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A Group Recommender System Based on Machine Learning for Hypertensive Patients

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Abstract

Hypertension, a severe chronic disease and a primary risk factor for cardiovascular issues, poses significant challenges in treatment and decision-making for physicians. Recommender systems present a promising avenue for enhancing hypertension care decision-making processes. However, traditional approaches such as collaborative filtering encounter challenges like data sparsity and scalability. To address these challenges, machine learning based recommender systems have been explored. This study presents an enhanced collaborative filtering method, integrating clustering and group recommendation techniques. The proposed research aggregates group recommendations for each cluster using static and dynamic methods. For new patients, three similarity measures are employed to select relevant recommendations from the most similar case cluster. The findings demonstrate the model's satisfactory performance, particularly when employing dynamic group recommendation and Euclidean similarity, showcasing improved accuracy in terms of Mean Absolute Error (MAE).

Keywords: Clustering, Hypertension, Machine learning, Recommender system

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Introduction

Hypertension, a severe non-communicable chronic illness, leads to various diseases and long-term consequences if left untreated [1]. It's a primary risk factor for cardiovascular issues, stroke, chronic renal failure, and diabetes [2,4]. With approximately 31% of adults affected globally, hypertension is becoming a significant worldwide health concern [5]. Predictions suggest it will impact over 1.5 billion people by 2025, driving extensive research to prevent, detect, control, and treat it [6,7].

Treating hypertension poses challenges as it is identified as a silent disease, often leading to undetected complications [8,9]. Additionally, clinical therapies are frequently ineffective due to human errors, biases, and high costs [10]. Indeed, numerous studies have been undertaken to prevent, detect, control, and treat this disease, aiming to handle these challenges. Among these studies, recommender systems based on machine learning offer promising avenues to address the challenges, particularly in healthcare systems [11]. By leveraging patient data and advanced algorithms, these systems can provide timely, cost-effective, and accurate recommendations for treatment optimization [12].

Recommender systems serve various purposes across different domains, notably aiding users in product selection [13]. In healthcare, particularly, they are extensively deployed as health recommender systems (HRS), enhancing medical decision-making processes[14,15]. HRS not only contribute to improving patients' health outcomes and fostering healthy lifestyles but also assist healthcare professionals in diagnosing and treating diseases efficiently, thereby optimizing the decision-making process while minimizing costs [16,17].

These recommender systems are typically categorized into four main types: collaborative filtering, content-based, knowledge-based, and hybrid approaches [18]. Collaborative filtering, a widely utilized method, evaluates user items' similarities to recommend relevant healthcare services based on similar user profiles or health conditions [14,16,19]. In contrast, the content-based approach relies on item similarities rather than user profiles to suggest services matching the patient's preferences and health status [14]. The knowledge-based approach, on the other hand, allows patients to specify their needs, which is particularly useful when the available item selection is limited [16]. Hybrid approaches, combining previous methods, present promising solutions to overcome inherent obstacles in recommender systems [20].

Recommender systems face some challenges, including cold start, sparsity, and scalability. Addressing these obstacles is essential to enhance efficiency and effectiveness [21]. Sparsity issues arise when an abundance of recommendations is directed towards a small subset of users, resulting in a scarcity of data necessary to ascertain similarity between users [20]. This limitation severely impacts the system's capability to furnish accurate and personalized recommendations tailored to individual preferences and requirements.

Moreover, scalability presents another formidable challenge, particularly as the volume of data within recommender systems burgeons with a growing number of users and items [12]. Managing and processing large datasets efficiently becomes increasingly hard, impeding the system's performance and agility. Additionally, the cold start problem emerges when new items or users are introduced to the system, leading to an inadequate dataset for generating meaningful recommendations [22]. This constraint undermines the system's adaptability and its ability to offer valuable suggestions to users, particularly in scenarios where user preferences are not well understood or established. Therefore, surmounting these challenges is essential to optimize the functionality and utility of recommender systems across diverse applications.

Researchers have increasingly relied on machine learning methodologies to tackle challenges in recommender systems. Notably, clustering techniques play a pivotal role in mitigating issues such as sparsity and scalability [21]. Additionally, the integration of group recommendation techniques with collaborative filtering presents a promising avenue to address the cold start problem [23]. These group recommendation strategies involve suggesting items to a collective user group based on their preferences, employing aggregation methods drawn from similar cases or items, whether statically or dynamically [24].

Accordingly, this paper proposes a clustering approach combined with group recommendation techniques to enhance the efficiency of decision-making processes in hypertension. Our study contributes in three key aspects:

1. Offering a clustering-based solution to address sparsity and scalability challenges in hypertension recommender systems.
2. Utilizing group recommendations to alleviate the impact of the cold start problem.
3. Implementing dynamic generation of group recommendations to enhance recommendation accuracy.

The rest of the paper has the following sections. In the second section, an overview of related works is provided, offering insights into the existing research landscape. Following this, the proposed model is detailed in the third section, outlining its methodology and key components. Subsequently, the fourth section evaluates the results obtained from the application of the proposed model. Finally, the paper concludes with a discussion of the findings and outlines potential directions for future research.

Related work

In recent years, there has been a noticeable rise in chronic diseases and associated mortality rates, underscoring the significance of early detection and awareness in mitigating their risks [25]. Consequently, the adoption of machine learning techniques holds promise in enhancing decision-making processes. The inception of machine learning dates back to the late 1970s, gaining traction with notable advancements such as neural networks, support vector machines, and hybrid methods in the 1990s [26]. In the field of healthcare, artificial intelligence has played a pivotal role since the 1990s, witnessing the application of various classification methods for disease diagnosis and prediction [27]. By the late 1990s, recommender systems became prominent, especially in healthcare, where studies started working on health recommendation systems [15].

Among recommender systems approaches, collaborative filtering is one of the most widely used methods. Collaborative methods typically rely on user-item interactions or similarities between users or items to generate recommendations. These methods include techniques like nearest-neighbor algorithms, matrix factorization, and learning models. Non-collaborative approaches, on the other hand, leverage additional information beyond user-item interactions, such as content features or domain knowledge, to enhance recommendation accuracy. These methods often include content-based filtering, knowledge-based recommendation systems, and hybrid models combining collaborative and content-based techniques. Many studies have been trying to overcome the problem of cold start, scalability, and sparsity in traditional collaborative filtering.

Some studies have explored the use of clustering techniques to group similar patients and reduce the search domain for new patients, thereby streamlining the recommendation process. In the research conducted by Mustaqeem et al., a recommender system was created for cardiovascular patients based on collaborative filtering and the use of clustering and sub-clustering in two stages[21]. On the other hand, some studies use hybrid approaches, leveraging the strengths of each approach and mitigating their limitations. In a study, an IoT-based hybrid recommender system is presented for cardiovascular patients using wireless sensors and patient clinical lab results to provide personalized recommendations [28]. The disadvantage of this method is that Using sensors to collect data is difficult and time-consuming. Also, the grouping of patients in this study according to gender and age may not be as accurate as clustering.

Others have focused on leveraging time-series data to predict patient recommendations, enabling personalized treatment plans based on historical patient outcomes. For example, in [10], using time series data, a CBR model was presented to track the results of drug treatment in patients with hypertension and find the most effective drug as a patient prescription by searching for the most similar patients. Study [29] also presented a recommender system using Fourier transform and machine learning techniques for predicting chronic heart disease that uses patient time series data. In the study [30], a system was developed to recommend physical activity to patients with hypertension. The main purpose of this study was to help patients have healthy habits and longer lives. In another study, a disease-based diet recommender system was proposed that focuses on creating a personalized diet according to a patient's nutritional needs, health conditions, and preferences using machine learning techniques with the content-based method [5].

Considering that collaborative filtering relies on identifying patients with similar characteristics, suggesting treatments to a group of similar patients may yield superior outcomes compared to individual recommendations. Research indicates that group dynamic-based principles could positively impact patients' health [27]. However, previous studies in hypertension have not explored the incorporation of group recommendation methods with collaborative filtering. This paper introduces a novel recommender system that integrates group recommendation methods, collaborative filtering, and clustering to address this gap. This approach aims to resolve current challenges and offer improved and more precise recommendations for patients.

Method

In this study, unsupervised learning techniques, specifically clustering algorithms, were implemented to group similar patients based on their characteristics. The primary objective was to utilize these clusters to provide recommendations for new patients. Clustering is a machine learning technique that partitions data points into groups, or clusters, based on their similarity. The K-means clustering algorithm was employed in this research to segment the patient population into distinct clusters. The algorithm assigns each patient to the cluster with the nearest mean, iteratively optimizing cluster centroids until convergence.

The proposed model, as depicted in Figure 1, is an enhanced collaborative recommender model designed to overcome challenges in collaborative filtering, including data sparsity and scalability. The data for this study on hypertensive patients was gathered from the heart department of Shohada Tajrish Hospital in Tehran. The data collection process involved administering surveys to gather information from 230 patient records and reviewing their medical files.

Patients were included in the analysis if they visited the heart department clinic and received prescriptions or advice from an expert doctor, which could involve medications or guidance on personal habits like smoking cessation. However, patients who didn't receive any recommendations or prescriptions from expert doctors were excluded from the study. It's important to note that there was no sampling method employed, and all available data from the heart department clinic was utilized for the analysis.

The patient characteristics outlined in this study are classified into two primary categories: demographic information and vital signs. Demographic data provide insights into the patient's personal details, while vital signs offer indications of the patient's current health status. Detailed information regarding both demographic and vital sign data can be found in Table 1.

For data analysis in this study, Python 3.10 was utilized, running on a machine with a quad-core Intel Core i7 processor and 16 GB of RAM. Jupyter Notebook served as the primary interface for code development and analysis. Python's versatility, supported by its extensive collection of libraries and tools, including NumPy, Pandas, and Scikit-learn, facilitated various data preprocessing and machine learning tasks.

Table 1. Patient's features

Demographic Information	Vital Sign Information
Age Gender Weight Height Family history of diabetes Family history of hypertension Fat intake Salt intake Exercise Smoking level	Diastolic blood pressure (DBP) Systolic blood pressure (SBP) Pulse rate Body mass index Chest pain, muscle pain Shortness of breath, cholesterol Fasting blood sugar (FBS)

The data features are classified into two distinct types: continuous and discrete. Continuous features include weight, height, DBP (Diastolic Blood Pressure), and SBP (Systolic Blood Pressure), while the other thirteen variables are categorical. The analysis of the continuous data involved calculating the mean and standard deviation, which are presented in Table 2, serving as measures of central tendency and dispersion, respectively.

Table 2. Continuous variables description

	Weight (kg)	Height (cm)	SBP	DBP
Mean	77.97	166.7	122.33	77.63
STD	15.01	9.07	10.04	6.51
Min	40	150	95	60
Max	130	199	160	100

Data collected from real-world sources often contains inconsistencies, errors, and missing information, making it necessary to preprocess the data before analysis. In this study, missing values were estimated using the KNN method with k=5, and outliers were identified and removed using the IQR method.

After pre-processing and implementing a 10-fold cross-validation approach to split the dataset into training and testing subsets, the training data undergoes K-means clustering to group patients. The K-means clustering algorithm is applied with a set number of clusters, k = 8, determined using the elbow method. Subsequently, three distinct aggregation methods are employed to select group recommendations for each cluster, incorporating two dynamic and one static approach. The step-by-step process followed in our proposed methodology is illustrated in Algorithm 1.

Algorithm 1

Inputs: the set of data *D*; the number of cluster *k*
Output: recommendation for a new patient
Set array *A* for cross-validation process
Set iteration count *k = 10*
Divide D randomly into ten categories and put them in array A

While (*K > 0*) **do**

    Put the *Kth* category as train data and the remaining categories as test data.
    Apply *K-means* clustering on training data with k = 8
    Extract a list of recommendations for each cluster
    For each *patient P in* D_{test} **do**
        Find a similar user to *P*
        Find the appropriate cluster for *P*
        Provide cluster recommendations to *P*
        save evaluation metrics for *P*
    K = K-1

Report the average evaluation results.

Recommendations are then generated for each cluster using two approaches: static and dynamic. In the static approach, a fixed numerical threshold is utilized to determine the top N recommendations, ensuring uniformity across all clusters. Here, a static threshold of 10 recommendations is established within the proposed model. Conversely, the dynamic approach employs a threshold as a percentage, allowing for varying recommendation numbers tailored to each cluster's characteristics. In this study, a dynamic threshold of 10% is adopted. Table 1 outlines the diverse methods utilized for selecting group recommendations, elucidating the contrasting strategies employed in the recommendation process.

Table 3. Methods of selecting group recommendations for each cluster

model	approach	Recommendation selection for each cluster
1	static	Select the top 10 recommendations
2	dynamic	Select the first 10% of the recommendations
3	dynamic	Select recommendations with the participation of at least 10% of the members

In the testing phase, when a new patient arrives, the model searches for a similar case using three similarity measures: cosine, Euclidean, and Jaccard similarity. It then identifies the cluster to which the most similar case belongs and presents the cluster's group recommendations to the new patient. This process is illustrated in Figure 2.

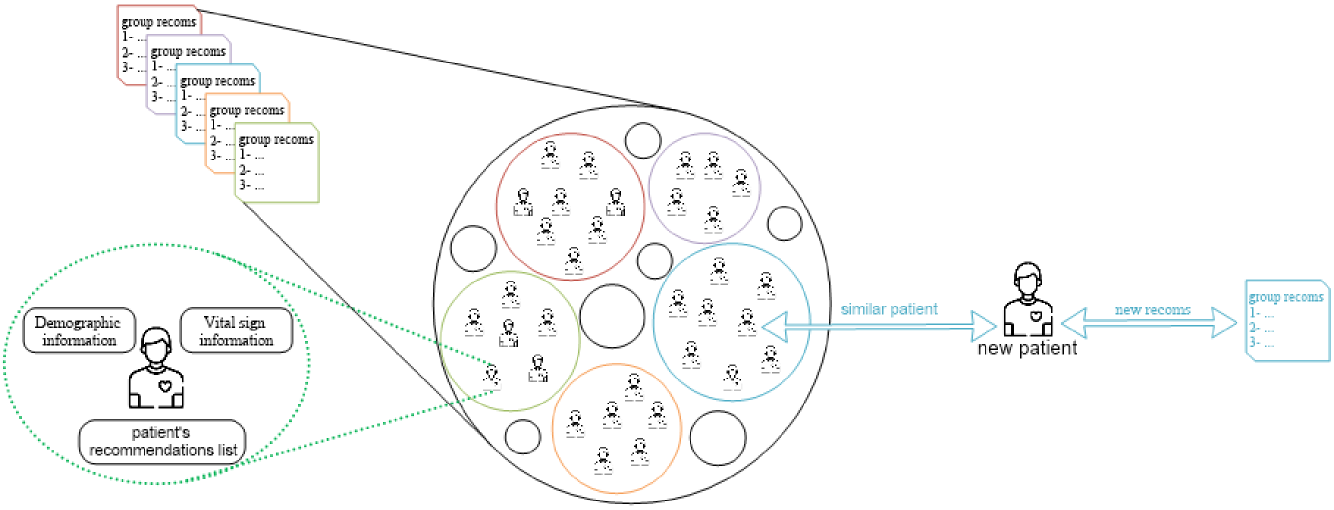

Figure 1. The overall process for a new patient

The cosine similarity measures how similar two objects are by considering them as vectors and calculating the angle between them. When two objects are most similar, they align perfectly (0 degrees), whereas if they are dissimilar, the angle between them is 90 degrees. Equation 1 demonstrates how to compute cosine similarity [31,32].

$$sim(a,b) = \frac{(a).(b)}{\|a\|\|b\|} = \frac{\sum_{i=1}^{n} a_i b_i}{\sqrt{\sum_{i=1}^{n} {a_i}^2}\sqrt{\sum_{i=1}^{n} {b_i}^2}} \qquad (1)$$

The Euclidean distance calculates the distance between two objects based on their properties. Equation 2 shows how it is computed, where n is the number of properties and a_i and b_i denote the values of the ith property for the data samples a and b [21].

$$d(a,b) = \sqrt{\sum_{i=1}^{n} (a_i - b_i)^2} \qquad (2)$$

The Jaccard similarity measures the similarity between two records by comparing the intersections of their neighboring sets to their unions. It focuses solely on the shared rankings between two users to assess similarity. Equation 3 illustrates how it is computed [33].

$$J(a,b) = \frac{|A \cap B|}{|A \cup B|} \qquad (3)$$

Evaluation

The model's performance is assessed on the testing dataset using four key metrics: Precision, Recall, F1-score, and Mean Absolute Error (MAE). These metrics are commonly used to evaluate the effectiveness of recommender systems. MAE measures the average difference between the predicted values and the actual results. Equation 4 demonstrates its calculation, where N represents the number of instances in the testing dataset, P is the predicted value, and A is the actual value [32].

$$MAE = \frac{1}{N}\sum_{i=1}^{N} \|P_i - A_i\| \qquad (4)$$

Precision and Recall are essential metrics for evaluating recommendation quality [34]. Precision measures the proportion of accurate recommendations made to patients out of the total recommendations given. It's calculated using Equation 5.

$$Precision = \frac{Correct\ recommendations}{Total\ recommendations} \qquad (5)$$

Recall, calculated from Equation 6, quantifies the ratio of correct recommendations provided to patients against the total number of recommendations generated by the system.

$$Recall = \frac{Correct\ recommendations}{Relevant\ recommendations} \qquad (6)$$

The F1-score, which combines Precision and Recall, serves as an average metric for assessing the model's performance.

$$F1\text{-}score = \frac{2 \times Precision \times Recall}{Precision + Recall} \qquad (7)$$

Each evaluation metric will produce nine outputs, considering three methods of selecting group recommendations and three methods of calculating patient similarity. These results are summarized in Table 2, where the "model" column indicates the aggregation method used for group recommendations as described earlier.

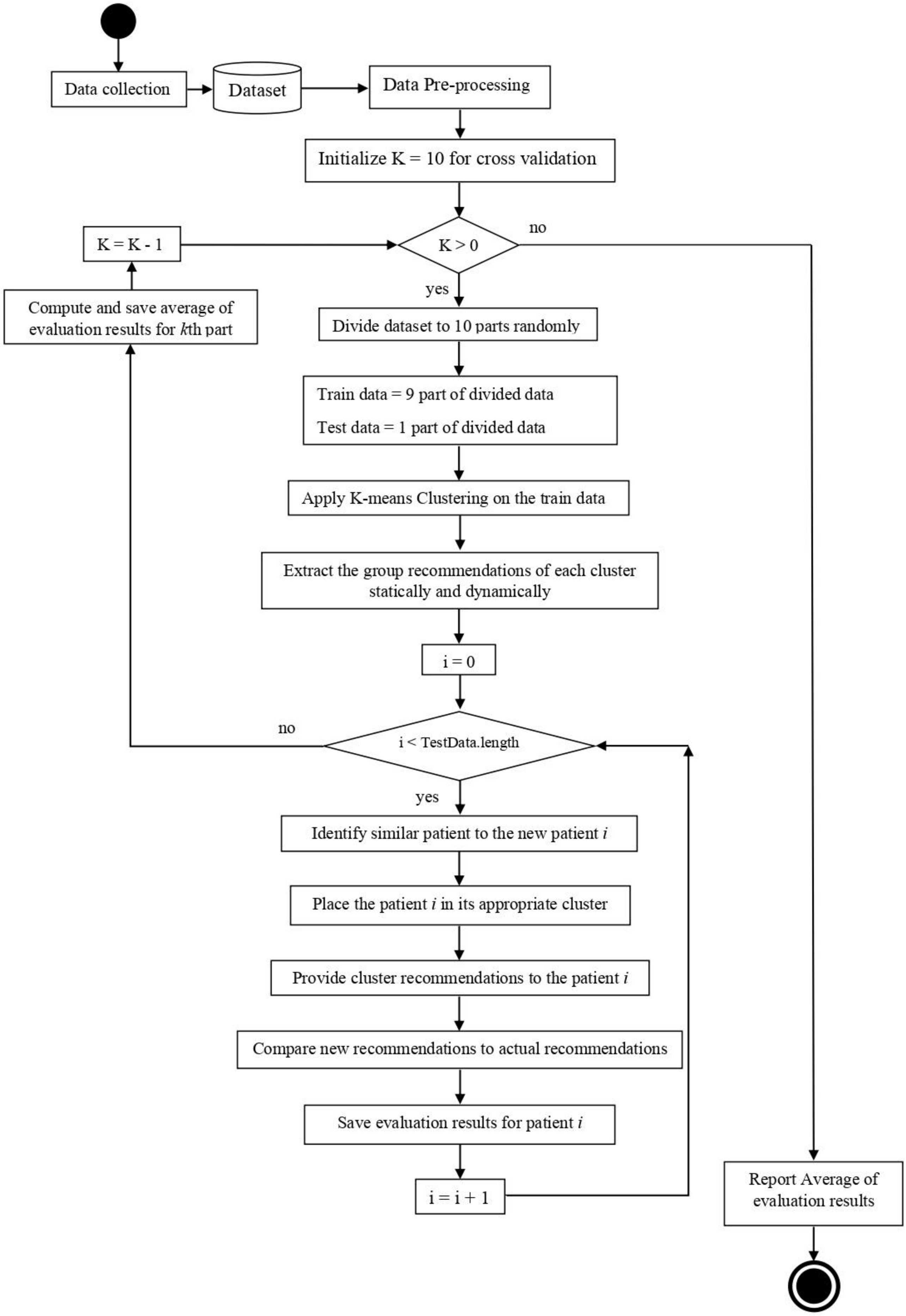

Figure 2. Flow chart of the proposed method

Table 4. Evaluation results

	cosine similarity metric				Euclidean similarity metric				Jaccard similarity metric			
Model	**MAE**	**F1**	**Recall**	**Precision**	**MAE**	**F1**	**Recall**	**Precision**	**MAE**	**F1**	**Recall**	**Precision**
1	15.97	27.95	65.95	15.50	15.88	27.95	66.06	15.52	16.04	30.74	64.74	15.39
2	5.29	52.52	35.04	35.68	5.20	52.19	35.64	37.11	5.21	54.31	33.31	35.31
3	9.27	38.54	63.10	26.18	9.00	37.23	60.53	26.88	8.26	46.65	58.15	28.02

The findings from Table 2 indicate that the Jaccard similarity method consistently achieved higher F1-score across all three models. However, while the first model exhibited a Recall above 60%, suggesting it can predict existing recommendations quite well, its lower F1-score indicates that the ratio of predicted recommendations to existing recommendations is significantly lower. Conversely, the second model demonstrated a lower error rate and higher F1-score across all similarity metrics. For a visual comparison of the model's performance based on the F1-score metric, refer to Fig. 2.

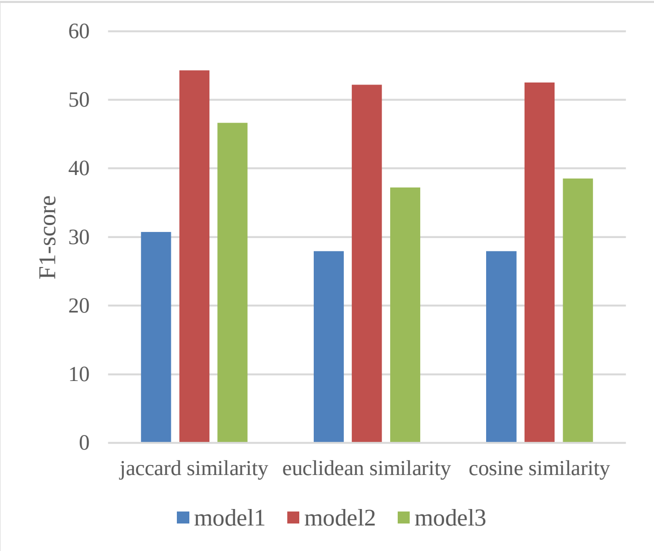

Figure 3. Comparison of results for F1-score

The results were compared to a study by Mustaqeem et al.[21] in terms of Mean Absolute Error (MAE). It was found that our models had lower MAE values than those reported in Mustaqeem's research.

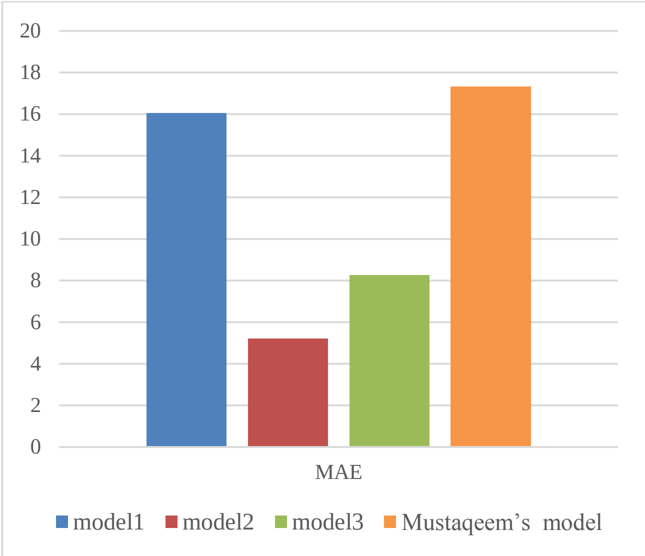

Figure 4. A comparison of the proposed model with Mustaqeem's research in terms of MAE

In table 2, a subjective comparison is made between the introduced model and previous studies which evaluating the overall performance of different approaches. The comparative analysis unveils several noteworthy distinctions among the studies. For instance, while the proposed model integrates multiple evaluation metrics such as MAE, Recall, Precision, and F1-score to comprehensively assess the recommender system's performance, prior investigations may have employed less extensive evaluation methodologies. Moreover, the incorporation of various similarity metrics, including Jaccard, Cosine, and Euclidean, in the proposed method distinguishes it from earlier studies that might have relied solely on a single similarity metric.

The diversity observed in the evaluation metrics and similarity measures highlights the evolving sophistication and robustness of recommendation systems over time. This diversity not only offers more nuanced insights but also enhances the effectiveness of these systems in real-world applications.

Table 5. Subjective comparison between other recommender systems and the presented recommender system

Reference	year	Scope	Goal	Recommendation model technique	Similarity computation technique	Evaluation
Proposed method	2024	Medicine recommendation	Improved collaborative filtering approach that relies on clustering and group recommending activities for hypertensive patients	Collaborative filtering	Jaccard, Cosine, Euclidean	MAE, Recall, Precision, F1-score
[35]	2023	Drug recommendation	To describe a digital recommendation system for the pharmaceutical treatment of hypertension	Hybrid approach	simple matching coefficient	Clinical Experts
[36]	2022	Medicine recommendation	To present a medicine recommender system to assist the physician in the process of prescribing hypertension drugs	association rule & graph mining	Jaccard Similarity	The results achieved by this system have been examined and confirmed by an expert in this area.
[37]	2021	Food recommendation	A personalized dietary plan that will be useful for maintaining a healthier lifestyle and curing diseases	Collaborative filtering	KNN	This model could be used as an efficient tool to enhance nutrient needs and can also help the user in maintaining and improving their health status.
[30]	2020	Physical activity recommendation	Developing a physical activity recommendation system for hypertensive patients, supporting them towards healthy habits and longevity.	Collaborative filtering	Pearson's Correlation Coefficient	The validation results of the based on the recommendations generated by the models revealed ~ 75% of approvals
[10]	2016	Medicine recommendation	follow the results of the drug treatment in hypertensive patients and identify the most efficient prescription	time-based CBR	Occurrence Frequency (OF) method	The initial results confirm that the proposed approach will provide a good recommendation for the treatment of hypertension.

Discussion

This study contributes to the growing body of research on recommender systems in healthcare, offering insights into novel approaches for hypertension management. The integration of clustering techniques with group recommendation methods represents a significant advancement in addressing the unique challenges of collaborative filtering in healthcare contexts, aiming for better performance.

Considering comparisons with other studies, it's important to note that although we utilized three evaluation metrics, many other studies either used less important metrics, no metrics at all, or only qualitative metrics. This variation complicates direct comparisons based on our metrics. Nevertheless, as mentioned in the previous section, we did compare our model to Mustaqeem et al. [21] study. Our most optimal model demonstrated a Mean Absolute Error (MAE) of approximately 5 units. In contrast, Mustaqeem et al. study reported a MAE of 17 units. This indicates that our model exhibited a reduction in error by a margin of 12 units or roughly one-third of the magnitude observed in the aforementioned study.

Another aspect worth mentioning is the selection of performance metrics in recommender systems. Selecting appropriate metrics is crucial for accurately assessing the effectiveness of the system in achieving its objectives. The choice of performance metrics in recommender systems is closely tied to the system's intended purpose. For instance, the emphasis on Recall becomes paramount when the goal is to ensure that the recommended items align closely with those already present in the dataset. In healthcare settings, where patient safety and adherence to established treatments are critical, maximizing Recall can help guarantee that essential recommendations are not overlooked.

Conversely, precision gains importance when the aim is to minimize discrepancies between the suggested items and those deemed relevant. Precision-oriented approaches are particularly useful when the focus shifts towards suggesting novel or less-known treatments, where the accuracy of recommendations takes precedence over coverage. In this study, having higher Recall is typically preferred, indicating that the recommender system retrieves relevant items effectively. However, a lower precision doesn't necessarily imply that the recommender system is malfunctioning.

In navigating the trade-off between Recall and Precision, it's essential to align the evaluation metrics with the overarching objectives of the recommender system. While improving Recall enhances the system's ability to capture existing recommendations accurately, enhancing precision fine-tunes its capacity to suggest newer or less familiar options. Striking the right balance between these metrics is crucial, especially in healthcare, where the stakes are high, and the recommendations directly impact patient well-being. Ultimately, a nuanced understanding of the goals and priorities of the recommender system guides the selection and optimization of evaluation metrics, ensuring that the system effectively serves its intended purpose in healthcare decision-making.

Conclusion

This research developed a recommender system tailored for individuals with high blood pressure, integrating collaborative filtering, machine learning techniques, and group recommendation methods to enhance disease management. The data was grouped into 8 clusters using k-means clustering, and model evaluation was conducted through a 10-fold cross-validation approach. The model's performance varied based on the chosen group recommendation method and similarity calculation technique, with low errors indicating satisfactory similarity between predicted and available recommendations.

A significant challenge faced in this study pertained to data collection, marked by missing information and the inability to verify patient details. Moving forward, enhancing the model with additional features, such as patients' laboratory results, could result in improved recommendations.

Highlights

What Is Already Known?

As decision-making is critical in hypertension care, machine learning approaches are increasingly being adopted to enhance recommendation accuracy. Traditional recommender systems for healthcare, such as collaborative filtering, face challenges like data sparsity and scalability. Group recommendation techniques have been recognized for reducing the cold-start problem by leveraging collective data, and clustering methods have shown promise in improving scalability.

What Does This Study Add?

This study introduces a clustering-based group recommender system tailored for hypertensive patients, using static and dynamic methods. For new patients, similarity measures are employed to personalize recommendations, addressing cold-start challenges. The proposed model demonstrates improved accuracy, as validated by lower Mean Absolute Error (MAE) metrics.

Authors' Contributions

All authors contributed equally to this study.

Conflicts of Interest Disclosures

The author declares no conflicts of interest.

Consent For Publication

All authors have reviewed the manuscript and consent to its publication.

Ethics approval

All participants provided informed consent for inclusion in the study and publication of the findings.

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