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MONOLITHIC HYBRID THERAPY RECOMMENDER SYSTEM FOR AUTISTIC CHILDREN USING MACHINE LEARNING

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ABSTRACT

Everyday tasks have been revolutionized by Machine Learning (ML), which has become essential in many different sectors. Its capacity to forecast and evaluate current data has greatly increased productivity across a range of industries. In order to support the development of critical skills in autistic children, this paper presents a Monolithic hybrid Therapy recommender system that offers customized therapy recommendations. It smoothly combines content-based filtering with multi-criteria collaborative filtering. Based on the severity of the symptoms, content-based filtering recommends therapies. This information is then fed into Multi criteria collaborative filtering, which creates cohorts of related therapies using a variety of similarity metrics. Multi Criteria approach for collaborative filtering is used for the first time to find similar children in all aspects. It ensures to find similar children and most common therapies. The results of Multi criteria collaborative filtering are then sent to a priority generator, which prioritizes treatment suggestions according to symptom severity. This novel combination represents a major breakthrough in the area, by customization of therapy recommendations for children with autism outperforming traditional content-based and collaborative filtering recommender systems with a precision of 80%. When compared to conventional methods, the approach suggested saves time and effort by recommending suitable therapy for autistic children, thereby benefiting physicians, parents, and caregivers.

Keywords: *Recommender System, Content based Filtering, Multi criteria collaborative Filtering, Monolithic Hybrid Recommender System.*

1. INTRODUCTION

Users are assisted by a recommender system in making goods purchases based on their personal interests. Recommendation systems can suggest a certain product to a user based on user or item interest, based on information gathered from users' blogs, social forums, reviews, and ratings. In addition to rating the products, a recommendation system can predict whether a user would purchase a specific item or not. These recommender systems are available in many different domains, including e-commerce, entertainment, food, health, and more. These systems gather user history data and forecast which products the user would be recommended. Recommender systems also attempt to predict the products that can be suggested to new users based on their individual and item interests [1-3]. A health care recommendation system is currently playing a crucial role in making decisions related to a person's health based on the health records available about their lifestyle, eating habits, and prior medical history. The phases of the recommender system are information collection, learning, and prediction. Recommender systems use different types of filtering, such as content-based filtering, collaborative filtering, Hybrid filtering, Demographic filtering, and Knowledge based filtering as discussed in [4]. In the proposed system Content based filtering, Collaborative filtering and Hybrid filtering are used. Content based filtering in recommender

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system is used to recommend products based on the interests and history of the customer. It provides recommendations by finding similarity between the products and the interest of the customer. Collaborative filtering provides recommendations to the customers by finding similarity between the users. Users or customers who share common interest will receive recommendations of the products which are used by similar users. Content based filtering suffers from over specialization and collaborative filtering suffers from cold start problem. Hybrid filtering is used to overcome these problems and provide appropriate recommendations. In this paper, A Monolithic hybrid therapy recommender system is proposed to provide appropriate therapy recommendations to autistic children. Autism is a mental illness that impedes a child's growth in a number of areas, including communication, gross motor skills, and interpersonal abilities. Autism is a spectrum disorder that influences how an individual with the disorder interacts with the outside environment. Although the precise source of it is unknown, chemical disruptions in the brain are thought to be the reason [5]. There isn't a suitable medication for it; the sole treatment that helps is , assistance to help acquire the required skills. Around 13 million people in India are estimated to have autism, and 2.2 million children between the ages of 2 and 9 suffer from the condition, according to Hindustan Times. According to a 2023 study on autism by the Centers for Disease Control and Prevention (CDC), 1 in in 39 children has autism [6]. There is no known precise cause of autism, and there is no medication that can treat the condition. Before the age of five, the child needs intervention to reach their full potential. Therefore, early detection of autism is crucial in order to assist the youngster in overcoming their learning impairments. When autism is identified, the kid will get a variety of therapies as part of an intervention, depending on their individual needs. These therapies may include occupational therapy, speech therapy, sensory integration therapy, etc. While a great deal of study is done to identify autism, less is known about the several therapies that can be recommended for the condition. Thus, it is imperative to create a machine learning-based therapy recommender system for children with autism. For the child's wellbeing, this will be a useful tool for parents, caregivers, and medical professionals. The Proposed Monolithic hybrid therapy recommender system helps to provide appropriate therapy recommendations to autistic children. It comprises of content based filtering and Multi criteria collaborative filtering. The therapy recommendations generated by content based filtering are given as an input to multi criteria collaborative filtering. Using a variety of similarity metrics, multi-criteria collaborative filtering generates therapy recommendations that are common for children who are similar to each other. Multiple criteria for collaborative filtering are used for the first time to generate similar children in several aspects. The severity of the symptoms determines which of these therapies are given priority. Existing systems of recommender systems for autistic children is based on clustering and collaborative filtering which provides recommendations to the group. The proposed system provides therapy recommendations to specific child based on the individual symptoms. The rest of the paper is organized as follows: Literature survey, Proposed Monolithic hybrid therapy recommender System, Results, Conclusion and Future scope.

2. LITERATURE SURVEY

In the contexts of content-based filtering, collaborative filtering, demographic filtering, and knowledge-based filtering, respectively, recommender systems assist users in offering recommendations about different products based on their interests, shared interests, and customer knowledge. Health Recommender Systems offer advice on medications, diet, counseling, and lifestyle modifications. The literature review of the many health recommender systems that are currently in use is given in this section. A system for recommending treatments and diagnosing diseases has been created by Jianguo Chen and others. Effective clustering of the illness symptoms has been achieved through the application of a density peaked clustering analysis algorithm. To conduct association analysis, the Apriori method was used for symptoms of the disorder, diagnosis, and therapy guidelines. Doctors and patients can receive recommendations for diagnostic and treatment regimens through the DDTRS interactive interface. It facilitates the diagnosis of the illness and its many stages of therapy, as well as aids novice clinicians in making the right decisions [7]. A five-stage intelligent health recommendation system has been proposed by Abhay Kumar Sahoo and colleagues. Gathering information from various sources, such as medical facilities and hospitals, is the first step. The second stage of data pre-processing, sometimes referred to as data cleaning, involves removing outliers and superfluous data, which may have an impact on the model's accuracy. The third step is data analysis, which involves processing various data formats and using analysis to identify high-risk patients, diagnose medical images, and analyze drug usage trends. The next step is the recommender engine, which uses the patient's symptoms as input and suggests different medical professionals based on the condition. The data visualization stage offers medical reports, health insurance plans, patient health monitoring, and suggestions for appropriate medications[8].As part of the PIUMA project (personalized Interactive Urban Maps for Autism), Noemi Mauro and collaborators have developed a suggested system of PoIs (points of interest) for individuals with autism.Based on a questionnaire about preferences and sensory peculiarities, the data is gathered. It is intended to assist those with autism in making recommendations for locations based on their preferred destinations and sensory issues[9]. A recommendation system for diagnosing heart illness has been developed by Manogaran G. and colleagues utilizing MKL (Multiple Kernel learning) with an Adaptive Neuro Fuzzy Inference System. First, the characteristics of cardiac patients and healthy individuals are distinguished using the MKL approach. The ANFIS classifier is then given the MKL output to differentiate between heart patients and healthy individuals. They obtained a 98% accuracy rate [10]. A recommendation system that automatically suggests meals to patients based on their ailment as well as other characteristics like age, gender, weight, calories, and so on has been proposed by Celestine Iwendi and others. Using LSTM (long-short term memory), they were able to reach an accuracy of 97.74% after gathering the information from hospitals and the internet and applying a variety of machine learning and deep learning algorithms[11]. Eighty youngsters were divided into two groups for the analysis that Ghalichi F. and colleagues did. A gluten-free diet (GFD) was provided to one group, and a regular diet (RD) to the other.In the first group that received GFD, there has been a noticeable decline in stereotyped behavior, communication, and interaction. The GFD diet also resulted in a reduction in gastrointestinal issues [12]. Premasundari et al. have put up a recommendation method that divides the food into five categories and first classifies the symptoms of autism into one of nine categories. In order to cluster the symptoms of autism and identify the best diet and treatment recommendations, they have combined association rule mining with the OKM (overlapping K-means) algorithm[13]. A recommendation system for hypertension patients has been proposed by Romeshwar Sookrah and colleagues. It offers advice on the DASH (Dietary Approaches to Stop Hypertension) diet. They have employed a multilayer perceptron, which functions as a classifier by receiving several inputs such as the user's chosen meal, allergies, and sodium intake in addition to other criteria like alcohol consumption and smoke computation, and then producing a range of food choices. The output of the multilayer perceptron will be used by the content-based filtering to create a diet plan for the consumers based on the different prior factors. This technique has 99% accuracy[14]. ProTripRs, an ontology-based recommender system created by V. Subramaniya Swamy and collaborators, makes suggestions based on user health, preferences, and weather. Three datasets were used: one based on climatic data, one on food information, and one with user data. The reaction time for the location and food recommendation is 2.5 seconds, which is adequate when using the hybrid filtering technique[15].Farman Ali and colleagues developed a recommendation system that can precisely recommend foods and medications for persons with diabetes based on data gathered

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from wearable sensors using Type 2 fuzzy logic and ontology [16]. Using mobile edge computing, Juyong Lee and colleagues have created a juice recipe recommendation system that can offer recipe-related suggestions based on language entered or an image supplied. When compared to other systems, their usage of the CNN machine learning method produced a short latency and response time [17]. A Recommeder system that offers individualized therapies to individuals with depression and notifies their family members about it was created by Shiqi Yang and colleagues. Users' data is gathered via the apps, and SVM and decision trees are used for additional analysis[18]. Fran Casino and colleagues have employed smart city sensors to gather data on patient health, preferred routes, and weather patterns. They then utilize collaborative filtering to suggest routes that can improve citizens' health[19].A recommender system has been developed by Seda Polat Erdeniz[20] and others. It suggests virtual coaches and virtual nurses based on data gathered from various sensors, gadgets, and activities. A web-based program created by Amelie Gyrarda[21] and colleagues analyzes users' discomforts using many knowledge repositories and offers recommendations for neuropathy, thereby contributing to their overall well-being. Using the movielens dataset, hybrid recommender systems have been deployed by Bogdan Walek[22] and others to suggest movies.Expert, collaborative, and content systems are all combined in the hybrid recommender system architecture. They were able to get 81% precision, 83% recall, and 82% F1-measure. Machine learning algorithms have been utilized by Manu Kohli[23] and others to tailor and suggest ABA therapy for children with autism. They obtained an accuracy of 81–84% by using collaborative filtering and patient similarity. Using IOT, Fouzia Jabeen[24] and colleagues have created a hybrid recommendation system that offers advice on food and exercise regimens in addition to detecting cardiovascular illness based on age and gender. Their accuracy rate was 98%.Patients with hypertension can use a medication recommendation system created by Arthur Mai et al. in 2023. The medications are suggested using knowledge-based filtering and patient similarities. The medications of patients who are similar are first collected, and the clinicians' expertise is then taken into account when the medications are ranked. The information was painstakingly gathered from the medical records of 14 doctors who treated patients with hypertension. Patients with hypertension were given suitable medication recommendations thanks to this hybrid approach[25]. Abolfazl Ajami and Dr. Bakhteimourpour (2023) developed a hybrid recommender system to give university students advice on a nutritious diet. It blends knowledge-based filtering, which takes into account the students' health issues, dietary needs, and other factors, with content-based filtering, which takes into account the interests of each particular student. The university provided the student statistics, the menu, and a nutritionist's analysis of the students' dietary needs. Utilizing the Adaboost machine learning technique, accuracy of 73.7% was attained[26].A recommender system was created by Y. A. Nanehkaran et al. (2022) to diagnose chronic patients using information from their medical records. Using the K-nearest neighbor method, collaborative filtering has been utilized to identify comparable users at various stages and suggest appropriate therapy in the early stages[27]. All the existing systems have used only one similarity metrics to find similar users in collaborative filtering and the hybrid filtering which combines the result of different types of filtering using ensemble or mixed method. The Fig 1 shows different types of Hybrid filtering.

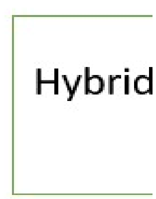

Fig 1: Types of Hybrid Recommender systems

In the proposed system, A Monolithic hybrid therapy recommender system is used which collects the result of content based filtering as an input to the Multi-criteria collaborative filtering which uses more than one similarity metrics to

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generate similar children. The result of the Multi-criteria collaborative filtering is given to the priority generator which assigns priorities to therapy recommendations. Thus, Proposed Monolithic hybrid therapy recommender system overcomes drawback of over specialization in content based filtering and cold start problem in collaborative filtering. The Table 1 shows various similarity metrics used in recommender systems.

Table 1: Similarity metrics used in various Recommender systems

S no	Author	Dataset used	Type of Filtering	Similarity measure used
1	V. Subramaniyaswamy et.al(2018)	climate-based dataset, food information dataset and user dataset.	Hybrid Filtering	SlopeOne recommender from Apache Mahout
2	Fran Casino et.al(2018)	Data collected from sensors	Collaborative Filtering	Euclidean distance with k=1
3	Seda PolatErdeniz et.al(2018)	Data collected from sensors	Collaborative Filtering for virtual coach and Content based Filtering for virtual nurse.	K nearest neighbor
4	Bogdan Walek and Vladimir Fojtik(2020)	Movielens Dataset	Hybrid recommender systems	Cosine Similarity
5	Manu Kohli et. al(2022)	Data of 29 children with ASD has been collected	Collaborative Filtering and Patient Similarity	Cosine Similarity
6	Fouzia Jabeen et.al(2019)	Data collected from biosensors	Hybrid Filtering	Community based similarity
7	Arthur Mai et. al(2023)	298 patients data was collected from 2014-2020	Hybrid Filtering	Patient similarity
8	Abolfazl Ajami & Dr.Babak Teimourpour(2023)	Data of 2519 students was collected from a university	Hybrid Filtering	K nearest neighbor
9	Y. A. Nanehkaran et.al(2022)	Data collected from PhysioNet	Collaborative Filtering	K nearest neighbor

3. PROPOSED SYSTEM

The Proposed Monolithic hybrid therapy recommender System generates most appropriate therapy recommendations to autistic children by assigning priorities to therapies based on the severity. It is for the first time that a therapy recommender system generates recommendations for specific child. The architecture of the proposed system is as shown in Fig 2.

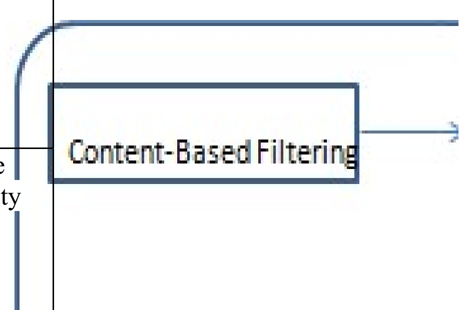

Fig 2: Architecture of Monolithic hybrid therapy recommender System

It Consists of content based filtering which generates therapy recommendations to autistic children based on the severity of the symptoms. It is used as an input to the Multi-criteria

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collaborative filtering which generates similar children calculating the similarity using multiple similarity metrics. The therapies common to these similar children are given as an input to the priority generator which assigns priorities based on the severity of the symptoms to the most appropriate therapy recommendations. The details of the Content based filtering, Multi-criteria collaborative filtering and priority generator are discussed in the following sub sections.

3.1 Materials and Methods used

The proposed Monolithic hybrid therapy recommender system uses autistic children dataset generated using Rule based classifier model which uses QCHAT dataset [28]. QCHAT is a screening tool used to detect autism in children at the age 18-30 months. It consists of 25 questions corresponding to various developmental factors such as communication skills, gross motor skills, sensitivity and so on. The Fig 3 shows the sample questions of QCHAT and all the questions can be accessed at [29]. The Therapies for the corresponding questions have been collected from Smiles Foundation Therapy Institute, Hyderabad which provides therapy sessions to autistic children. Sample Therapies for questions in QCHAT are shown in Fig 4. Each question in QCHAT screening tool has 5 options with the rating from 0 to 5 where 0 indicates low severity and 4 indicates high severity. For each question corresponding therapies are collected as shown in Fig IV. One question may need more than one therapy.

1. Does your child look at you when you call hi

o always o usually o sometimes o rarely o evei

2. How easy is it for you to get eye contact witl

o very easy o quite easy o quite difficult o very

3. When your child is playing alone, does s/he

o always o usually o sometimes o rarely o nev

Fig III Sample questions of QCHAT screening tool

There are 103 autistic records collected and 33 therapy total for 25 questions of QCHAT screening tool. The therapy dataset consists of question number and corresponding therapy as shown in Fig 4. These datasets are available upon request.

Qno	Therapy
qchat1recode	Applied beh
qchat1recode	Discrete tra
qchat1recode	Social skills
qchat1recode	Occupation
qchat1recode	Speech and
qchat2recode	Applied beh
qchat3recode	Behavior int
qchat4recode	Structured p
qchat5recode	Picture Exch
qchat6recode	Early Intens
qchat7recode	Sensory Inte
qchat8recode	Speech The

Fig IV: Sample records in Therapy dataset

3.2 **Content based Filtering**

It is used to generate recommendations based on the history of the user. Based on the

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user's interest, similar products are recommended for the user. The Fig 5 shows an example of content based filtering which recommends articles to the user based on his/her interest. Content-based filtering is essential for providing patients with individualized healthcare recommendations. This approach is based on evaluating the characteristics and features of healthcare products, including therapies, prescription drugs, healthcare professionals, publications, and wellness routines. The fundamental idea behind content-based filtering is to provide healthcare information suggestions based on the user's prior interactions or interests. This method assumes that people are more likely to accept health recommendations that share characteristics with their previous choices. Healthcare platforms can provide personalized recommendations that are in line with patients' medical histories, treatment preferences, and health goals by utilizing content-based filtering algorithms. This approach improves patient engagement and encourages proactive healthcare management.

Fig 5: Example of Content based filtering

In the proposed system, content based filtering is used to generate therapy recommendations for each autistic child based on the rating for questions in QCHAT screening tool. The algorithm for content based filtering is as follows:

Algorithm: Content based filtering

Input: Dataset consisting of Autistic children from Rule Based classifier r and Therapy dataset s

Output: Therapy Recommendations for autistic children

Procedure:

1. Load the data frame of autistic children i.e. relation r
2. Feature Extraction to extract features corresponding to the questions.
3. Creating Child profile for each child such that it consists of various questions and their ratings for each child i.e r'.
4. The corresponding therapies for each question are appended based on child profile and therapy dataset i.e (i.e., $Qno=Qno(r\times s)$).
5. Identify therapies that are most relevant to the children by comparing their ratings in the children profile.
6. Generate therapy recommendations for each child based on the severity of the symptoms

The autistic children are given as an input to the Monolithic hybrid therapy recommender system. The content based filtering will generate therapy recommendations to autistic children based on the rating for each question. The sample autistic records are shown in Fig 6. Initially, an autistic record consists of features corresponding to personal details and it is termed as r with 103 records and 37 features. After feature extraction, only the features corresponding to QCHAT questions for each child are available. The child profile is created by transforming relation r to r' such that it consists of child_id, question and rating resulting in 2575 records with 3 features.. The corresponding therapies for each question and each child are generated based on the common feature of Qno in therapy dataset s and dataset r'.

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	child_id	age	Autistic	sex	group	preterm	birthweig	siblings_y	siblings_n	mothe
0	220	18	1	1	1	1	1500	0	0	
3	FS/2571	18	1	1	1	1	1820	0	0	
5	FS/1736	18	1	2	1	1	2600	0	0	
6	FS/2178	18	1	2	1	0	2760	1	1	
8	FS/2357	18	1	1	1	0	2930	1	1	

Fig 6: Sample autistic records.

The result consists of 3296 records with 4 features namely child_id,Qno,Rating,Therapy. The Therapy recommendations for each child are generated based on the severity indicated by rating. The result consists of questions, ratings and corresponding therapies for each child as shown in Table 2. The result of content based filtering is given as an input to multi criteria collaborative filtering.

3.3 Multi-Criteria Collaborative Filtering

Collaborative filtering is widely used to generate recommendations based on the similarities among different users. The Fig 7 shows example of collaborative Filtering that generates item recommendations based on similar users in case 1 and based on similar items in case 2.

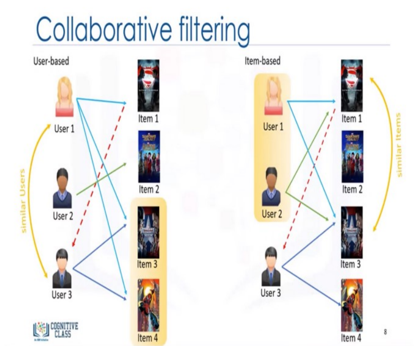

Fig 7: An Example of Collaborative filtering.

To provide personalized healthcare recommendations, collaborative filtering in healthcare leverages the interests and behaviors of multiple patients. Collaborative filtering finds trends and similarities by looking at past interactions between patients and healthcare options. It gives priority to shared experiences over explicit item features or content information. The underlying idea of collaborative filtering in healthcare is that patients with similar past behaviors would probably have similar illnesses in the future. Here, the technology finds patients who have shown preferences similar to the target patient by using user based collaborative filtering. It then suggests medical treatments that the intended patient hasn't looked into yet but that comparable patients have connected with or found beneficial. Higher similarity scores between the user and the target patient are recognized. Then, recommendations for the healthcare solutions that these comparable patients have found most appealing are given to the target patient. The Existing system has used only one similarity metrics to find similar users. In the proposed Multi-criteria collaborative filtering, more than one similarity metrics has been used. The result of content based filtering is given as an input to the Multi-criteria collaborative filtering. In this filtering, cosine similarity and Euclidean distance has been used to find similar autistic children using K-nearest neighbor. It ensures to find autistic children who are similar in multiple aspects. Cosine Similarity: measures the cosine of the angle between two vectors.

$$\cos(\theta) = \quad \text{-(1)}$$

Where A and B are the i^{th} components of vectors A and B. In the context of an autistic dataset,

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children are assessed based on various developmental attributes of QCHAT screening tool. It measures the similarity between the children based on the rating of the questions available in autistic dataset. The Cosine Similarity for this dataset is given by:

$$Cosine\ Similarity\,(u1,u2) = \left(\sum^{25} u1i\right. \quad \text{-(2)}$$

Here, $u1,i$ and $u2,i$ are the values of the ith question for children $u1$ and $u2$ respectively.

Euclidean distance measures the distance between two points in Euclidean space, defined as:

$d = \sqrt{[(x_2 - x_1)^2 + (y_2 - y_1)^2]}$ – (3)

For the autistic dataset, it is employed to compare the magnitude of children's attributes:

Euclidean distance

(u1,u2)= $\sqrt{\sum_{i=1}^{25}(u1,i - u2,i) pow2}$ -(4)

Here $u1,i$ and $u2,i$ denote the values of the sum of the attributes for children $u1$ and $u2$ respectively.

K- nearest neighbor algorithm: A non-parametric, supervised learning classifier, the k-nearest neighbors (KNN) algorithm use proximity to classify or predict how a single data point will be grouped. It is among the most widely used and straightforward regression and classification classifiers in machine learning today. A majority vote is used to designate a class label for classification problems; that is, the label that is most frequently expressed around a particular data point is utilized. In the proposed system, KNN with cosine similarity and Euclidean distance has been used to find similar children in multiple aspects. The architecture of Multi-criteria collaborative filtering is shown in Fig 8.

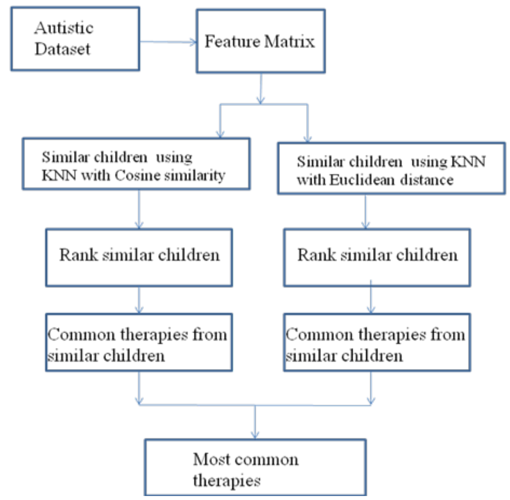

Fig 8: Multi-Criteria collaborative Filtering

The algorithm for Multi criteria collaborative filtering is as given below:

Algorithm for Multi-Criteria Collaborative Filtering

Input: Data frame consisting of Autistic children and content recommendations

Output: Therapies most common to all the similar children

Procedure:

1. Load the data frame of autistic children i.e. relation r

2. Create feature matrix where rows represent children and column represent Questions of QCHAT

3. Finding similar children by computing the cosine similarity between children using KNN.

The cosine similarity is given by

$$Cosine\ Similarity\,(u1,u2) = \left(\sum^{25} u1i\right.$$

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where $u_{1,i}$ and $u_{2,i}$ are the values of the i^{th} question for children u_1 and u_2 respectively.

4. Finding similar children by computing the Euclidean distance between children using KNN.

Euclidean distance (u1,u2)=$\sqrt{\sum_{i=1}^{25}(u1,i-u2,i)pow2}$

Where $u1,i$ and $u2,i$ denote the values of the sum of the attributes for children $u1$ and $u2$ respectively.

5. Rank the similar children based on the threshold for both similarity metrics respectively

Collect the top 5 children therapies based on the ranking from content recommendations for both similarity metrics respectively.

5. The common therapies of all the top 5 children are generated using cosine similarity and Euclidean distance.

6. The most common therapies from both the similarity metrics are calculated.

Feature matrix indicates the features which are considered for calculating the similar children. The features related to questions of the QCHAT, their ratings and the sum of the ratings are considered. Cosine similarity is used to find similar children based on the rating of the questions and Euclidean distance is used to find similar children based on the sum of the ratings of the questions using K-nearest neighbor algorithm with k=5. The similar children are ranked and common therapies are generated in both similarity metrics. The most common therapies from the above therapies are generated as the result of Multi criteria collaborative filtering. The result of Multi criteria collaborative filtering is given as an input to the priority generator which assigns priorities to the therapies.

3.4 Priority Generator

The result of Multi criteria collaborative filtering is given as an input to the priority generator. The priority generator uses set of rules to generate priorities for the most appropriate therapy recommendations. It assigns priority 1(high) to the therapies related to questions with high severity and priority 2,3,4 to other questions based on the severity. The Fig 9 shows the process of assigning priorities.

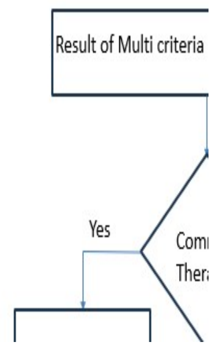

Fig 9: Priority generator

If the result of Multi-criteria collaborative filtering consists of common therapies of both the similarity metrics then priorities are assigned to them. If there are no common therapies from both similar metrics, then priorities will be assigned to the therapies with high severity for both similarity metrics. If one of the similarity metrics do not have common therapies for similar children, then priorities will be assigned to the therapies for only one similarity metrics based on the severity. If no similar children exists for both similarity metrics, then priorities will be assigned to recommendations generated by content based filtering. The algorithm for priority generator is as follows:

Algorithm: Determine Therapy Recommendations based on priority for a Specific Child

Input: Output from multi criteria collaborative filtering

Output: Most appropriate therapy recommendations for the specific child

Procedure:

1. Load the therapy recommendations for a specific child

2. Identify the similar questions and their ratings for all children:

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- Extract the similar questions shared among all children associated with the specific child.

- Obtain the ratings of these similar questions for each similar child.

3. Set priorities for therapies based on the ratings of similar questions:

- For each similar question:

- If the rating is 4, assign Priority 1 to the therapy.
  - If more than half of the similar children have a rating of 4 for the question, assign Priority 2 to the therapy.
  - If more than half of the similar children have a rating of 3 for the question, assign Priority 3 to the therapy.
  - If the rating is 3, assign Priority 4 to the therapy.

4. Determine the most appropriate therapy recommendations for the specific child:

– Display therapy recommendations ordered by priority:

– Priority 1 therapies first, followed by Priority 2, Priority 3, and Priority 4.

The result of priority generator is the set of therapy recommendations for a specific child with priorities assigned based on the severity of the symptoms. The proposed monolithic hybrid therapy recommender system for autistic children is very helpful for the parents, caregivers, doctors and physicians to provide most appropriate therapy recommendations to autistic children.

4. RESULTS

The proposed Monolithic hybrid therapy recommender system is a helpful for providing most appropriate therapy recommendations to autistic children. It consists of content based filtering, multi-criteria collaborative filtering and priority generator. The autistic children data is collected from [28] and is sent to content based filtering. The recommendations generated by content based filtering consist of Questions with high ratings and associated therapies for each child. Sample recommendations generated by Content based filtering are as follows:

Child: 12

Qno: [17, 18, 24, 0, 2, 5, 5, 7]

Value: [3, 4, 4, 4, 4, 4, 4, 3]

Recommendations: ['Applied behavior Analysis', 'Behavior intervention strategies ', 'Relationship Development Intervention', 'Occupational Therapy', 'Speech Therapy', 'Social Relational approaches', 'Relationship development intervention', 'Speech Therapy']

Child: 71

Qno: [19, 20, 21, 23, 24, 0, 5, 5, 6]

Value: [4, 4, 4, 3, 4, 4, 3, 3, 3]

Recommendations: ['Structured play & speech and language therapy', 'Picture Exchange', 'Early Intensive Behavioral Intervention (EIBI)', 'Speech Therapy', 'Relationship Development Intervention', 'Occupational Therapy', 'Social Relational approaches', 'Relationship development intervention', 'Applied behavior analysis']

Child: 41

Qno: [19, 23, 24, 5, 5, 6]

Value: [3, 3, 3, 4, 4, 3]

Recommendations: ['Structured play & speech and language therapy', 'Speech Therapy', 'Relationship Development Intervention', 'Social Relational approaches', 'Relationship development intervention', 'Applied behavior analysis']

Child: 59

Qno: [19, 23, 0, 2, 8, 11]

Value: [3, 3, 3, 3, 3, 3]

Recommendations: ['Structured play & speech and language therapy', 'Speech Therapy', 'Occupational Therapy', 'Speech Therapy', 'Speech Therapy', 'Sensory Integration Therapy']

These content based filtering recommendations are given as an input to Multi criteria collaborative filtering. It generates common children with KNN using cosine similarity and

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Euclidean distance. The common children using cosine similarity along with the similarity is shown below:

Child: 12

- Neighbor: 23 | Similarity: 0.9938184455786782
- Neighbor: 7 | Similarity: 0.9936477511329074
- Neighbor: 21 | Similarity: 0.9931080951438378
- Neighbor: 5 | Similarity: 0.9921519926061644
- Neighbor: 9 | Similarity: 0.992143739791566

Child: 71

- Neighbor: 64 | Similarity: 0.9946594515324773
- Neighbor: 42 | Similarity: 0.9943890849059688
- Neighbor: 53 | Similarity: 0.9929953069917546
- Neighbor: 68 | Similarity: 0.9927619432000836
- Neighbor: 85 | Similarity: 0.9925327010087529

Child: 41

- Neighbor: 42 | Similarity: 0.9943223881233767
- Neighbor: 102 | Similarity: 0.9937467670768634
- Neighbor: 88 | Similarity: 0.9936437557684114
- Neighbor: 101 | Similarity: 0.9931341549829019
- Neighbor: 64 | Similarity: 0.9928655696780072

The cluster visualization of KNN using cosine similarity is as shown in Fig 10

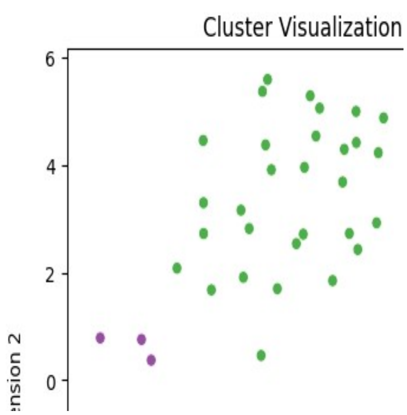

Fig 10: Cluster visualization of KNN using cosine similarity with KNN

The common children using Euclidean distance along with the similarity is shown below:

Child: 12

- Neighbor: 86 | Similarity: 1.0
- Neighbor: 72 | Similarity: 0.5
- Neighbor: 47 | Similarity: 0.5
- Neighbor: 71 | Similarity: 0.5
- Neighbor: 92 | Similarity: 0.5

Child: 71

- Neighbor: 47 | Similarity: 1.0
- Neighbor: 71 | Similarity: 1.0
- Neighbor: 75 | Similarity: 1.0
- Neighbor: 4 | Similarity: 0.5
- Neighbor: 49 | Similarity: 0.5

Child: 41

- Neighbor: 41 | Similarity: 1.0
- Neighbor: 46 | Similarity: 0.5
- Neighbor: 16 | Similarity: 0.5
- Neighbor: 22 | Similarity: 0.5
- Neighbor: 50 | Similarity: 0.5

The cluster visualization of KNN using cosine similarity is as shown in Fig 11

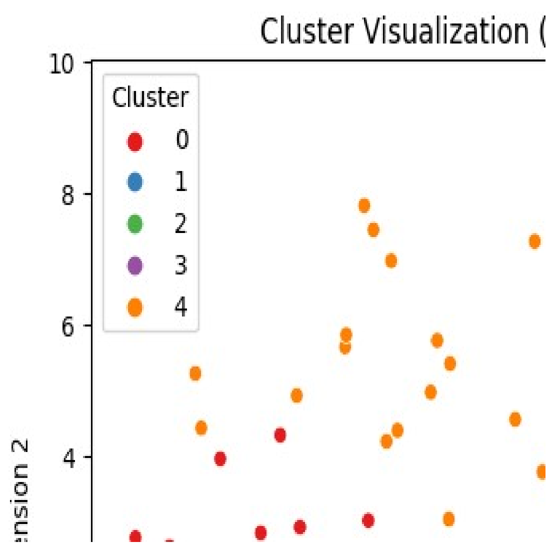

Fig 11: Cluster visualization of KNN using Euclidean distance with KNN

The common therapies generated by cosine similarity for a specific child with child_id 12 are:

For child 12:

- Question No: 19
- Value: 4
- Recommendations: Structured play & speech and language therapy

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- Question No: 23
- Value: 4
- Recommendations: Speech Therapy

The common therapies generated by Euclidean distance for a specific child with child_id 12 are:

For child 12:

Question No: 24
- Value: 4
- Recommendations: Relationship Development Intervention
- Question No: 0
- Value: 4
- Recommendations: Occupational Therapy
Question No: 18
- Value: 4
- Recommendations: Behavior intervention strategies

Question No: 22
- Value: 4
- Recommendations: Sensory Integration Therapy

Question No: 20
- Value: 4
- Recommendations: Picture Exchange
- Question No: 19
- Value: 4
- Recommendations: Structured play & speech and language therapy
- Question No: 21
- Value: 3
- Recommendations: Early Intensive Behavioral Intervention (EIBI)

The result of Multi criteria collaborative filtering is common therapies for similar children for a specific child with child id 12 generated by cosine similarity and Euclidean distance as shown in Fig 12

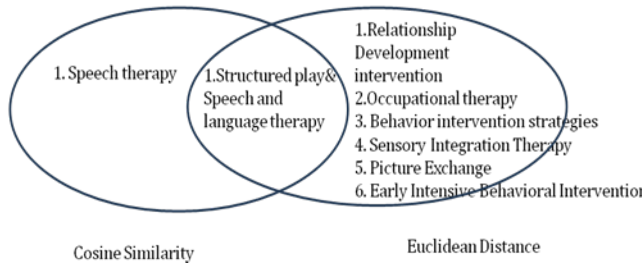

Fig 12: Result of Multi criteria collaborative filtering

The result of Multi criteria collaborative filtering is given as an input to priority generator. It assigns priorities for most common therapies based on severity for child with child id 12.

Case 1: Result from multi criteria collaborative filtering has common therapies :

For child 12:

- **Priority 1:**
- Question No: 19
- Value: 4
- Recommendations: Structured play & speech and language therapy

Case 2:Common therapies of Cosine similarity assuming no common therapies between cosine and Euclidean distance similarity metrics

Priority 1:

- Question No: 19
- Value: 4
- Recommendations: Structured play & speech and language therapy

Priority 2:

- Question No: 23
- Value: 3
- Recommendations: Speech Therapy

Priority 3:

Case 3:Common therapies of Euclidean distance assuming no common therapies between cosine and Euclidean distance similarity metrics

Priority 1:

Question No: 24
- Value: 4

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- Recommendations: Relationship Development Intervention
  Question No: 0
- Value: 4
- Recommendations: Occupational Therapy
  Question No: 18
- Value: 4
- Recommendations: Behavior intervention strategies

  Question No: 22
- Value: 4
- Recommendations: Sensory Integration Therapy

  Question No: 20
- Value: 4
- Recommendations: Picture Exchange

  Question No: 19
- Value: 4
- Recommendations: Structured play & speech and language therapy

Priority 2:
- Question No: 21
- Value: 3
- Recommendations: Early Intensive Behavioral Intervention (EIBI)

Priority 3:
- Question No: 7
- Value: 4
- Recommendations: Speech Therapy

Priority 4:
- **Case 4:Assigning priorities for content based recommendations**
- **Priority 1:**
- Question No: 0
- Value: 4
- Recommendations: Occupational Therapy
- Question No: 2
- Value: 4
- Recommendations: Speech Therapy
- Question No: 24
- Value: 4

  Recommendations: Relationship Development Intervention

- Question No: 5
- Value: 4
- Recommendations: Social Relational approaches
-
- Question No: 5
- Value: 4
- Recommendations: Relationship development intervention
-
- Question No: 18
- Value: 4
- Recommendations: Behavior intervention strategies
- **Priority 2:**
- **Priority 3:**
- **Priority 4:**
- Question No: 17
- Value: 3
- Recommendations: Applied behavior Analysis

Thus, the proposed system is helpful for parents, caregivers, doctors and physicians for providing most appropriate therapy recommendations to autistic children. Early intervention plays a vital role in developing the necessary skills in autistic children and hence the proposed system can be used as an important tool in this process, to start with high priority therapies. It is cost effective and reduces time when compared to performing the task manually. In order to compare our approach with the existing, therapists were asked to provide therapies for the autistic children available. They were asked to provide therapies for 12 children along with priority. These therapies were compared across proposed approach marking the therapies as relevant and irrelevant. Precision is the ratio of relevant recommendations to the actual recommendations generated by the proposed system. The details are shown in Table 2. The proposed system achieved a precision of 80% and can be used as a helpful tool for providing therapy recommendations to autistic children.

Table 2: Precision metric Assessment

Child	Total	Irrelevant	Relevant	Precision
12	3	1	2	0.666667
71	9	2	7	0.777778
41	6	1	5	0.833333
5	15	5	10	0.666667
6	5	0	5	1
7	9	1	8	0.888889
40	9	2	7	0.777778
10	9	0	9	1
42	4	1	3	0.75
34	12	3	9	0.75
65	8	2	6	0.75
Total	8.090909	1.636364	6.454545	0.805556

The proposed method outperforms the traditional methods as shown in fig 13 and the precision assessment of the proposed and traditional methods is shown in table 3.

Table 3: Precision assessment of the traditional and proposed approach

child	Content Based Filtering	Collaborative Filtering	Hybrid	Our Approach
12	66%	50%	68%	72%
71	86%	71%	78%	84%
41	58%	60%	65%	67%
5	70%	68%	75%	76%
6	76%	72%	78%	80%
7	74%	75%	70%	73%
40	68%	68%	70%	72%
10	64%	70%	72%	74%
42	47%	55%	60%	65%
34	67%	64%	70%	72%
65	72%	70%	72%	74%
Total	0.748	0.723	0.778	0.809

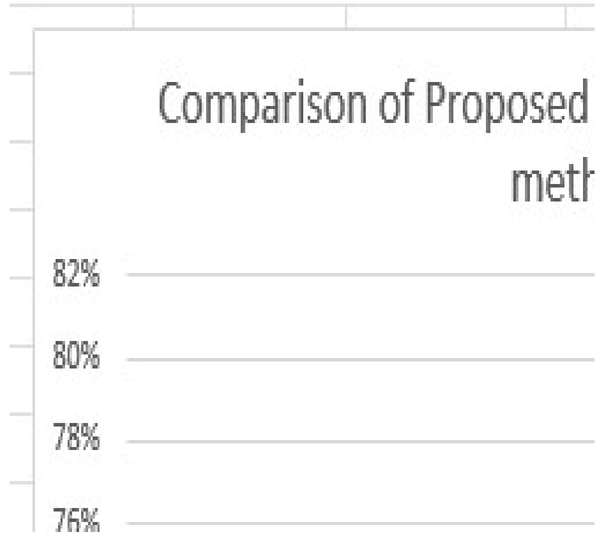

Fig 13: Comparison of proposed method with traditional methods

5. DISCUSSION

Autistic records generated in [28] are used to provide therapy recommendations. It has 103 records with 37 attributes. Autistic records combined with therapy recommendations results in 3296 records with 4 attributes namely child_id, Qno, value and therapy. Content based filtering generates therapy recommendations to each autistic child based on the severity of the symptoms as shown in the results section. Multi criteria collaborative filtering helps to find similar children based on multiple similarities namely cosine and Euclidean distance. Content based therapy recommendations for these similar children are used to find most similar therapies to given for a specific autistic child as shown in fig 12. These most similar therapy recommendations are assigned priority using priority generator with 1 indicating high priority and 4 indicating low priority. The proposed monolithic hybrid therapy recommender system is first of its kind to provide therapy recommendations to individual child. Existing systems provide recommendations to a cluster or group of children. The proposed system results are evaluated by therapy experts and compared with traditional methods resulting in a precision of 80%.

6. CONCLUSION AND FUTURE SCOPE

Recommender systems plays a vital role in providing recommendations related to various products based on different aspects. A health care recommender system provides recommendations related to food, medication and products based on various aspects. The proposed Monolithic hybrid therapy recommender system provides prioritized therapy recommendations to each autistic child which helps to develop necessary skills at an early age. The proposed system has a precision of 80% and it helps to provide most appropriate therapy recommendations when compared to content based filtering which suffers from over specialization and collaborative filtering which suffers from cold start problem. Hence it can be used as a helpful tool by parents, caregivers, doctors and physicians to provide most appropriate therapy recommendations to autistic children.

Small size of the autistic dataset and unavailability of benchmarked therapy dataset are the limitations of the proposed research. More data can help to provide more appropriate therapy recommendations. Future work includes providing therapy recommendations using large language models (LLMs). The proposed work can also be extended for diagnostic tools if the dataset is made available.

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