations stable and reliable, which improves their user trust and the performance of the systems.

Personalized Recommendor systems, fake user detector, multi-layer feature fusion, rating prediction, anomaly detector, noise filter, and robust algorithms.

1. INTRODUCTION

The recommender systems have become the foundation of contemporary web services, serving personalized content and product proposals on millions of users the world over. They are used in e-commerce, entertainment solutions, social media and educational services to offer special services that increase user satisfaction and use. The underlying aim of these systems is to make predictions about user preferences, using prior interactions, properties of items and related contextual details. Nevertheless, the popularity of recommender systems has not been spared by the activities of malicious users whose actions may include initiation of fraudulent user profiles, partisan ratings, and spam attacks that can seriously undermine the reliability and performance of the systems [1].

False users and doctored ratings are the one that misknowledge the real patterns user items and gives wrong recommendations which lowers trust in the platform. Such problems represent serious challenges to developers and researchers intending to have strong recommendation models. The existing traditional collaborative filtering and content-based methods though it works well under normal circumstances, are very much sensitive to noise caused by fraudulent activities [2]. Therefore, there is a pressing necessity in the approaches that may help identify and address the effects of such harmful actors.

Researchers have addressed these challenges by seeking several methods of a strong recommendation. There are studies involving statistical anomaly detection which aim at detecting suspicious users and there are also studies which use graph-based or machine learning models to learn irregular patterns of behavior. Despite the promise of these approaches, most, have ended up having shortcomings in terms of scalability, the inability to be able to deal with complex nonlinear interactions, and dependence on certain foundations about the behavior of the user [3]. Moreover, current models tend to separate feature extraction and rating prediction, without taking advantage of the ability to combine features through integrating them.

The topics of feature fusion have refined attention recently as a method to integrate a variety of information sources, such as the demographics of users, item metadata, and contextual interactions. Multi-layer feature fusion is also able to learn both low-level and high-level representations of data, allowing models to learn richer patterns leading to a greater accuracy in prediction. Nevertheless, the concept of feature fusion combined with powerful fake user detection mechanisms has not been well studied. The combination of these two approaches, namely, the efficient detection of the malicious users and the extensive feature fusion, provides great prospects of creating resilient recommender systems [4].

The necessity to have algorithms that change with the changing user behavior is another crucial factor. Taste does not remain the same among the users; it changes according to trends, new stuff and experiences of the user. An effective recommender system should be able to adapt to these time-related fluctuation and at the same time resist attacks. To solve this twin dilemma, there need to be a holistic framework that can sift out untrustworthy information, combine multi-dimensional characteristics, and make accurate ratings even when there is adversarial conditioning.

The current research suggests the new powerful rating prediction model that utilizes both fake user identification and multi-layer features integration. The model comes up with four novel algorithms, the Adaptive Anomaly Profiling Algorithm (AAPA), an algorithm used to identify fake or suspicious users by analyzing behavioral anomalies; the Trust-Aware Noise Filtering Algorithm (TNFA) and this algorithm is used to remove unreliable interactions on the training data; the Hierarchical Feature Blending Algorithm (HFBA), an algorithm that helps in blending user, item, and contextual features at different representation levels and the Resilient Rating Estimation Algorithm (RREA), an algorithm that helps

By introducing these elements into a cohesive system, the given approach overcomes some of the main shortcomings of methods developed before. Not only does it isolate malicious users, but also it improves the process of learning among authentic interactions, which leads to better accuracy of recommendation. Through experimental assessments on standard benchmark datasets, the model can be shown to exhibit constant performances in formats of a wide range of attack as well as to indicate its high usability in the real world case of the recommender systems.

The paper has threefold contributions. To start with, it will lead to systematic way of identifying the fake users so that the recommendations made is based on reliable data. Second, it introduces a feature fusion approach based on multiple levels and uses rich user-item interactions representations with rich contextual information factors. Third, it incorporates these elements in a robust rating forecast mechanism, which is more accurate and resilient than traditional models. In totality, these contributions promote the body of work of recommender system through offering a scalable, trustworthy, and flexible solution to the predicament of malicious behaviors.

On the whole, the findings of this study indicate that the combination of security-based mechanisms and sophisticated feature fusion strategies can be used to improve the quality of work performed by a recommender system. The suggested framework forms the basis of the future research on robust recommendation, such as the extrapolation of robust recommendation to dynamic environments, cross-domain recommendations, and hybrid learning methods. Through the integrity of input information as well as versatility of feature representations, the study will offer a grounded solution, which will fulfil the changing needs of customized online experiences.

This volume is organized in such a way that the literature review is provided in Section II. Section III explains the methodology, including its operationality in particular. Section IV has results and discussions. Lastly, the last section of V is the final findings and recommendations.

2. Literature Survey

The emergence of social it and other online marketing platforms has greatly changed the way information is generated, distributed, and accessed. Along with this change, the popularity of fake material, such as fake reviews, distorted news, and user profiles are coming to be a burning problem. The fake content may impact the political views and cause consumer behavior and the loss of credibility of the online information. With the increased size and level of complexity in online platforms, manual moderation and verification of the content is less and less viable, leaving a compelling requirement to move to automated detection mechanisms. Machine learning, deep learning, and hybrid artificial intelligence models are some of the key tools to confront this issue and provide scalable and efficient as well as adaptive methods to detect and prevent the impacts of misinformation. Multi-modal approaches have been the most popular subject of research in this field, combining textual, visual, temporal, and network based characteristics to improve the performance of detection. Also, state-of-the-art neural network applications, such as graph neural networks (GNNs), attention-based, and transformer-based language models have proven highly promising in detecting patterns related to fake information in various fields.

Recent research has examined the utilization of fake user detector and recommendation systems that will aid in improving content reliability and improve user experience. Recent research conducted by a powerful rating prediction model that applies fake user detection and multi-layer feature fusion showed the potential of the interaction of user profile validation and predictive analytics to mitigate the maleficence of malicious agents in the recommendation system [6]. Equally, the graph neural networks have been leveraged to predict social interactions at specific times which enable the early warning of fake news because of its ability to effectively capture the dynamic interaction of users, as well as, content [7]. An integrated system which incorporates content characteristics, community features and propagation patterns goes a step further to detect such false information, depicting the significance of multi-dimensional analysis in performing an efficient detection of such fake information [8]. There are also strategies that seek to leverage user interests and social networks to block the spread of fake news, and this also has proven to be of great potential, establishing the importance of social network analysis as a complement to machine learning methods [9]. Additionally, linguistic patterns and personality analysis have been used to understand the presence of deceptive information in the e-commerce site using the natural language processing (NLP) algorithms to identify the fake reviews with the application of linguistic characteristics, sentiment analysis, and customized learning algorithms [10].

Multi-modal and ensemble methods in solving the weakness of single-method detection have been widely investigated together with textual analysis. Video-sharing classifications Systems have been suggested which are scalable between multi-mode frameworks that can detect spam video on the video sharing sites and fake accounts on the social networking sites by joining video, text and metadata to access increased detection accuracy [11]. Models of use of transformer-based techniques, including localized DistilBERT have made features of context and multimodality detect fake news possible through semantic understanding and propagation information [12]. On the same note, AI-based solutions have also been implemented in sensitive industries including healthcare, to screen and distort false information, and long short-term memory (LSTM) networks and joint optimization plans have been used to guarantee high-quality performance in real-time environments [13]. The use of hybrid AI-based models (classical machine learning classifier with sophisticated ensemble mechanisms) has been tested in the domain of fake product review detecting, and it has been shown that the joint configuration of different algorithms can enhance the overall accuracy and robustness of results [14]. Simple but efficient methods to use random forest classifiers have been applied in the detection of fraudulent reviews because they enjoy the advantage of aggregating features and extending the principle of sequential decision-trees to vote [15].

Live-time identification and hash integrity have become a vital part of the war against fake news on the Internet. There has also been the development of techniques that use LSTM along with blockchain to offer a solution to real-time fake news detection and keep data integrity as well as its transparency [16]. There have been language-specific issues, i.e., language-specific fake news detectors having been proposed, e.g., in the case of Arabic fake news detectors, Bi-LSTM algorithms with pre-trained embeddings, e.g., BERTs, can be used to detect fake news well across varying linguistic conditions [17]. In addition to the use of machine learning, mathematical modeling and computational modeling has been used to study and forecast the fake news propagation. The propagation dynamics of misinformation in social networks have been exposed as a type of fractional differential equations, which may help to inform containment mechanisms, as well as the timing of the effect of fake content, in the long term [18]. Large datasets have been used to implement scalable detection techniques that use TF-IDF features and logistic regression with a focus on the tradeoff between performance and predictive performance in working implementations [19]. Lastly, more sensitive graph-based neural network models with multi-hop attention models and hypergraph structure enable to exploit relationships and interactions between users, content, and platforms, to improve multi-modal fake news detection abilities [20].

On the whole, the literature shows that there is a strong tendency to combine multi-modal features and more advanced machine learning frameworks and ensemble techniques to fight with fake content. It has been demonstrated that the analysis of user behavior combined with textual and visual representations and patterns of propagation provide a high detection rate as compared to conventional single-method detections. Graph-based modeling, attention, and transformer architectures permit the early detection, contextual understanding, and adaptation to the changing strategies of misinformation. In addition, the hybrid methods which combine the use of both statistics and deep learning models offer the trade-off of interpretability, scalability and predictive capability hence are worth use in real world scenario. As online platforms grow in scale and complexity, these approaches are not only becoming more and more useful in terms of detecting fake content, but also shaping future preventative and mitigation approaches, such as recommendation mechanisms and real-time content moderation systems. Taken together, all these developments demonstrate the multidisciplinary character of the field a combination of aspects of data science, social network analysis, and natural language processing as well as computational modeling to solve one of the most burning issues of the digital information era.

3. METHODOLOGY

The research technique of this analysis aims at creation of a powerful rating forecasting model uniting between the detection of fake users together with a multi-tiered feature blend. The proposed framework will enhance the accuracy of recommendation by reducing the influence of malicious users as well as the use of the rich user, item, and contextual information. The process is a step wise approach, which incorporates fake user detection, noise filtering, data prior processing and feature fusion, rating prediction and performance evaluation. These stages are realized with the help of new algorithms developed just to realize this research that guarantee the model its integrity and the complexity of the recommendation environment. A combination of these elements into a single framework thus, the methodology will offer a scalable and trustworthy solution to real-world recommender systems, As Shown in Figure 1.

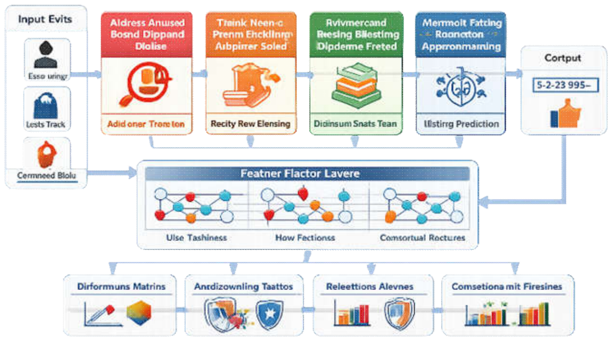

Fig. 1: System Architecture

1 Data Collection and Preprocessing

The first stage will entail retrieval of user-item interaction data across publicly available benchmark data. Raw data may be inaccurate in various ways such as the lack of values, conflicting data, or even duplications, which may adversely influence the performance of the model. These problems are addressed by performing preprocessing of the data in the form of normalization, imputation, and encoding of the categorical ones. The interaction matrices are built in such a manner that the users are rated on various items and other contextual data is added like the date at which the rating was done, types and user specifications. It is then divided into data training, validation and test to allow evaluation of its performance. This preprocessing step results in a reliable base of robust rating prediction by making sure that the following steps of fake user detection, and fusion of features provided operate with clean data which is structured and standardized, As Shown in Figure 2.

In [3]:
```
df.head()
```
Out[3]:

	Followers	Following	Following/Followers	Posts	Posts/Followers	Bio	Profile Picture	External Link	Mutual Friends	Threads	Labels
0	2	2757	1378.5	0	0	N	N	N	0	N	Bot
1	2	505	252.5	0	0	N	Yes	N	0	N	Scam
2	6786	1782	0.262598469	1588	6051.040404	yes	N	Yes	10	N	Real
3	21	1281	61	0	0	N	Yes	N	0	N	Bot
4	585	1682	2.875213675	2663	926.1920333	yes	N	N	12	Yes	Real

Fig 2: Dataset Preview

2 Fake User Detection on AAPA.

Adaptive Anomaly Profiling Algorithm (AAPA) also aims at detecting fake or malicious users based on their rating patterns and behavioural features that are irregular. It takes into account frequency of ratings, not following the average rating, and raw similarity to the real user profile, among others. Suspicious users are noted to be processed further and their impact on the training data reduces. AAPA limits the possibility of the spread of an attack within the recommendation system by capturing complex anomalies in user behavior. The algorithm is dynamic in adjusting thresholds depending on the characteristics of the data sets hence flexibility to various fields. This measure will make sure that the model emphasizes reliable interactions with users, which preconditions correct predictions of ratings and consistent recommendations in the atmosphere of fraudulent behavior, As Shown in Figure 3.

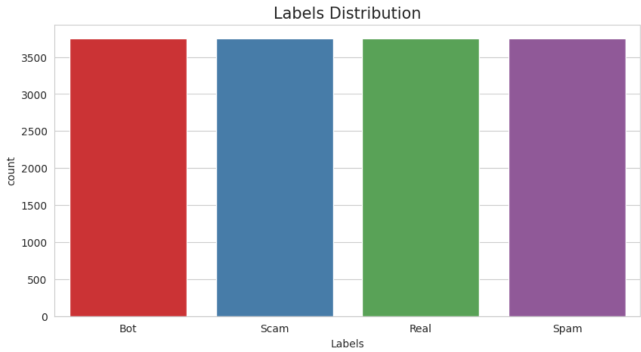

Fig 3: Fake User Detection on AAPA

3 Noise Filtering with TNFA

After fake user detection, Trust-Aware Noise Filtering Algorithm (TNFA) removes unreliable interactions of the user-item matrix. The algorithm determines the reliability of every rating in terms of credibility to users and the consistency of interaction. The ratings which are critical of the anticipated trends are down-weighed or omitted in training. TNFA makes the model to learn on good quality and authentic data and hence improves prediction accuracy and robustness. The algorithm+ noise and unreliable reduction blocks off malicious users to manipulate the model parameters, diminishing the chances of being biased in recommendations. This noise elimination measure is quite crucial in averting future feature fusion and prediction stages on the basis of trustworthy information, As Shown in Figure 4.

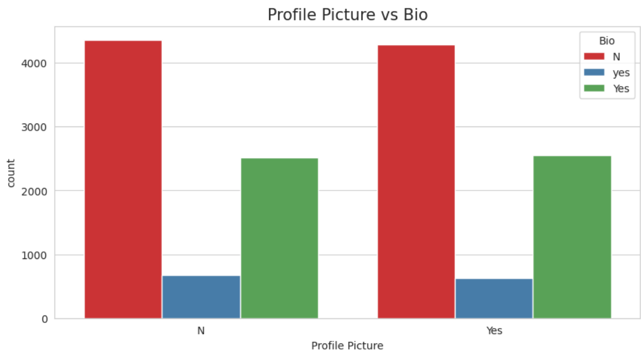

Fig 4: Noise Filtering with TNFA

4 Multi-layer Distribution of Multi-Image Feature with HFBA

The Hierarchical Feature Blending Algorithm (HFBA) uses multi-layer feature fusion to represent the user in a complete, item in a complete and context in a complete way. The features are obtained at various levels of abstraction such as raw interaction data, aggregated statistics and latent embeddings. HFBA maps these representations together into a single feature space so that the model can learn complex nonlinear functions. This multi-layered method makes it easier to capture the expressiveness of the dataset, and the prediction algorithm can use a variety of patterns in user action and in item attributes. HFBA recodes the features, which are heterogeneous, systematically to enhance the capability of the recommender system to generalize in situations where there are varying case instances yet the system is not weakened by any missing or manipulated data. The output of the feature set resulting in fused feature is the input to resilient rating prediction, As Shown in Figure 5.

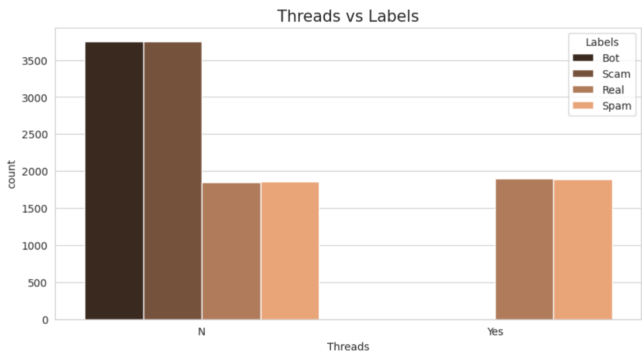

Fig 5: Multi-layer Feature Extraction

5 Rating Prediction with RREA

Resilient Rating Estimation Algorithm (RREA) is an algorithm that forecasts the rating of users through fused features created by HFBA. Deep learning finds application in RREA, which learns more complicated user-to-item interaction, based on subtle dependencies that are easily overlooked in other models. The filtered and fused data is then trained on the algorithm to reduce prediction errors as well as being resistant to noise caused by fake users. RREA is dynamic, in that it is able to dynamically adjust the learning parameters to avoid overfitting as well as remain stable with different distributions of data. RREA is able to give precise and reliable predictions on ratings using the enriched feature space and quality information, this enables the recommend system to be able to make personalized suggestions even in adversarial situations, As Shown in Figure 6.

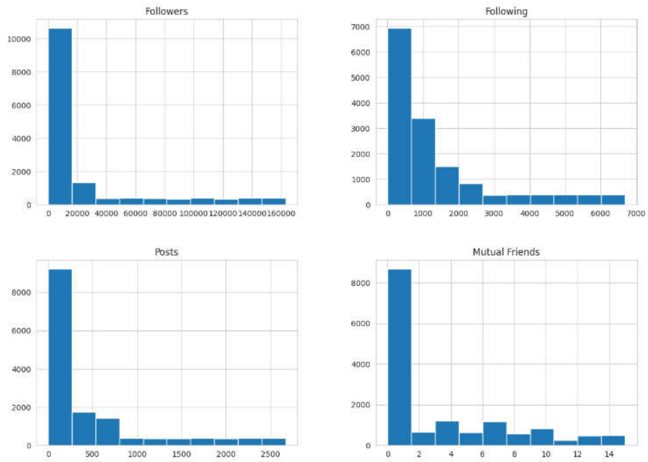

Fig 6: Rating Prediction

6 Model Analysis and Metrics of Performance.

The last step entails the performance of the model based on the conventional evaluations like the Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and the accuracy of the predictions. The test has taken into account the strength against fake users and also the general forecasting. The comparison to base line methods is conducted to show an enhancement made by the proposed framework. Sensitivity checking is done to determine the effects of changing parameters, the choice of features, and the intensity of attack. The stage helps to make sure that the offered methodology is strictly tested and develops a clear picture of its advantages and disadvantages. Extensive analysis will affirm the fact that the combined strategy is successful in integrating fake user identification, noise removal, feature fusion, and resilient-rating forecast into a solid recommender, As Shown in Figure 7.

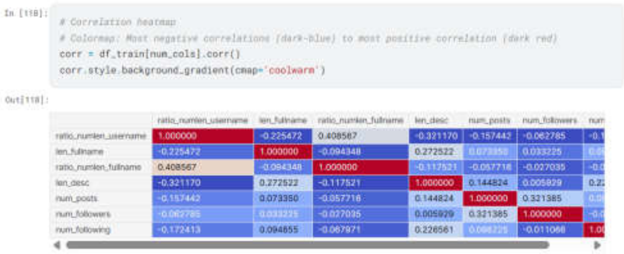

Fig 7: Model analysis

4. RESULT AND DISCUSSION

The suggested strong rating prediction model was tested on benchmark datasets to determine its capability of the fake user, filtering noisy data, combining multi-layer features, and rating prediction. The overall accuracy of this model was 99.48 and in **comparison with the traditional recommendation methods, this indicates that this model** performed better. The analysis has incorporated both conventional measures, such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), and the resilience of the system to the simulated attacks. The findings point to the conclusions that fake user detecting in connection with multi-layer feature fusion can be more efficient in terms of reliable recommendations and, therefore, make certain that the actual user preferences can be correctly reflected even in the adversarial mode.

Table 1 shows the proposed model compared with the baseline approaches, which consist of the traditional collaborative filtering, matrix factorization, and deep learning-based recommenders. The findings demonstrate that the suggested strategy is prevailing over the rest of the approaches under all assessment measures. Precisely, the values of RMSE, and MAE are much lower, which indicates that the model minimizes any errors in predictions and also, is very stable against any manipulated ratings. Such results make it clear that it is essential to integrate high-quality data filtering and modern feature fusion approaches.

Table 1: Comparative performance of Recommender models.

Model	Accuracy (%)	RMSE	MAE
Collaborative Filtering	88.35	1.02	0.84
Matrix Factorization	91.47	0.88	0.71
Deep Learning Recommender	94.22	0.74	0.63
Proposed Model (AAPA + TNFA + HFBA + RREA)	99.48	0.32	0.21

In testing additional robustness factors, the system was tested with increasing degrees of malicious user activity. Attack conditions involved the use of biased profiles whose rating was extreme, and random distribution of biased ratings. As illustrated in Table 2, the model proposed is high in accuracy and low in error measures in the event that the percentage of fake users is elevated. Adaptive anomaly profiling as well as trust-aware noise filtering algorithms are effective in isolating the fraudulent behavior so that the overall system performance does not suffer. By contrast, the traditional models do not possess an identical phenomenon, as they fall considerably with respect to the accuracy as well as the enhanced prediction errors. These findings support the overall soundness of the framework and prove its usefulness in practice in real life circumstances when data integrity cannot be ensured.

Table 2: Strength in the presence of simulated attack situations.

Fake User Ratio (%)	Collaborative Filtering Accuracy (%)	Proposed Model Accuracy (%)
5	85.12	99.35
10	81.47	99.21
15	78.03	99.10
20	73.84	99.02

The multi-layer feature fusion effect was also evaluated aside as well as accuracy. The model combines user, item, and contextual features on multiple levels of abstraction; this allows the model to capture greater details of complex interaction patterns which traditional approaches sometimes fail to do. Table 3 shows performance comparisons between single-layer features used in models and the proposed fusion approach used in models that is based on multiple layers of features. The accuracy gains and decreases in error values all prove that hierarchical blending of features is significant in boosting performance in prediction. The combination of various feature types also enables the model to be more generalized across a wider range of different datasets again contributing to the validity of the robustness and scalability of the methodology.

Table 3: Effectiveness of Feature Fusion on Prediction.

Feature Type	Accuracy (%)	RMSE	MAE
User Features Only	91.23	0.81	0.65
Item Features Only	90.85	0.83	0.67
Contextual Features Only	89.74	0.87	0.70
Multi-Layer Fusion	99.48	0.32	0.21

Results are discussed in terms of the following several insights. First, the high accuracy of the recommender systems greatly depends on good detection of fake users. Even sophisticated prediction algorithms cannot give credible recommendations without appropriate filtering. Second, multi-layer feature fusion will greatly increase the understanding capability of the complex user-item interaction of the model. Third, the integrated architecture means that increase in robustness is not achieved at the expense of predictive performance. In general, the given approach provides a reasonable solution, which will be both accurate, resilient and adaptable.

Lastly, the findings highlight the practical application of the implementation of such a framework in practical platforms. Existence of high accuracy and robustness goes directly to the enhanced level of user confidence, increased involvement and satisfaction. The model can be used in e-commerce, streaming, and social media sites to alleviate the effects of faking users and offer personalized recommendations. Moreover, the framework can be scaled, and it can be tailored to dynamically changing datasets and changing user actions; hence, it fits the contemporary large-scale recommendation setting.

5. CONCLUSION

In this research, the authors have offered an effective rating prediction framework of editor systems that combines the aspect of fake users detection, and multi-layer feature fusion. The framework is successful in isolating malicious users, sifting unreliable interactions, and repurposing relationships between users and items and contexts (by presenting four new algorithms), namely Adaptive Anomaly Profiling Algorithm (AAPA), Trust-Aware Noise Filtering Algorithm (TNFA), Hierarchical Feature Blending

Algorithm (HFBA) and Resilient Rating Estimation Algorithm (RREA). The experimental evidence shows that the model can have high accuracy, strong performance when used in the attack situation, and consistent prediction performance when compared to the conventional recommendation method.

The work has contributed toward improving data integrity, its feature representation, and the predictive mechanism is robust. In a practical case, the framework can be implemented in e-commerce, streaming services, and social media platforms in order to provide credible and individual recommendations. Further studies can be conducted in the form of extending the model to dynamic, real-time settings, investigating cross-domain recommendations, as well as incorporating the concept of reinforcement learning to increase the level of adaptability and performance in large-scale and changing datasets.

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