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To Enhance the Quality of HCRS using Fuzzy-Genetic Approach

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ABSTRACT

Social media is recent generation of Recommender Systems (RS). Health Care Recommender System (HCRS) term used to analyse the medical data and then predict the disease of a patient with the help of various techniques used in RS. To ensure the quality and trustworthiness of medical data, machine learning algorithms are applied. Even though, there is a much gap between health care diagnosis and IT solutions. To evade this gap, the hybrid Fuzzy-genetic approach is used in HCRS. In this, Genetic algorithm is used for similarity computations with the help of mutation and crossover operators. Later fuzzy rules are generated for the data set with the additional personalized information of a user. Considering these approaches, the proposed model enhances the quality of recommendation in HCRS.

1. Introduction

Managing data is difficult in social media networking sites. To manage the data and to generate proper information, the recommender systems (RS) is used. RS is recommending items to user and RS is classified as content based, collaborative, hybrid filtering and demographic filtering. Now a days, health care RS is more popular and this recommends various hospitals, doctors and prediction of diseases etc. In every Health care Recommender Systems (HRS), the symptom checker is used to generate some prediction of diseases of the patients or users. According to the interest of users and his/her profiles HCRS gives the recommendations. There are many issues and challenges of RS are discussed as follows:

1.1. Privacy

In HCRS, the patient data is very much important for analysing and predicting the disease. However, the data is scattered in various geographical information. Connecting with this information from different sources of regions is challenging. Different sites may share the data of various patients in networking sites, this may not provide any privacy to the users. Due to legal and privacy issues the health care RS does not achieve data confidentiality. Many researchers worked on HCRS with privacy issues in which they could not target the computation cost of confidentiality when it is in offline. Generating offline data with privacy is also known as homographic encryption technique. To implement for online data of patient Kaur H et.al (2018) presented paillier homographic encryption system which is used for online patient data and various techniques were compared with the consideration of parameters such as confidentiality, integrity and etc. Sahoo, A.K et.al (2019), proposed the jaccard similarity with Single Value Decomposition (SVD) may target the privacy issues in which the optimization of nearest neighbor is computed. This would help in achieving privacy and accuracy of the proposed model.

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1.2. Trust and distrust Cold start user solutions

One of the recommendation issues is cold start user or item problem in which the problem arises when a new user or item introduce in online website applications. The recent research work is focused on this issue to achieve the accuracy and quality of RS. There are many techniques applied to target the cold start user or item problem. Mu, R et al (2016), presented Deep learning which is one of the renowned techniques in neural network used in many advance technologies such as speech recognition, image analysis, and natural language processing in the area of RS. For more complex abstraction levels of data representations the deep learning technique is used. Social recommendation sites are playing a major role in the area of HCRS. Trust and distrust taken into consideration when there are many social relations in prediction of recommendations. Yuan, W (2018), presented these trust distrust relations between users with the comparison of active user. If the user is more similar to active user, then this is known as trust otherwise it is distrust. The trust and distrust relations based on similarity computation threshold. In this work deep learning socialized healthcare service recommender model introduced which may count the node and structure information to target the prediction accuracy and coverage and may reduce the cold start and sparse issues. To achieve this trust and distrust relations SVD clustering is used. Ma, X et al (2017), presented the computation of indirect trust between trusted users. Here in this a trust neighbours mining algorithm is proposed to compute the relations between trusts of users. To achieve the efficiency of recommendation of trusted users a sparse rating complement algorithm is also proposed and this may give the prediction accuracy and coverage. Due to insufficient information of new user or item the predictions and recommendation are difficult to achieve in recommender engine. Gope, J and Jain, S.K. (2017), presented the missing value prediction where the entries are missed in the analysis of prediction and recommendations with the classes' information of implicit and explicit solutions. These cold start problems are categorized into complete cold start (CCS) and incomplete cold start (ICS) problems where in CCS, no information available and in ICS small number of users' information is available. Wei, J. et al (2017), proposed a framework for CF in which the approach is based on tightly coupled CF with a specific deep learning neural network SADE and this counter the problem of cold start users and items.

1.3. Sparsity solutions

Managing huge data is the problem of Collaborative Filtering and missing entries is also need to be identified. When the data is less in user item matrix the problem is called sparsity. To achieve the prediction accuracy or quality of recommendation the sparsity problem is also need to be resolved. Banda. L and Singh. K (2020), proposed a hybrid filtering approach which is the combination of content based and collaborative filtering techniques with demographic filtering. In this the user profiles have been considered and applied real value genetic algorithm on offline and online data so that the sparsity and scalability issues may resolved. They introduced an incremental clustering and trust to remove sparsity, scalability and cold start user problems. In this the data is taken of collaborative filtering with tagging information.

1.4. Scalability solutions

In HCRS, managing huge data is a difficult task. When user and item data increase in the database then predictions and recommendations of users is difficult and the problem is also known as scalability problem. Shahabi, C. et al (2001), proposed a recommendation model Yoda is designed for a large-scale web-based application data. In this the content based and collaborative filtering techniques are merged to achieve higher accuracy. To maintain online large-scale data the author proposed a filtering technique FLHS (Filtering Locality Sensitive Hashing Technique) which enhances the accuracy of recommendations. Kumar A and Sharma A (2013), presented two CF algorithms focussed on weighted slope with item clustering and item classification & item clustering. In this, the algorithm targets the problem of scalability and sparsity problem which may enhance the accuracy of recommendation.

2. Literature Review

Presently Health Care Recommender Systems (HCRS) become an important system for every user who is a part of social recommendation sites. This HCRS is a part of Decision Support Systems in this the user or patient data is analysed and then predicted. Many researchers worked on this HCRS and they could achieve various challenges such as scalability, sparsity and cold start user or item problem. In HCRS, machine algorithms used for finding useful information which may be applied on other applications. There are many tools available in machine learning to handle huge data and unstructured or hidden structure. For this, intelligent optimization techniques used for future prediction and classification. Priyadarshini et al (2018), presented DL tools in this area of HCRS applications. Other than Machine learning tools, Internet-of-Things (IoT) are trending technology is affordable in HCRS. Wearing a smart gadget and using many software applications are a part of IOT. Prediction of disease, diagnosis and prediction of disease and health care related data may use of IOT applications. Wearable smart gadgets are also an example of these IOT applications of HCRS. Priyadarshini, R et al 2018, presented a fog-based deep learning model (DeepFog) that collects the data from individuals and predicts the wellness status using a deep neural network model which may handle heterogeneous and multidimensional data. In this, they have focused on diabetes, hypertension and stress type related diseases. Dai et al (2018) proposed a frame work based on deep learning module in which they presented deep neural network to diagnose the health status of a patient and later the action evaluation module is developed on the basis of Bayesian inference graph.

In HCRS, the user or patients share their personal health information. In this the prediction of health information of a user is a challenging task which may induce data overload. When it comes to the knowledge at the back-end of health care data of recommender engine, it is very difficult in analysing a patient data and the searching skills makes very harder with lack of information. Here in this Yang, C.C and Jiang, L (2018) used the data set of HCRS in which the heterogeneous data is considered of users and threads and their relationship on MedHelp data. Baldominos, A et al (2018), proposed a Big Data Analytics for Intelligent Healthcare Management which covers both the theory and application of hardware platforms and architectures in the area of HCRS and this

is implemented using machine learning algorithms. Wang, Y et al (2018), also worked in the area of big data analytics of HCRS. They have identified 26 big data implementation cases which are unstructured and these factors have been mapped with information technology. To bridge the knowledge gap between IT applications and health care organizations. Wang, Y and Hajli, N (2017), proposed big data analytics-enabled business value model using resource-based theory which increases the accuracy of model in prediction of health cases of a user. In order to solve the health recommendation problems, Archenaa1, J and Mary Anita, E.A (2017), given a study on HCRS in which the analysis is done on multi structured healthcare data. The Evidence-based medicine tool is used to minimize the cost and treatment variations.

In addition to this machine learning algorithms the data sets of HCRS need to be classified for high quality analysis. Portugal I et al (2018), presented various machine learning algorithms in RS and finally they have focussed on Bayesian and decision tree algorithms for better recommendations. Chen, J et al (2018), proposed a Disease Diagnosis and Treatment Recommendation System (DDTRS) identified disease symptoms more accurately. In this a Density-Peaked Clustering Analysis (DPCA) algorithm was introduced for disease-symptom clustering to get higher accuracy of prediction of a disease of a patient.

3. Proposed Framework Health Care Recommender Systems using Fuzzy-Genetic Approach

The Personalized recommender system for health care provides health care information services to the users. The system may have user profiles which are updated by the users gradually. The profiles include the demographic and health data of the users. The system provides information to the users, based on their query and as well proactively based on their profile the appropriate information of hospitals and doctors data is provided.

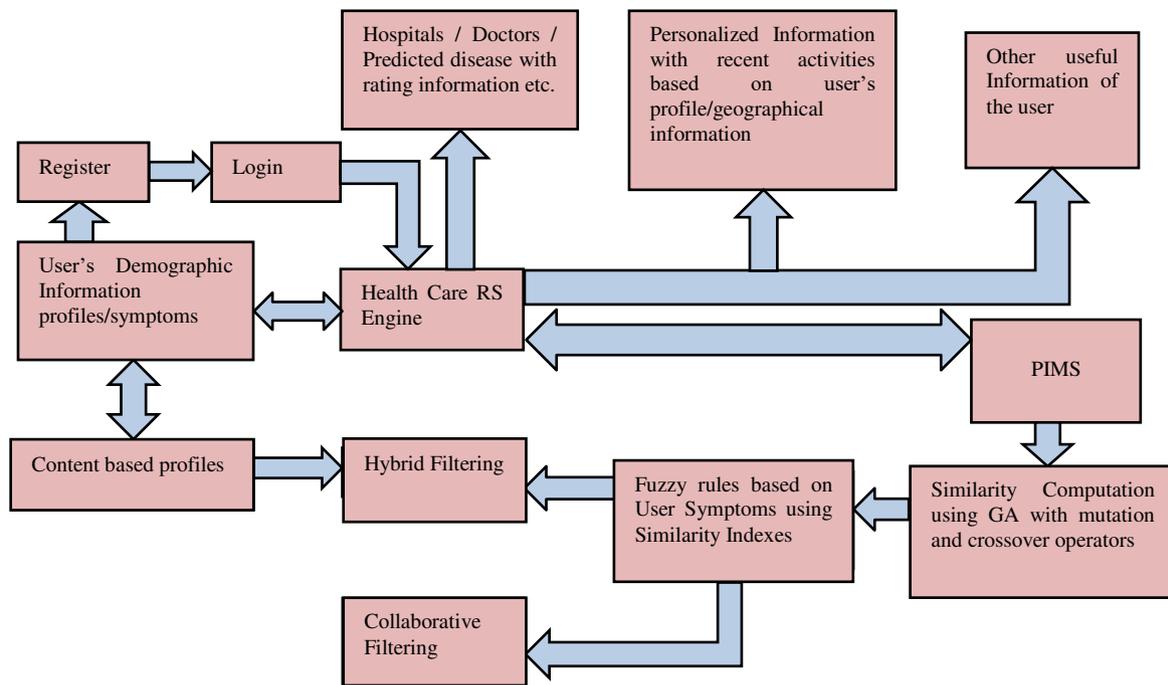


Fig.1- Proposed Framework for HCRS using Fuzzy-genetic approach

The system may send email, SMS and Ad post alerts/advices to the users regarding the regular checkups/actions which may based on their profiles such as particular medical checkups, vaccinations, age related diseases etc. The users will be encouraged to provide ratings for the hospitals, doctors and this information will be available to the users to enable them in making decisions. The collection of data from social networking sites and hospitals is to provide to the users the current information of their interest. First aid information will be provided through video lectures and other procedures. Alerts will be provided for the vaccination of child care, age oriented diseases and free check-up through the SMS or e-mail or Ad post alert. Generally, user do not have appropriate information regarding Hospitals, Doctors and their specialties required for them to identify the apprehensive hospital and doctor to address their certain health Information. The aim of the proposed framework to develop a model which provides appropriate information to the user about the hospitals, doctors based on their profile along with dynamic changes. In this fuzzy logic and genetic algorithm is used to find the similar users and to enhance the quality of recommendation for HCRS.

Table 1 - Personalized information of users

User	Age	Sex	Occupation	Height	Weight	Region	Rating	Symp1	----	Symp19
#12	32	F	Teacher	5'6"	56	Delhi	4	1		0
#14	45	M	Scientist	5'10"	75	Orissa	3	0		1

#18	67	M	Navy	5'11"	77	Jammu	2	1	1
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The existing health care software which provides only the information of hospitals and doctors based on user profile, which is static in nature because there is no update is done with user data. These applications do not provide any personalized recommendation to the user. Because when a user enter into the system according his symptoms, it generates possibility of disease by recommending information to the user rather giving personalized information. This descriptively includes the recommendation using some parameters of user are based on location, climate, region, economic background and demographic user data etc. The detailed flow of work is as follows:

- The user register into the HCRS and he/she may login the system with his/her identification or demographic information. Here three types of recommender systems used to maintain the personalized data of user's Information systems.
- Content based RS: provide the past data of user.
- Collaborative filtering: similarity calculation done using rule based fuzzy and real value genetic approach.
- Healthcare RS is the intermediates between front end in which it provides all information to the users and back end in which it maintains all the data of the users.
- HCRS, basically provide information to the user. But here in this approach we give our best efforts to provide personalised information and accurate recommendations to the user.
- In this the demographic information of user is age, sex, occupation, height, weight, region and symptoms etc.
- The classes will be generated based on this information with rule based fuzzy classification. There are number of users whose information is to be classified and weights will be assigned to this information using real value GA.

Here in this the personalized information of the user is given as in Table 1. In this the user profiles have been considered such as age, sex, occupation, height, weight, region, rating and symptoms. According to the various datasets availability in different websites it is difficult to consider every symptom. For a disease it may show many number of symptoms, so here some general symptoms have been identified. Based on these symptoms, the rules generated using fuzzy by intuition with similarity computation and using GA the proposed algorithm is as shown below:

Proposed Algorithm

- Step # 1: Arrange the dataset according to the hybrid approach
 Step # 2: Select the data from PIMS (Personalized Information Management System)
 Step # 3: Extract the data from step 1 with attributes of users, profiles and their symptoms.
 Step # 4: Pre-process the data set using clean, removal of missing values and transform the data, time stamp or time sensitivity 28 features.
 Step # 5: Neighborhood generation: Compute similarity using real value GA with mutation and cross over operators.
 Step # 6: Fuzzification of data by intuition
 Step # 7: Set the membership function based on parameters of age, sex, occupation, height, weight and region.
 Step # 8: Compute the evaluation metrics RMSE and MAE

3.1. Existing Approaches

There are many techniques have been applied in the area of Healthcare Recommender Systems based on machine learning. The proposed HCRS application developed using big data analytics, IOT and many other areas. But the most efficient technique here we discuss Convolutional Neural Networks (CNN) and Restricted Boltzman Machine (RBM).

Convolutional Neural Networks (CNN)

This technique is used in the area of deep learning in which the images classification is done when the data is based on visual. Here in this the operations are applied such as identifying the image, edge detection, sharpen the image, box blur and Gaussian blur etc. The main advantage of this technique is instinctive and this detects the important feature scanning of an image. As far as the structure of the data it is unable to encodes the position of objects in an image.

Restricted Boltzman Machine (RBM)

In an RBM, we have a symmetric bipartite graph where no two units within the same group are connected. Multiple RBM would also be stacked and can be fine-tuned through the process of gradient descent and back propagation. This network is also called as deep belief network. Although RBMs are occasionally used, most people in the deep-learning community have started replacing their use with General Adversarial Networks or Variational Auto encoders. RBM is a Stochastic Neural Network which means that each neuron will have some random behaviour when it is activated. There are two other layers of bias units (hidden bias and visible bias) in an RBM. This is what makes RBMs different from auto encoders. The hidden bias RBM produce the activation on the forward pass and the visible bias helps RBM to reconstruct the input during a backward pass. The reconstructed input is always different from the actual input as there are no connections among the visible units and therefore, no way of transferring information among themselves. The main advantage of RBM

is sampling looks like they come from the data distribution and pattern completion is also can be done when there is missing data. But when it comes to training part of sampling is more difficult.

3.2. Proposed approach for HCRS using Fuzzy-genetic approach (FG-HCRS)

The construction of our model is based on fuzzy rule based and genetic algorithm which is a key task is applied on large datasets. This huge amount of data needs a very large space and a long processing time. The fuzzy systems and GA are explained as follows.

3.2.1 Fuzzy Rule based Systems

The digital value is used before fuzzy logic introduced. Fuzzy logic involves the range of 0 and 1. This fuzzy logic is used for both hardware and software. In digital the Boolean values are considered like 0 and 1 where in fuzzy logic all the possible values taken into consideration in the range of yes or no. So, the fuzzy logic deals with the uncertainty of mechanism. For fuzzy methods we use the following steps:

1. Variable declaration
2. Fuzzification
3. Fuzzy Rules implementation
4. Conversion to graph

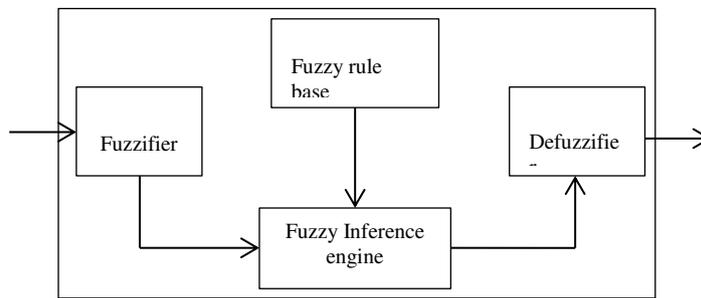


Fig.2 - Fuzzification process of linguistic variables

In this the first step is fuzzification process; the linguistic variable declaration is done for all membership functions as shown in Fig.2 Later the crisp value declaration is done using dataset which converts into fuzzy values. Finally rule base algorithm is applied on these fuzzy values and the convert into graphs. Here, the fuzzification is applied on six parameters based on user profiles such as age, gender, occupation, height, weight and region. The description of these parameters is as follows.

$$\mu_{V_Y}(A) = \begin{cases} 1, & A \leq 13 \\ \frac{20-A}{7}, & 13 < A \leq 20 \\ 0, & A > 20 \end{cases} \quad (1) \quad \mu_Y(A) = \begin{cases} 0, & A \leq 13, A > 31 \\ \frac{A-13}{7}, & 13 < A \leq 20 \\ 1, & 20 < A \leq 24 \\ \frac{31-A}{7}, & 24 < A \leq 31 \end{cases} \quad (2)$$

$$\mu_M(A) = \begin{cases} 0, & A \leq 24, A > 42 \\ \frac{A-24}{7}, & 24 < A \leq 31 \\ 1, & 31 < A \leq 35 \\ \frac{42-A}{7}, & 35 < A \leq 42 \end{cases} \quad (3) \quad \mu_O(A) = \begin{cases} 0, & A \leq 35, A > 53 \\ \frac{A-35}{7}, & 35 < A \leq 42 \\ 1, & 42 < A \leq 46 \\ \frac{53-A}{7}, & 46 < A \leq 53 \end{cases} \quad (4)$$

$$\mu_{V_O}(A) = \begin{cases} 0, & A \leq 46 \\ \frac{A-46}{7}, & 46 < A \leq 53 \\ 1, & A > 53 \end{cases} \quad (5)$$

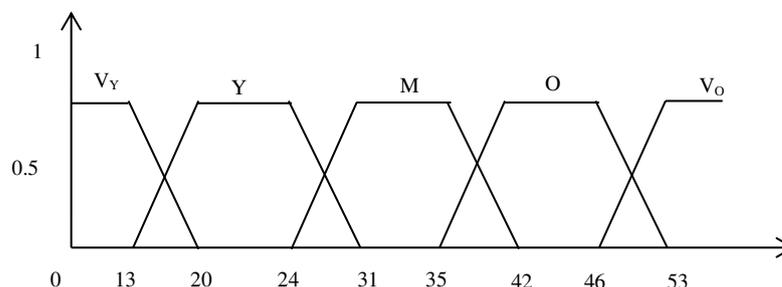


Fig.3 - Membership function for Age

The gender and occupation values are considered as fuzzy points with membership value of one. Finally, the genre interestingness measure is fuzzified into five fuzzy sets. The GIM is of age is Very Young (V_Y), Young (Y), Middle age (M), Old (O) and Very old (V_O) as shown in Fig. 3. These are the five linguistic variables and corresponding membership functions are defined in following equations.

The GIM is of age is Very Light (V_L), Light (L), Average (A), Heavy (H) and Very Heavy (V_H). These are the five linguistic variables and corresponding membership functions are defined in following equations.

$$\mu_{V_L}(W) = \begin{cases} 1, & W \leq 30 \\ \frac{38 - W}{8}, & 30 < W \leq 38 \\ 0, & W > 38 \end{cases} \quad (6) \quad \mu_L(W) = \begin{cases} 0, & W \leq 30, \quad W > 40 \\ \frac{W - 30}{8}, & 30 < W \leq 38 \\ 1, & 38 < W \leq 42 \\ \frac{49 - W}{8}, & 42 < W \leq 49 \end{cases} \quad (7)$$

$$\mu_A(W) = \begin{cases} 0, & W \leq 42, W > 60 \\ \frac{W - 42}{8}, & 42 < W \leq 49 \\ 1, & 49 < W \leq 53 \\ \frac{60 - W}{8}, & 53 < W \leq 60 \end{cases} \quad (8) \quad \mu_H(W) = \begin{cases} 0, & W \leq 53, W > 71 \\ \frac{W - 53}{8}, & 53 < W \leq 60 \\ 1, & 60 < W \leq 64 \\ \frac{71 - W}{8}, & 64 < W \leq 71 \end{cases} \quad (9)$$

$$\mu_{V_H}(W) = \begin{cases} 0, & W \leq 64 \\ \frac{W - 64}{8}, & 64 < W \leq 71 \\ 1, & W > 71 \end{cases} \quad (10)$$

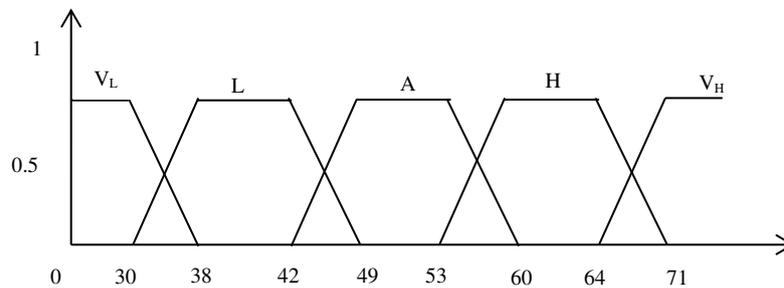


Fig.4 - Membership function for Weight

The GIM (Genre Interestingness Measure) is of age is Very Small (V_S), Light (S), Average (A), Tall (T) and Very Tall (V_T). These are the five linguistic variables and corresponding membership functions are defined in following equations.

$$\mu_{V_S}(H) = \begin{cases} 1, & H \leq 76.2 \\ \frac{96.2 - H}{30}, & 76.2 < H \leq 96.2 \\ 0, & H > 96.2 \end{cases} \quad (11) \quad \mu_S(H) = \begin{cases} 0, & H \leq 76.2, \quad H > 126.2 \\ \frac{H - 76.2}{20}, & 76.2 < H \leq 96.2 \\ 1, & 96.2 < H \leq 106.2 \\ \frac{126.2 - H}{20}, & 106.2 < H \leq 126.2 \end{cases} \quad (12)$$

$$\mu_A(H) = \begin{cases} 0, & H \leq 106.2, H > 156.2 \\ \frac{H - 106.2}{20}, & 106.2 < H \leq 126.2 \\ 1, & 126.2 < H \leq 136.2 \\ \frac{156.2 - H}{20}, & 136.2 < H \leq 156.2 \end{cases} \quad (13) \quad \mu_T(H) = \begin{cases} 0, & H \leq 136.2, H > 186.2 \\ \frac{H - 136.2}{20}, & 136.2 < H \leq 156.2 \\ 1, & 156.2 < H \leq 166.2 \\ \frac{186.2 - H}{20}, & 166.2 < H \leq 186.2 \end{cases} \quad (14)$$

$$\mu_{V_T}(H) = \begin{cases} 0, & H \leq 166.2 \\ \frac{H - 166.2}{20}, & 166.2 < H \leq 186.2 \\ 1, & H > 186.2 \end{cases} \quad (15)$$

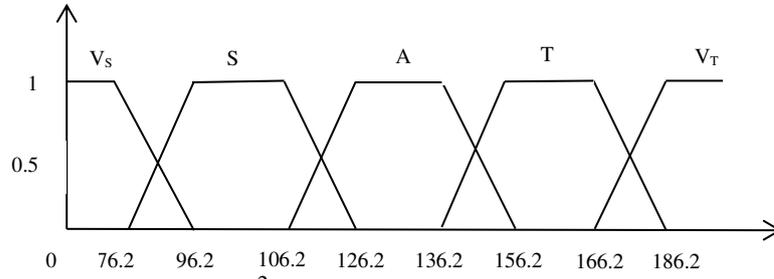


Fig.5 - Membership function for Height

3.2.2. Hybrid fuzzy-genetic approach

The proposed model contains 28 feature weights which are used for similarity computation. The weights of these features in HCRS systems changes over time dynamically. To learn these weights, Genetic Algorithm (GA) is used and then fuzzy rules are applied on these weights which leads to a hybrid fuzzy-genetic HCRS. For this approach the following formulas are used:

$$\sum_{i=1}^{28} W_i X (f_i(x_i, y_i))^2 \quad (16)$$

$$Fitness = \frac{1}{n_R} \sum_{j=0}^{n_R} |r_j - p(r_j)| \quad (17)$$

4. Experimental Results and Discussion

The several experiments are conducted on healthcare datasets. In these datasets, user's data of HCRS is modelled 60% for training and 40% for testing. We collected 12000 patients' data of 600 hospitals in which the user data rating ranges from 1 to 5. Here for training, 10-fold cross validation is used for the evaluation of results which is implemented in python. To ensure the quality of HCRS the evaluation metrics MAE and RMSE is used which are shown in Table 2 and 3.

Table 2 - RMSE comparison of different schemes based on Healthcare Dataset

No. of users	CNN	RBM	FG-HCRS
5	2.89	2.64	2.54
10	2.83	2.58	2.43
15	2.75	2.54	2.44
20	2.62	2.56	2.41
25	2.53	2.58	2.38
30	2.34	2.52	2.39

Table 3 - Comparison of different schemes based on Healthcare Dataset

Training set	Schemes	A.U (5)	A.U (10)	A.U (20)
100	CNN	0.951	0.900	0.778
	RBM	0.903	0.854	0.723

200	FG-HCRS	0.701	0.648	0.716
	CNN	0.856	0.846	0.786
	RBM	0.678	0.778	0.681
300	FG-HCRS	0.703	0.703	0.659
	CNN	0.903	0.756	0.867
	RBM	0.867	0.678	0.761
	FG-HCRS	0.698	0.656	0.732

In this experiment, here in Table 2 and 3 MAE is calculated for number of users and compared the results of CNN (Convolution Neural Network), RBM (Restricted Boltzman Machine) and FG-HCRS (Fuzzy Genetic Health Care Recommender Systems). When the number of users are less the MAE result is high and when the users are increased where the maximum ratings are considered for comparison then MAE reduced. In this the classical approach CNN and RBM are having more MAE (Mean Absolute Error) as compared to FG-HCRS.

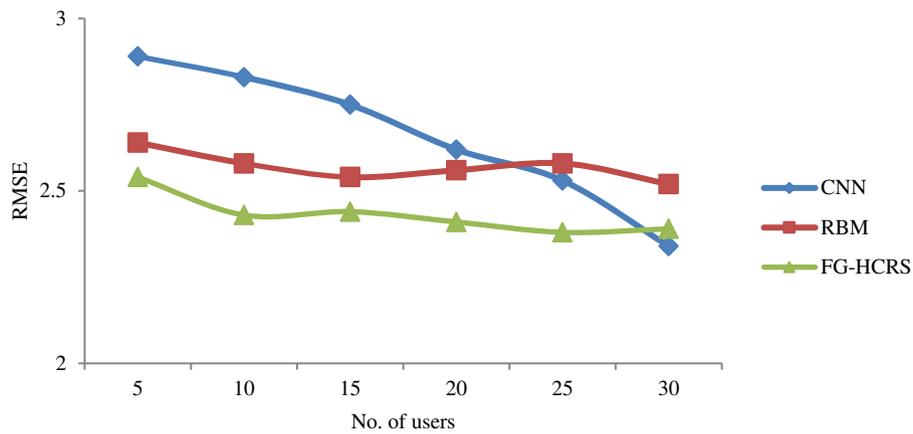


Fig.6 - RMSE comparison of CNN, RBM and FG-HCRS

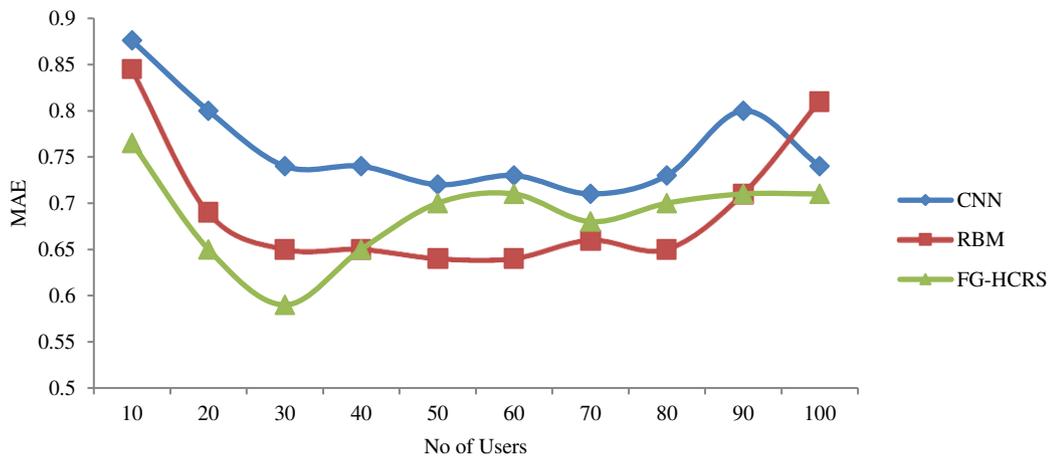


Fig.7- MAE comparison of CNN, RBM and FG-HCRS

The training sets are split into 100, 200 and 300 and the active users are considered in each set in the above table 3 in the split of 100 users, if we consider active users 5 then the MAE is high because the possible comparisons of number of users with active users is complex where as active users are 10 and 20 then the comparisons would be easier and predictions and recommendations are also done very efficiently because the user sample comparisons are provided

more. In this when the splits and active users are increasing the MAE is fewer. The results of these three methods are shown in Fig.6 and Fig.7. The result concludes that the system with a smaller number of recommendation and high precision, it would perform better and the outcome of recall vs. number of recommendations will be shown. Undoubtedly, it exposed in a table that the FG-HCRS has lesser range of MAE as compare to other three methods i.e. CNN and RBM. With hybrid Fuzzy-Genetic approach, the health recommender systems outperform other than two methods in respective of MAE (Mean Absolute Error), RMSE (Root Mean Square Error), Precision and Recall as shown in following Fig.8 and Fig.9

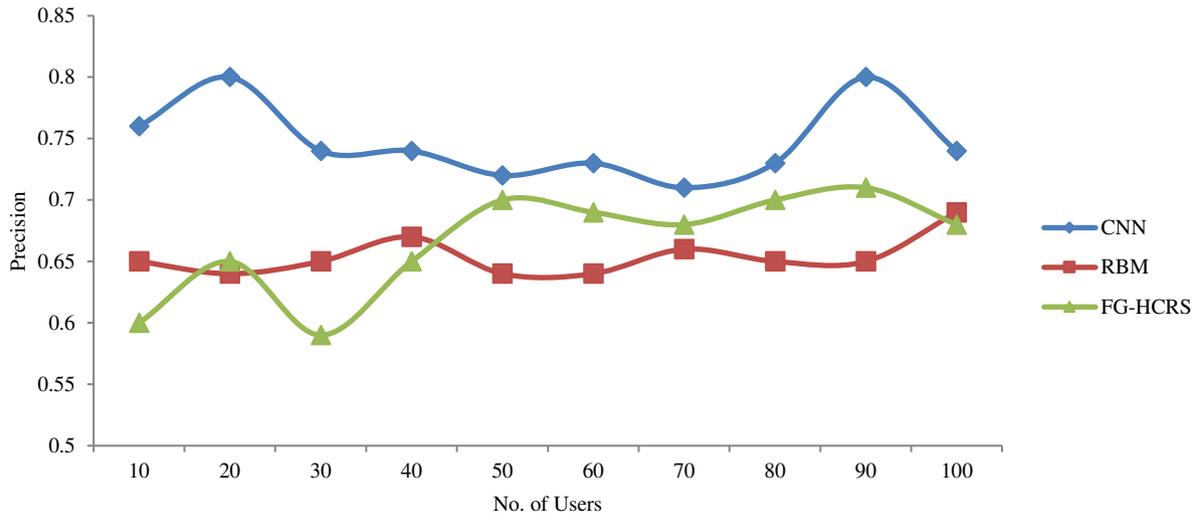


Fig.8 - Precision comparison of CNN, RBM and FG-HCRS

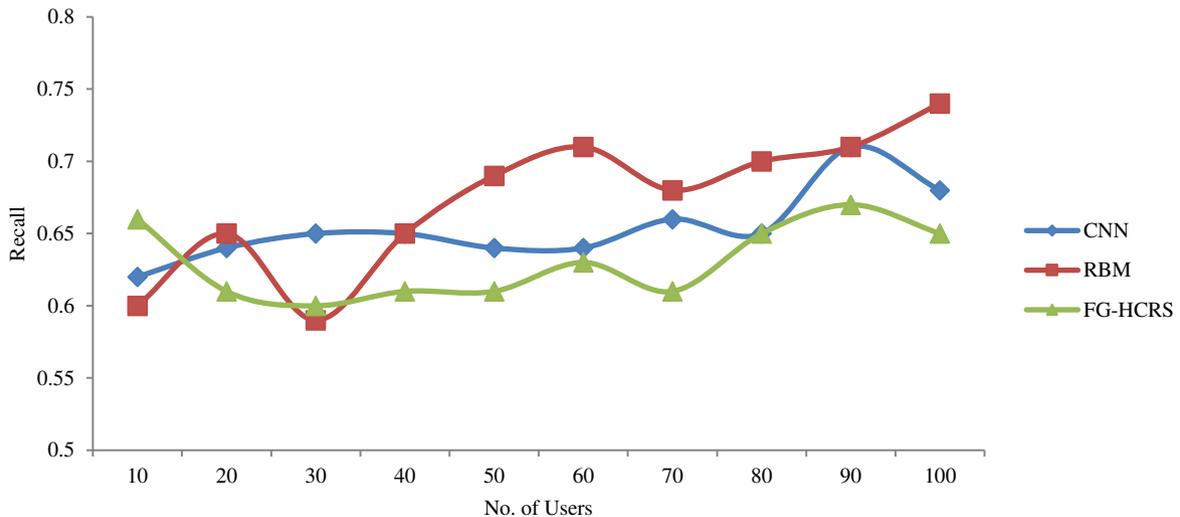


Fig.9 - Recall comparison of CNN, RBM and FG-HCRS

Here, we have used multi point crossover with the population size of 25, crossover rate of 0.5, Real GA would run for more than 1000 trials. Multiple runs were done to tune parameters, over 1000 experiments at every mutation range from 0.002 to 0.02 in steps of 0.002, more than thousands of executions can perform at each combination of mutation size and rate. The fuzzy membership functions are used in five variations with the help of genre interestingness measure.

5. Conclusion and Future work

This research proposes and implements a unique and efficient framework for Healthcare Recommendation Systems produce the quality recommendations. The proposed approach uses hybrid Fuzzy-Genetic approach to learn appropriate weights for the similarity measures to enrich the quality and accuracy of recommendation. The observational results reveal the suggested scheme could extensively enhance the quality, exactness of expectations. Experimental results show the working mechanism that can significantly advance the quality of recommendations. In future we would like to work on the personalized Healthcare using machine learning techniques with the consideration of geographical data.

Ethical Statement for Solid State Ionics

Hereby, Dr. Latha Banda, Dr. Karan Singh, Mr. Vikas Arya, Mr. Devendra Gautam and Dr. Ali Ahmadian Dr. consciously assure that for the manuscript /insert title/ the following is fulfilled:

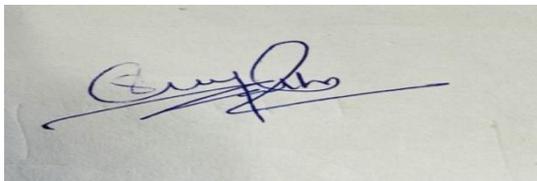
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Authors Contribution

The authors confirm contribution to the paper as follows: study conception and design: Dr. Latha Banda, Vikas Arya analysis and interpretation of results: Dr. Latha Banda and Devendra Gautam draft manuscript preparation: Dr. Latha Banda, Vikas Arya, Dr. Ali Ahmadian and Dr. Karan Singh and all authors reviewed the results and approved the final version of the manuscript.

Data Availability

1. The datasets generated during and/or analysed during the current study are available in the healthcare data set repository, <https://healthdata.gov/d/j4ip-wfsv>.
2. The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.
3. All data generated or analysed during this study are included in this published article (and its supplementary information files).

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