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(Research Article)

Optimizing researcher mentorship matching: A particle swarm optimization-based recommendation model

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Abstract

Mentoring is an essential collaborative practice among academic researchers, fostering growth and expertise. It is widely believed that scientific knowledge, practices, and skills are transferred from one generation of scientists to the next through mentorship. The increasing significance of collaboration among academic researchers necessitates innovative, effective tools for optimal mentor-mentee matching, facilitating successful mentorship and knowledge transfer. Despite existing expert-finding recommender systems, matching mentors with mentees remains understudied. This research addresses this gap by developing a novel metaheuristic-based approach to optimize mentor-mentee pairing. Utilizing profile and publication datasets from Academic Family Tree, a Support Vector Machine (SVM) classifier is employed to categorize researchers as experts or young researchers. Term Frequency-Inverse Document Frequency (TF-IDF) extracts research area features, generating researcher vectors. These inputs are then optimized using Particle Swarm Optimization (PSO) algorithm to facilitate mentorship connections. The results demonstrate exceptional performance: the Support Vector Machine (SVM) classifier achieves 99% accuracy, while the optimized recommendation model based on PSO algorithm, which achieves 100% accuracy, outperforms three baseline models, collaborative filtering (CF), content-based filtering (CBF) and Hybrid CF-CBF models. This study's findings can inform research institutions seeking to enhance researcher-mentor connections, fostering collaborative excellence. Future research will explore expanded datasets and algorithmic refinements.

Keywords: Particle Swarm Optimization (PSO); Researcher Mentorship; Optimization Technique; Scholarly Recommender System; Academic Researchers

1. Introduction

Mentorship is vital for the academic and professional trajectory of emerging researchers especially during the critical early stages of their careers [1]. A well-suited mentorship pairing can lead to improved research productivity, increased confidence, and enhanced career prospects. The increasing significance of collaboration among academic researchers necessitates innovative, effective tools for optimal mentor-mentee matching, facilitating successful mentorship and knowledge transfer. Despite existing expert-finding recommender systems (RSs), matching mentors with mentees remains understudied. This research addresses this gap by developing a novel metaheuristic-based recommendation model to optimize mentor-mentee pairing. Numerous recommendation algorithms have been proposed and developed to recommend personalized items over the years. These recommendation algorithms are utilized to run recommender systems. In the past, RSs have been successfully utilized to suggest scholarly items, including research papers [2] [3], reviewers [4] [5], publication venues [6] [7], experts [27] [8] and so on. A recommender system is a software application that uses data and algorithms to suggest relevant items (products, services or people) to users based on their preferences and interests [9] [10].

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In scholarly recommender systems, features (which are often profile and publication data; rating data are rare) are usually in textual form which always needed to be converted into numerical form for it to be useful in machine learning. So, authors have employed various natural processing language techniques such as bag of words (BoW), term frequency-inverse document frequency (TF-IDF) and Latent Semantic Analysis (LSA), to convert textual data into numerical data. Authors in the field of recommender systems also classify items into desired categories using various classification algorithms such as support vector machine (SVM) [11], Artificial neural network [12] and Naïve Bayes [28]. Likewise, several metaheuristic algorithms, including Genetic Algorithms [13], Differential Evolution [14], and Particle Swarm Optimization [15], have been employed in recommender systems to optimize recommendation process.

The aim of this study is to develop a novel approach to matching and recommending researchers for mentorship using Particle Swarm Optimization (PSO) algorithm [16]. In this work, two types of data are employed, namely profile data and publication data. TF-IDF is employed to obtain the researcher vectors employing features related to researchers' areas of expertise. The researchers are classified using SVM classifier. The PSO algorithm is then applied to preprocessed (classified and vectorized) data to optimize the mentor-mentee matching process. The performance of the proposed model is evaluated using a comprehensive set of metrics, such as precision, recall, F1-score, and Mean Reciprocal Rank (MRR).

The remainder of this paper is organized as follows: Section 2 reviews the literature on mentorship, scholarly recommender systems and applications of PSO in recommender systems. Section 3 describes the experimental setup, including dataset description, data pre-processing, and algorithm implementation. Section 4 presents the experimental results and discussion. Finally, Section 5 concludes the paper and outlines future research directions.

2. Literature Review

Mentorship plays a critical role in fostering career growth, job satisfaction, and research productivity, as evidenced by numerous studies [1] [18] [21] [17]. However, traditional mentorship matching methods are largely dependent on manual process, personal connections, and self-selection. Recent breakthroughs in data mining and machine learning have paved the way for innovative solutions in various domains, such as the application of recommender systems in solving information overload problems and optimization algorithms for enhancing recommendation accuracy. This literature review aims to synthesize existing research on mentorship, PSO in recommender systems and scholarly recommender systems, highlighting gaps and opportunities for developing a PSO-based recommendation model to optimize researcher mentorship matching- an approach that is rare in scholarly recommender systems.

The authors in [17] investigated the key factors contributing to successful mentorship among academics. The study revealed that researchers who achieved greater success were those who had been mentored by experts with diverse skill sets, and were able to effectively integrate this expertise into their own research. In [18] the authors shared the findings of an assessment on mentoring and scientific collaborations facilitated by the National Institute of Mental Health (NIMH), an initiative backed by Implementation Research Institute (IRI). The results underscored the crucial role of mentoring in driving progress in both implementation science and team science. In [21] the authors study the experiences of young researchers in Tanzania who received mentorship as part of a research capacity-building program. The authors aimed to understand the benefits and challenges of mentorship in resource-limited settings. Their findings showed that mentorship had a positive impact on the young researchers' career development, research skills and confidence. Despite the acknowledged importance of mentorship in academia, existing studies on mentorship have overlooked the potential benefits of leveraging recommender systems to facilitate effective mentor-mentee matching and recommendations.

The authors in [19] presented a scholarly recommender system designed to facilitate efficient discovery of relevant publication for researchers. The authors proposed a novel hybrid RS in order to solve cold start and copyright restriction problems. They carefully introduced public contextual metadata and paper-citation relationship information into collaborative filtering and content-based approaches separately to improve the recommendation accuracy. The results of their experiments using metrics such as precision, recall, F1-measure, mean average precision, and mean reciprocal rank gave 0.63, 0.37, 0.45, 0.60 and 0.92 respectively. In [20], a content-based recommender that suggests articles corresponding to datasets was developed. The authors aimed to develop a system that encourages datasets reusability. The authors pre-processed and obtained 50,159 articles from PubMed and 72,791 datasets from Gene Expression Omnipus (GEO). The system's performance was evaluated using MRR@K, Recall@K, Precision@K and MAP@K metrics, yielding results of 0.72, 0.80, 0.68 and 0.72, respectively. However, the results of these works could have been better if metaheuristic approaches had been employed.

The authors in [22] utilized the PSO to identify similarity measure for consumer rating, mitigating data distortion caused by sparsity. The study also employed BERT to extract key features from consumer reviews. Furthermore, PSO was used to optimize the weight matrix, integrating rating and review data to enhance recommendation accuracy. The method was evaluated on six Amazon datasets, demonstrating superior performance compared to existing methods in terms of mean square error and absolute squared error. In [23], the authors proposed an approach to collaborative filtering-based recommender systems using the PSO algorithm and fuzzy features. The PSO algorithm is employed to optimize the weights of the fuzzy features, enhancing the recommendation accuracy. The authors applied movielens dataset for experiments employing metrics such as MAE and coverage. The results from the experiments demonstrate the effectiveness of combining PSO and fuzzy features in collaborative filtering-based recommender systems, leading to improved accuracy and recommendation quality. The authors were able to improve accuracy and effectiveness of recommender systems by incorporating fuzzy logic, and swarm intelligence offered by PSO, a metaheuristic algorithm. However, their application in the area of scholarly recommender systems is relatively rare.

Despite the ability of PSO to improve recommendation accuracy, some of the limitations and challenges to using PSO in recommender systems include the need for careful tuning and validation of the algorithm, the risk of getting stuck in local optima, the computational complexity, and the difficulty in selecting optimal parameters and hyperparameters. While PSO offers promising benefits for enhancing recommendation accuracy, its limitations and challenges must be carefully weighed when integrating it into recommender systems.

3. Experimental Setup

This section describes the experimental setup and configuration utilized to develop and evaluate the proposed recommendation model based on PSO algorithm. The architecture of the proposed model is presented in Figure 1.

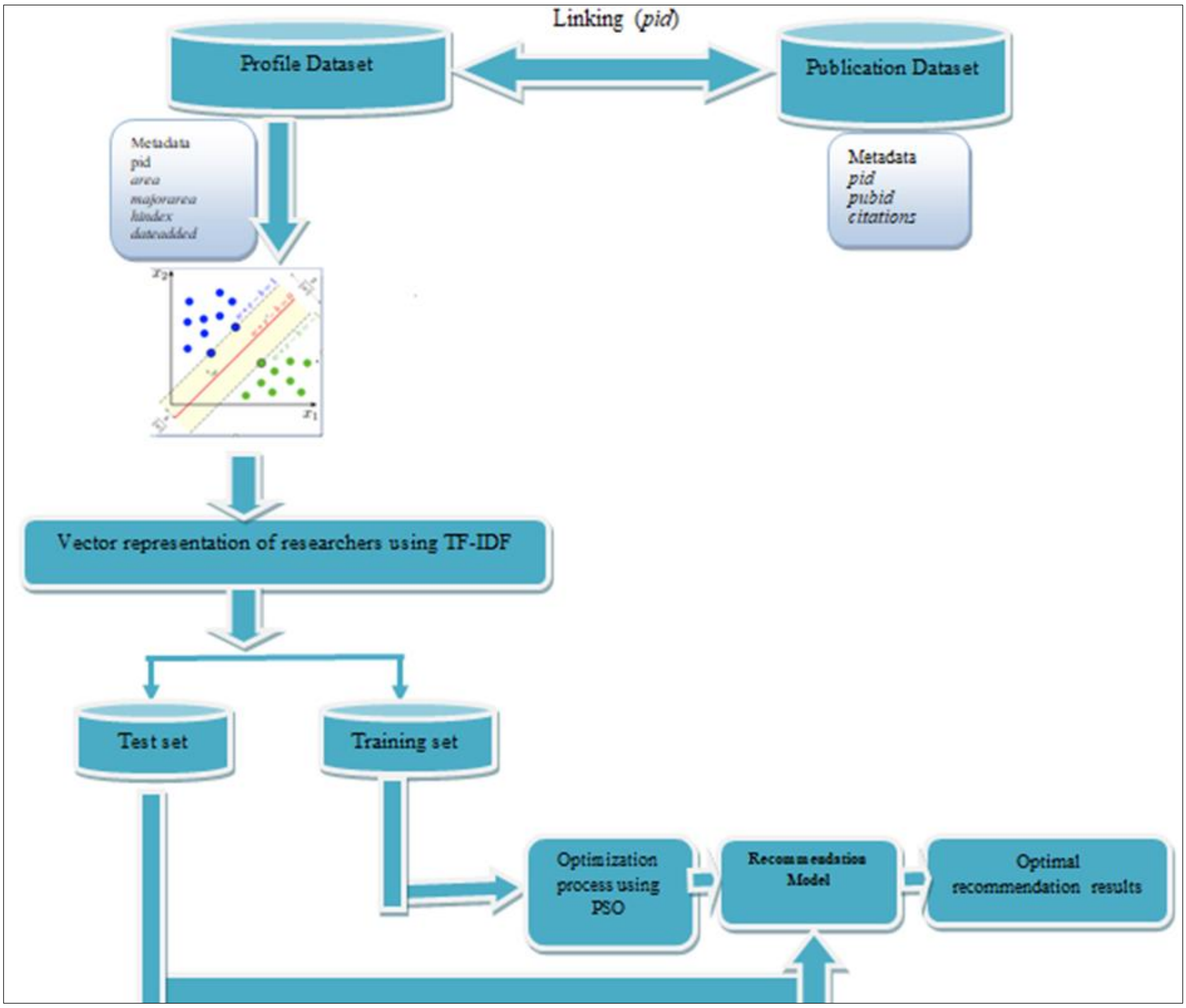

Figure 1 Architecture of the Proposed Model

3.1. Experimental Procedure

For this research, profile and publication datasets were obtained from the Academic Family Tree (AFT) database, a collaborative project documenting academic mentoring relationships. The two datasets underwent feature selection, retaining only relevant features to enhance model performance. The feature selection process resulted into 807,230 instances and 5 features in profile dataset and 15,401,889 instances and 3 features in publication dataset. The profile and publication datasets were integrated by matching features using the common identifier, "pid" (User ID). This merged dataset combined profile features (pid, area, majorarea, hindex, and dateadded) and publication features (pid, pubid, and citations).The integration resulted in a unified dataset containing the following features: pid, area, majorarea, hindex, dateadded, pubid, citations. The result of data integration gives 15, 371,421 instances and 7 features each.

Following this, rows containing missing data were eliminated, resulting in a cleaned dataset of 4,306,451 instances with 7 features. The following tasks were then carried out on features at this stage; counting of each researcher's publications, summation of each researcher's citations, choosing minimum value for dateadded, removing duplicate data for hindex. The feature names were changed from pubid, citations, hindex and dateadded to num_publications, total_citations, h_index and earlier_year respectively. The result of data aggregation produced 120,644 instances with 7 features.

Thereafter, a support vector machines (SVM) classifier was employed to categorize the researchers into two groups, expert and young researcher, using features related to their number of publications, total citations, h-index, and year of research experience as obtained from the dataset. Researchers with number of publications of more than twenty, more than two hundred citations, and researchers with h-index of more than fifteen, or year of research experience of more than fifteen years are considered an expert in their areas [24] [25]. The researcher is categorized as a young researcher otherwise.

This classification process yielded a new column labeled 'category' which resulted into 120,644 X 8 instances. Data normalization was done using Min-Max Scaler to scale features between 0 and 1. In anticipation of vectorization, the features "area" and "majorarea" were merged to form the "research_areas" feature. TF-IDF (Term Frequency-Inverse Document Frequency) transformation was then applied to the "research_areas" feature to generate numerical vectors representing researchers. This process was performed on a random sample of 10,000 instances from the dataset. Experiments were performed on vectorized dataset of 10,000 samples. A simple holdout method (80% training, 20% testing) was used for evaluation.

3.2. PSO Algorithm Characteristics

Particle Swarm Optimization (PSO) is inspired by the social behaviour observed in certain animal groups, such as swarm of bees, flocks of birds and school of fish, where members interact, learn from each other, and adapt to pursue shared goals. In PSO, each particle represents a potential solution to the optimization problem. The following steps are involved in the proposed PSO-based recommendation model:

3.2.1. Step one (initialization)

The initialization of population and hyperparameters is the first step in PSO as common to metaheuristic algorithms. A swarm (population) of particles is generated from the dataset. Parameter initialization in metaheuristc algorithms permits the agents in the population to be randomly distributed across the search space and this can be achieved by equations (1) and (2).

$$x_i^{(t)} = x_{min} + \theta(x_{max} - x_{min}) \quad \ldots\ldots\ldots\ldots\ldots (1)$$

$$v_i^{(t)} = v_{min} + \theta(v_{max} - v_{min}) \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

where θ is a random number between 0.0 and 1.0, $x_i^{(t)}$ and $v_i^{(t)}$ represent initial position and initial velocity respectively. Also, the algorithm hypeparameters are set. To ensure optimal performance of the proposed model, careful hyperparameter tuning was conducted through experimentation. This involved testing various values for the algorithm's hyperparameters to achieve superior results. In this research work, the values assigned to the PSO hyperparameters are shown in Table 1.

Table 1 PSO Hyperparameter Tuning

Hyperparameter	Value	Desciption
N	200	The number of particles
D	Vectorized features	The dimension of the optimization problem
max_it	100	The number of iterations
β_1	1.494	The cognitive acceleration coefficient i.e. the constants that pull each particle in the swarm towards its personal best (p_{pb}) position
β_2	1.494	The social acceleration coefficient i.e. the constants that pull each particle in the swarm towards the global best (p_{gb})position
w	0.729	The Inertia weight i.e. a parameter that regulates the balance between exploration and exploitation - a value in between 0.0 and 1.0
Top_N	3, 5, 10	The best N recommendations

3.2.2. Step two (Evaluation)

The most essential step in solving optimization problem is to determine a suitable fitness function for the problem at hand. The fitness function is used to guide the population towards optimal recommendations. In this work, the average precision is employed as the fitness function. In order to find the fitness score for each researcher, the optimization problem is represented as shown in equation (3).

$$fitness = \frac{1}{n}\sum_{k=1}^{n} P@n * R_n \qquad \text{..................... (3)}$$

where n is the number of thresholds, P represents precision and R represents recall. Fitness function is presented as maximization problem since the researcher with higher fitness score is considered the optimal value.

At this stage, fitness function is evaluated to determine the fitness score for each particle in initial population. The particle with highest average precision score is considered the best particle (solution) in the swarm.

3.2.3. Step three (Update)

The velocity and position of each particle is updated using equations (4) and (5) [26].

$$v_i^{(t+1)} = wv_i^{(t)} + \beta_1\theta_1\left(p_{pb} - x_i^{(t)}\right) + \beta_2\theta_2\left(p_{gb} - x_i^{(t)}\right) \text{.............. (4)}$$

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \qquad \text{.................. (5)}$$

where $w \in (0.0, 1.0)$ is an inertial weight, β_1 and β_2 are constants that pull each particle in the swarm towards p_{pb} and p_{gb} respectively, $\theta_1$and θ_2 are random numbers between 0 and 1. The best position experienced by a particular particle and the best position experienced by the entire population are denoted by p_{pb} and p_{gb} respectively. $x_i^{(t)}$ is the current position of a particular particle i, while $v_i^{(t)}$ is the velocity of particle i.

3.2.4. Step four (Iteration)

Iterate through steps 2 and 3 until either a stable solution is reached or the predetermined maximum number of iterations is met.

3.2.5. Step five (Termination)

Finally, the recommendation optimization based on PSO algorithm phase outputs the particle (solution) with the best fitness as the optimal recommendation list.

3.2.6. Code Implementation

The proposed recommendation model was implemented using Python programming language (version 3.12) on a Core i5 processor, leveraging the intuitive interface of Spyder IDE. The code uses labelled data to train and evaluate the model. The model recommends mentor/mentee based on areas of expertise similarities. The code consists of the stages such as data loading, model optimization, model evaluation, recommendation generation, and performance metric evaluation. Researchers' labels and vectors are loaded into the system. This data serves as the foundation for the model, providing the necessary information for mentor-mentee recommendation. Model optimization stage employs PSO algorithm to optimize the model using average precision as the fitness function. PSO is a stochastic optimization technique that repeatedly refines the model's hyperpameters to achieve optimal performance. The optimized model is evaluated using four key metrics: precision, recall, F1-score and MRR. The trained model generated recommendations for the top experienced researchers in the user's field. The recommendations are provided for three different scenarios: top-3, top-5, and top-10 mentor-mentee recommendations.

4. Results and Discussion

This section presents the results of experiments performed on the AFT datasets, followed by a comprehensive discussion on the developed model's performance in facilitating effective mentoring relationships. The discussion encompasses both researchers' classification and expert recommendation effectiveness with a focus on optimally matching mentors with mentees. The model's performance is evaluated using a comprehensive set of metrics, precision, recall, F1-score and MRR. The discussion section provides an in-depth analysis of results, highlighting the strengths and limitations of the proposed model, and exploring avenues for future research and improvement.

4.1. Classification Evaluation Results

Evaluating the SVM classifier's performance through confusion matrix, accuracy, precision, recall, F1-score metrics is crucial, as its output directly impacts the quality of input data for PSO-based recommendation model, and ultimately ensures reliable mentor-mentee recommendation. A confusion matrix was employed to assess the performance of the SVM classifier on the test dataset. This matrix enables us to quantify accuracy, precision, recall and F1-score, providing a nuanced understanding of the classifier's strengths and weaknesses. The Table 2 presents the values of the true positives, false positives, true negatives, and false negatives.

Table 2 True Positives, False Positives, True Negatives, and False Negatives

Result	Predicted Positive	Predicted Negative
Actual Positive	16788 (TP)	107 (FN)
Actual Negative	190 (FP)	7044 (TN)

This result shows that the classifier excels at distinguishing between positive and negative classes. There is low false positive rate of only 190, indicating a low risk of incorrectly classifying negatives as positives.

This section delves into a detailed analysis of the classification results, exploring the accuracy, precision, recall and F1-score of the SVM classifier. The accuracy is 0.99, with support of 24,129, which shows that 99.00% of instances (24,129) are correctly classified. The results of precision, recall and F1-score for the two classified classes are presented in Table 3.

Table 3 Result of Researcher classification

Class	Precision	Recall	F1-score	Support
0: Young Researcher	0.99	0.99	0.99	16895
1: Expert	0.99	0.97	0.98	7234

In class 0, precision of 0.99 shows that 99% of predicted young researcher instances are true positives. Recall of 0.99 implies that 99% of actual young researcher instances are detected while 0.99 of F1-score shows 99% which is an excellent balance between precision and recall. In class 1, precision of 0.99 shows that 99% of predicted expert instances are true positives. Recall of 0.97 implies that 97% of actual expert instances are detected while 0.98 of F1-score shows

98% which is also an excellent balance between precision and recall. Figure 2 presents the values of precision, recall and F1-score.

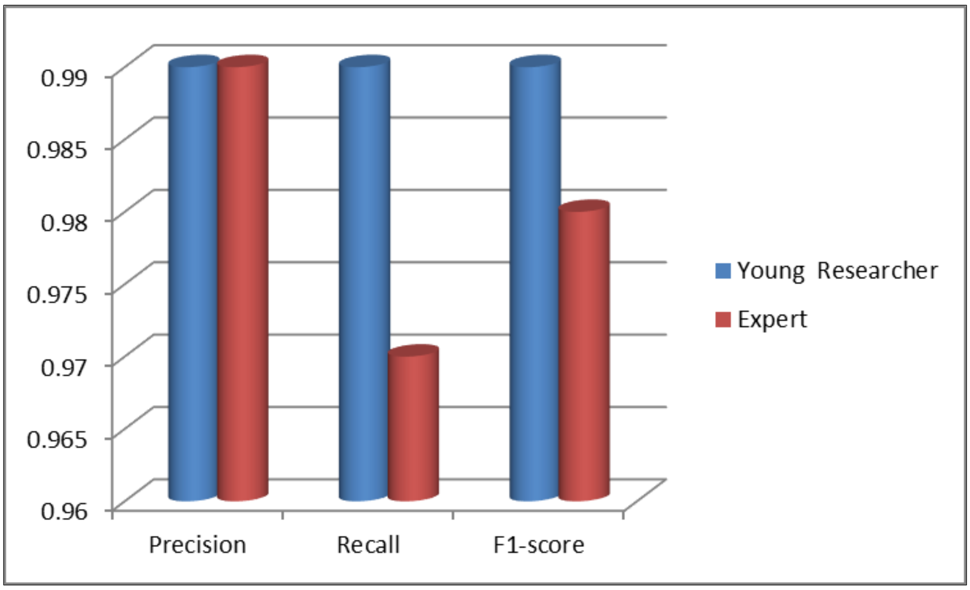

Figure 2 Bar chart visualization of Precision, Recall and F1-score

4.2. Recommendation Evaluation Results

In order to address the challenge of matching young researchers with experienced researchers effectively, a recommendation model, namely PSO-based recommendation model was developed and optimized. In this section, the results of the experiments are presented, evaluating their performance in terms of precision, recall, F1-score and MRR, in recommending suitable mentors for young researchers. Table 4 shows the experimental results of different top N recommendations.

Table 4 Results of Evaluation Metrics at Different Top N Recommendations

Evaluation Metric/ Top N Recommendation	Precision	Recall	F1-Score	MRR
@3	1.00	1.00	1.00	0.91
@5	1.00	1.00	1.00	0.87
@10	1.00	1.00	1.00	0.80

The results of the experiments demonstrate the exceptional performance of the PSO algorithm in optimizing mentor-mentee matching and recommendations. Across all metrics, the PSO algorithm achieves outstanding results. The precision values @3, @5 and @10 are all 1.00, indicating that the PSO algorithm is able to identify the most suitable researchers for mentor-mentee connection with perfect accuracy. This suggests that the algorithm is highly effective in filtering out irrelevant researchers and recommending only the relevant ones. The recall values @3, @5 and @10 are also 1.00, indicating that the PSO algorithm is able to retrieve all the relevant researchers for mentoring relationship. This suggests that the algorithm is highly effective in identifying all the relevant researchers and recommending them for mentorship. F1-score values @3, @5 and @10 are all 1.00, indicating that the PSO algorithm achieves a perfect balance between precision and recall. This suggests that the algorithm is highly effective in recommending relevant researchers for mentorship while avoiding irrelevant ones. The Mean Reciprocal Rank (MRR) values @3, @5 and @10 are 0.91, 0.87, and 0.80, respectively. While these values are not perfect (1.00), they are still relatively high, indicating that the PSO algorithm is able to rank the most suitable researchers for collaboration at the top of the recommendation list. The ability of the model to rank the most suitable researchers for mentoring relationship at the top of the recommendation list enables users to quickly identify potential mentor/mentee, saving time and increasing research productivity.

This study compares the performance of the optimized recommendation model based on PSO algorithm with three baseline models (CF, CBF, and Hybrid CF-CBF). The three baseline models are chosen for their relevance and popularity in recommender systems. The comparative analysis is structured to evaluate the performance of each model across various metrics, including precision, recall, F1-score and mean reciprocal rank (MRR). Table 5 presents the results of precision, recall, F1-score and MRR of the optimized model and the three baselines.

Table 5 Comparison of Optimized Model with Baseline Models

Model	Precision	Recall	F1-Score	MRR
CBF	0.15	0.5	0.23	0.73
CF	0.42	0.58	0.49	0.63
Hybrid CF-CBF	0.35	0.67	0.46	0.58
PSO	1.00	1.00	1.00	0.80

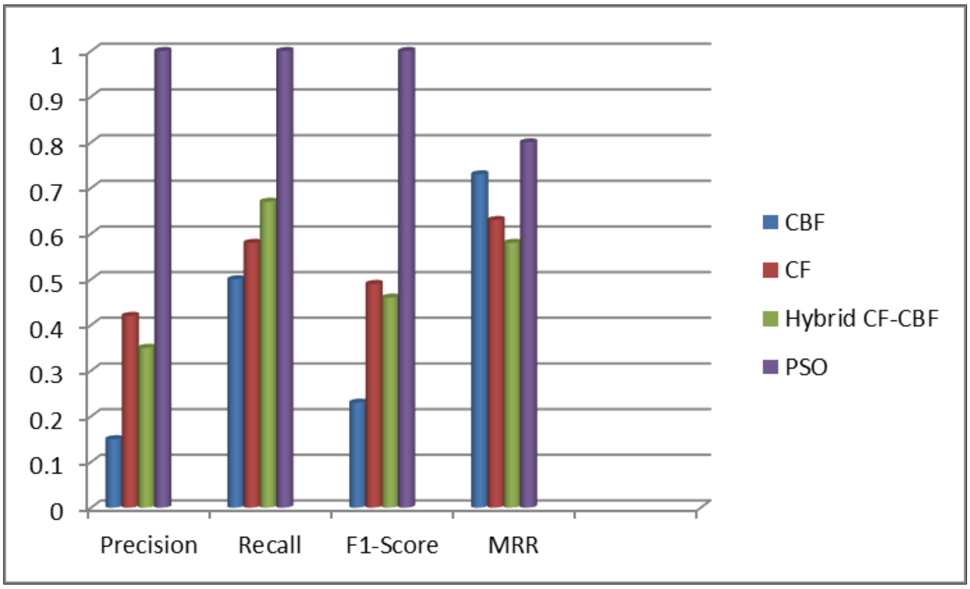

Figure 3 Illustration of comparison of results of three baseline models and the proposed optimized recommendation model based on PSO

5. Conclusion

This study successfully addresses the gap in mentor-mentee matching within academic research communities. By leveraging a novel metaheuristic-based approach, integrating SVM classification, TF-IDF feature extraction and PSO optimization algorithms, an unparalleled performance in mentor-mentee pairing was achieved. Our findings demonstrate:

- Effective researcher categorization and vector generation
- Exceptional accuracy (SVM classifier - 0.99, PSO optimizer - 1.00)

The developed model's exceptional performance highlights its potential for real-world applications. The results of this study can be used by research institution for enhancing mentor-mentee connections.

It is recommended that the researchers in scholarly recommender systems explore metaheuristic algorithms, a relatively unexplored approach in this field, to enhance recommendation accuracy. It is also suggested that the research institute maintain updated researcher data and employ recommender systems to facilitate precise matching, capitalizing on the ability of these tools to identify key features.

Future investigations can focus on expanding datasets, refining algorithms and exploring real-world applications. Our study paves the way for transformative mentorship frameworks, elevating the landscape of academic research collaboration.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

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