DeepReco: Deep Learning Based Personalized Mental Health Support and Coping Mechanism Recommender System

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ABSTRACT

Individualized resources and standard therapies are increasingly being provided to people through the use of personalized recommender systems for mental wellness. This study presents DeepReco, a deep learning-based personalized mental health support and coping mechanism recommender system designed to provide context-aware recommendations while ensuring privacy, reliability, and trustworthiness. The proposed framework integrates multimodal healthcare data, including user health profiles, behavioral patterns, and clinical information, to generate personalized recommendations for mental health support. Deep learning techniques are employed to analyze complex relationships within heterogeneous healthcare data, enabling accurate identification of user preferences and mental health needs. Recent studies that focus on using massive amounts of medical data while integrating multimodal data from many sources are highlighted, which lowers healthcare costs and workloads. Recommender systems and big data analytics play a significant part in the healthcare industry when it comes to patient health decision-making procedures. It shows how big data analytics can be used to implement an efficient health recommender engine and shows how the health care sector can move from a conventional scenario to a personalized model in a tele-health setting.

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1. INTRODUCTION

Recommender systems, also known as information filtering support, use ML algorithms to anticipate or suggest items that a user might find interesting, including movies, products, material, and more. It generates recommendations based on user habits, behavior patterns, and other pertinent data using collaborative filtering, content-based filtering, and a hybrid recommendation engine system. Recommendation systems are currently the most widely used tools for individualized assistance, and they have the ability to further customize mental health care and enhance treatment results in the context of digital mental wellness.

Recent years have seen a substantial shift in the field of mental health therapies, with an emphasis on recognizing the wants, needs, and traits of individuals seeking assistance. One in three Malaysians suffers from a mental illness, although half of those evaluations mistakenly raise mental health issues. Many mental health issues are common, including schizophrenia, bipolar disorder, anxiety, depressive disorders, and more [1]. This indicates that there is reason for concern and highlights the necessity of mental health education and assistance in Malaysia. Although addressing people's wellness requires mental health interventions, the current field primarily employs traditional, long-standing techniques, such as clinical evaluation and pharmacological administration. Despite their usefulness, these conventional methods have numerous drawbacks [2].

The understanding that there is no one-size-fits-all strategy for mental health care has spurred the demand for individualization, where treatments can be tailored to each person's particular needs.

Although there is still a serious problem, the necessity for customization in mental health treatments is becoming more widely recognized [3]. The current methods of providing mental health care do not sufficiently enable therapies to be tailored to the unique needs of each patient. Traditional approaches may only fully realize the potential of customisation, notwithstanding their usefulness. This problem is a serious challenge since it may affect user happiness and engagement as well as, more crucially, the wellbeing of individuals seeking mental wellness assistance. There is still little research on the efficacy of recommender systems created especially for mental health treatments. It is challenging to assess the usefulness and efficacy of these strategies in the absence of solid scientific data. With a particular focus on their use in the field of mental health, this study intends to perform a comprehensive literature review on the application of standard recommending systems. Additionally [4], it compares different methods, noting their advancements, difficulties, and constraints related to their application in this area.

2. LITERATURE REVIEW

As a remedy, the study presents the MQAD-Net (Multi-Modal Quantum-Attentive Deep Learning Network), a sophisticated framework for predicting psychological health and recommending individualized therapy. Using Graph Attention Networks (GAT) for temporal-spatial EEG feature extraction [5], and transformer-based embedded elements for behavioral text analysis, the proposed method combines many types of data, including EEG signals, voice normal patterns, and behavioral text replies. Dense-DualLSTMNet (DDL-Net) classifying is carried out, which creatively combines three approaches—DenseNet, DPN-68, and BiLSTM—for improved sequence modeling and multi-modal feature acquisition.

Two stages were used to gather qualitative information about the viewpoints of young people. In phase 1 [6], 37 youths took part in examinations where they were asked to describe the main features of care after being shown two depressive vignettes that were separated by clinical stage. Eight young people took part in a group workshop to co-design digital care routes during phase 2 [7]. Key service, framework, and digitized care aspects were identified through a thematic analysis of the audio. Youth-friendly, welcoming settings that enable prompt access to care were highlighted as key service qualities. Needs-led care that was bolstered by adolescent and family involvement, individualized care planning, care management, oversight, and peer support were all important components of the program. Facilitating access to treatment, centralized evaluations, client decision support, monitoring, and design concepts of adaptability and human assistance were all important aspects of digitized care.

The purpose of this study is to comprehend therapist behaviors and find novel ways to distribute intervention content in between in-person CBT therapy sessions. It included a set of ideation exercises, informal interviews, and theme data analysis. The findings demonstrated the importance of clients in determining the topics covered in treatment sessions, their difficulties with assignments [8], and the variety of approaches used by therapists. An examination of the ideation exercises clarified the possible involvement of therapists in customizing anxiety apps.

An example of a mixed-method case study of a seventy-year-old patient with avoidant personality disorder and recurrent depression whose schema therapy had failed [9]. She completed a customized ESM diary five times a day during eight weeks of standard schema therapy in an outpatient facility for geriatric mental health care. The diary was customized to her diagnosis and treatment objectives and assessed momentary affect (such as sadness), routine tasks, (social) setting, core beliefs, and coping methods. Three sessions of interactive reports showing ESM data paths, person-specific networking graphs, and contextual annotations were used to provide feedback.

ERS is still a major problem that frequently causes delays in diagnosis, restricts the number of suitable treatments, and makes it harder for epileptic patients to integrate socially. Failure to address ERS can hinder social integration, lower quality of life [10], and impede long-term social rehabilitation even in cases where therapy successfully stops seizures. According to earlier research, evaluation and therapy outcomes can be greatly enhanced by a holistic and customized medicine strategy that treats the psychological and medical aspects of epilepsy, with an emphasis on lowering ERS [11]. The regular management of epilepsy can improve clinical and psychosocial results and assist patients in reintegrating into daily life by including culturally appropriate mental health assistance and community-specific advocacy campaigns aimed at ERS elimination.

In order to customize a mental e-health treatment for older persons who have lost a spouse, we chose user profile factors in this study. An international and multidisciplinary expert panel (N = 16) participated in a three-round Delphi research with two goals. In order to dynamically modify the response to the user's demands, the first goal was to elicit adaption techniques [12]. The second goal was to find a set of useful indicators for tracking the user from within the grief treatment so that, when necessary, they may transition from self-help to integrated treatment. An assessed text-based grieving intervention consisting of 10 modules, comprising psychoeducation about sorrow and cognitive-behavioral activities to assist the user in changing their lives following bereavement, served as the foundation for this Delphi study.

3. METHODS AND MATERIALS

By tailoring interventions to each user's needs, recommender systems have the ability to completely transform mental health care [13]. These systems employ algorithms to forecast information or content that is pertinent to the user, and they can be applied in a variety of ways in mental wellness applications to ascertain what would be most pertinent. In the domain of mental health recommendations, traditional recommendation systems, such as shared filtering or content-based techniques, have been used in a number of research and methods.

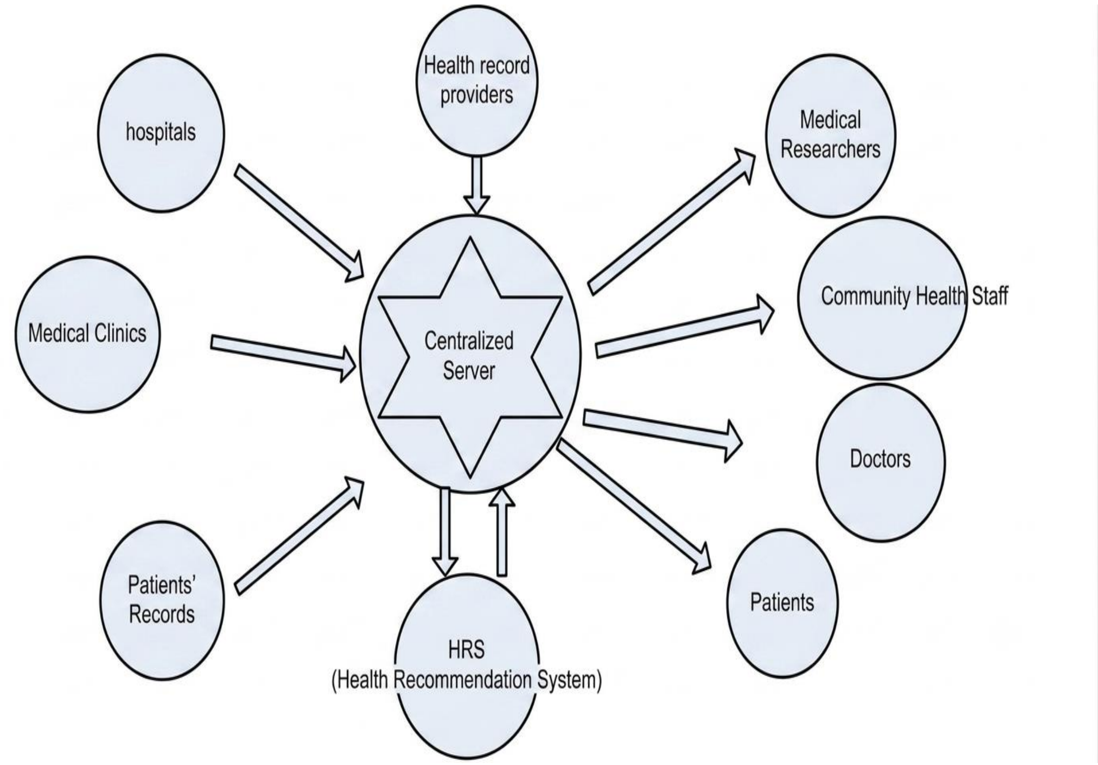

Figure 1. Proposed Deep Learning-Based Health Recommender System Architecture

This shift reflects a broader realization that people in need of assistance could gain from more interesting, efficient, and the Proposed Deep Learning-Based Health Recommender System Architecture in Figure 1 [14].

3.1 Method of Collaborative Filtering

Recommender systems utilize a technique called collaborative filtering to generate customized suggestions by looking at information from a user's past actions or the records of other users who are assumed to have similar preferences. In a group filtering system, the user frequently communicates their choices by rating things, which can be interpreted as a rough indicator of the user's interest in the pertinent subject.

Strong recommender system prediction power and the ability to provide personalized information by identifying the user's preferences based on previous interactions are just two benefits of collaborative filtering [15]. However, a new item needs to receive a lot of user evaluations in group filtering before it is suggested. The cold start, sparsity, and scalability issues are some of its drawbacks. In the area of mental wellness, collaborative filters can be used to suggest mental health tools based on a user's prior behavior or the past behavior of other users who are thought to have comparable mental health requirements.

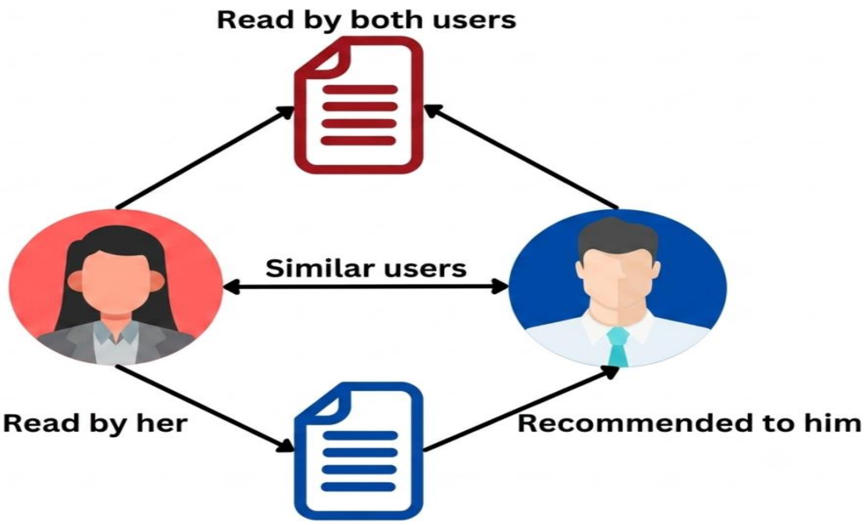

Figure 2. Principle behind Collaborative Filtering

The user's neighbors' tastes are then combined and weighted by the algorithm to produce customized recommendations. The collaborative filter principle is illustrated in Figure 2.

3.2 Content-based Filtering

Numerous studies have investigated content-based filtering methods in recommender systems. The closeness between the traits or characteristics of the objects and the user's tastes is the basis for recommendations [16]. These systems employ algorithms to filter data and give users tailored recommendations. In the field of mental health, patients have received tailored advice through content evaluation of mental health sources.

In one study, for example, the effectiveness of two systems in suggesting knowledge-based content to individuals seeking mental health support and assistance was evaluated. The study looked at factors like suggestion accuracy [17], customization, recommending speed, user engagement, and the effect on patient results.

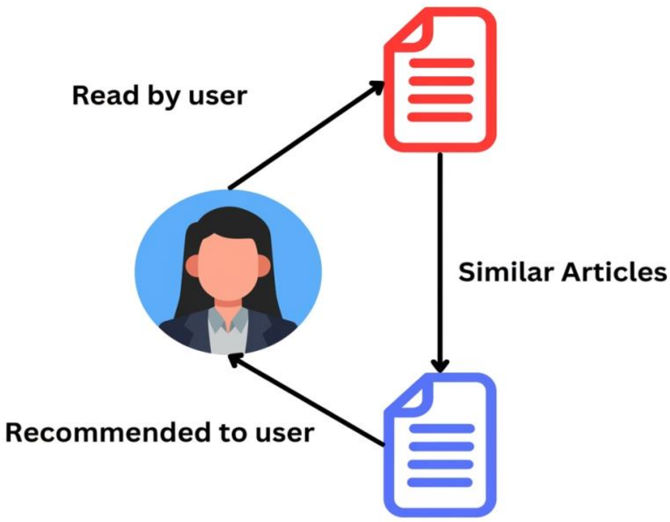

Figure 3. The Underlying Idea of Content-Based Filtering

The idea underlying content-based filtering to locate the suggested paper is depicted in Figure 3

3.3 Neural Networks and Deep Learning

Deep neuronal networks are computational structures made up of neuron-like elements coupled by interconnections that resemble synapses. Similar to spike rates, these units transfer scalar values that are calculated by multiplying the power of the transmission synapse by the sum of their outputs or the action of previous units [18]. Notably, non-linear functions applied to these units' inputs control their activity. Because of this non-linearity, systems with several layers of units placed between the "output" and "input" sides can be created, giving rise to what are known as "deep" neural networks. Any function that maps activity inputs to activated outputs can be approximated by these deep networks. Furthermore, "recurrent" neural networks (RNNs) are capable of computing functions based on input patterns because loops in the link architecture allow their network activation to retain information from prior occurrences.

The difficulty of modifying a deep neural network's link weights to get the intended input-output mapping is referred to as "deep learning." Back propagation has been used for more than thirty years; however it has mostly been used in unsupervised and supervised learning contexts. While unsupervised learning concentrates on producing meaningful depictions of incoming data, supervised learning aims to learn from labeled information.

RL, in which the learner must choose actions that maximize rewards, is very different from these models. Additionally, RL presents the idea of exploration, in which the learner must strike a balance between utilizing previously learned information and searching for novel behaviors. In contrast to conventional unsupervised and supervised learning, RL makes the assumption that the learning apparatus's actions impact its subsequent inputs, resulting in a sensory-motor return loop. The simulated data's non-stationary adds complexity, and RL's intended results frequently need several decision-making stages as opposed to straightforward input-output translations.

4. EXPERIMENTAL RESULT AND DISCUSSION

We experimented with the healthcare data set. Discrete ratings ranging from 1 to 5 of 10,000 individuals for 500 institutions are included in this medical dataset. The training and test portions of this dataset are separated in a ratio of 74:25. In this case, the findings are evaluated using a 10-fold cross-validation approach. We use Python and Tensor Flow to implement the suggested CRBM approach. A health dataset that describes rating information together with details is used to create and test our HRS using various methodologies.

The number of closest neighbors, or parameter "K [19]," must be selected. The data would lose important information if K was very little, and its data confidentiality property would be lost if K was too large. As a result, parameter K needs to be chosen carefully. In this case, the root mean absolute error (RMSE) approach is employed since it is simple to recognize and quantify, making it easy to calculate the value aspect of recommenders. It is used in this paper to demonstrate the precision and efficacy of the various methods.

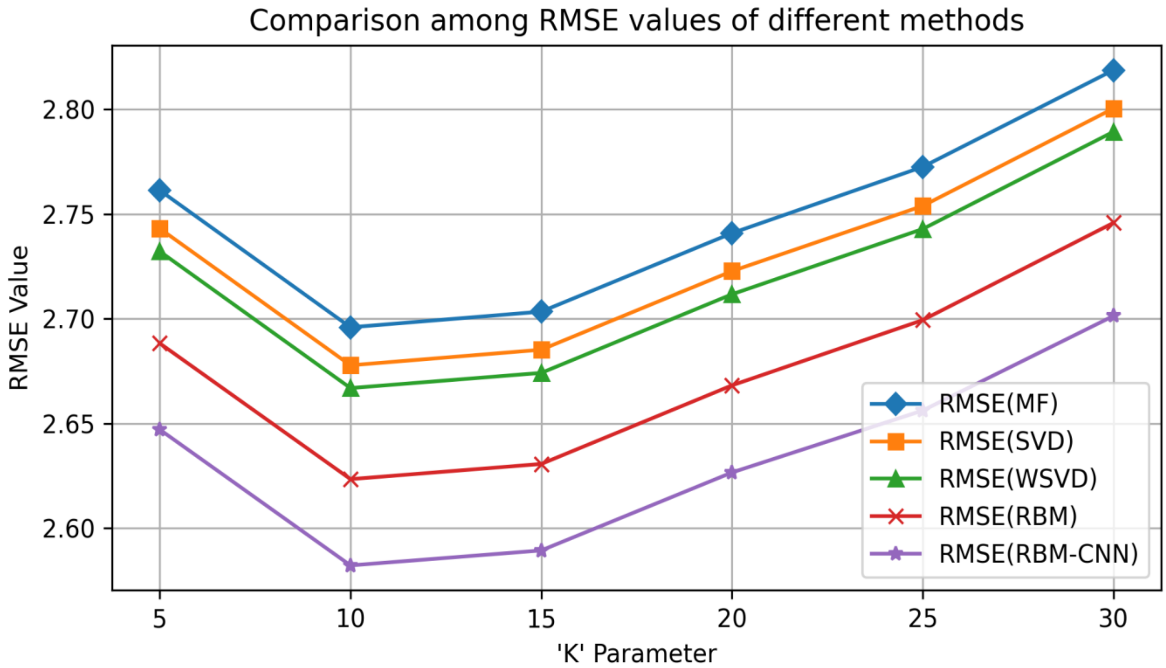

Figure 4. Comparing the K and RMSE of Several Approaches

The RMSE of the Comparing the K and RMSE of several approaches with variable K, as shown in Figure 4 [20], and reaches an ideal value when K equals 10. The accuracy increases with decreasing values. Better recommendation quality results from this. Therefore, RBM-CNN ought to be the joint filtering method of choice. Other metrics, such MAE (Mean Actual Error), precision, recall, and ROC, can also be used to gauge the quality of a recommender. Every deep learning-based recommendation system is evaluated using a varying number of epochs.

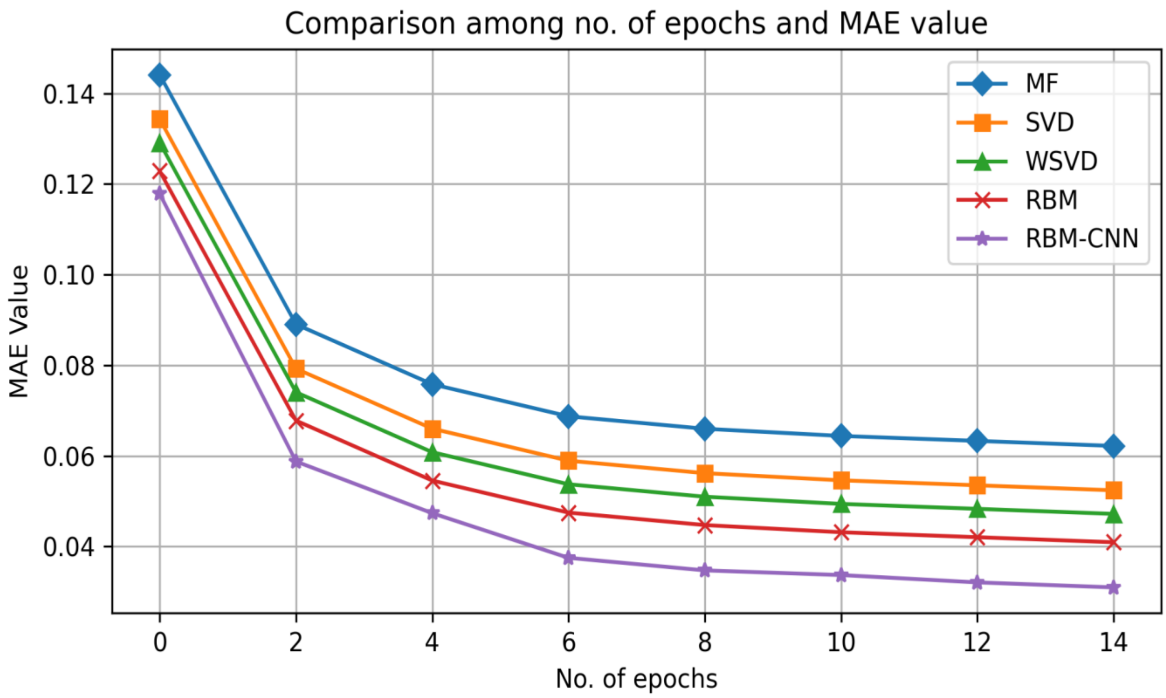

Figure 5. MAE vs. Number of epoch's Graph

As seen in Table 2, each approach is assessed using MAE. It is evident from Figure 5 that accuracy increases with the several epochs. Better recommendation quality results from this.

Table 1. Comparing the K and RMSE of Several Approaches

MF	SVD	WSVD	RBM	Proposed RBM-CNN
2.76137	2.74313	2.73219	2.68828	2.64707
2.69592	2.67776	2.66688	2.62337	2.58216
2.70339	2.68520	2.67413	2.63062	2.58931
2.74089	2.72274	2.71169	2.66818	2.62657
2.77257	2.75391	2.74288	2.69937	2.65616
2.81879	2.80047	2.78935	2.74584	2.70136

In particular, Table 1 shows that RBM-CNN is optimal with respect of RMSE for K=10.According to the testing data, the RBM-CNN technique has the highest accuracy.

Table 2. Comparing the MAE and the Count of Epochs of Various Techniques

No. of Epochs	MF	SVD	WSVD	RBM	Proposed RBM-CNN
0	0.14412752	0.13432652	0.12912452	0.12286516	0.11785
2	0.08904246	0.07924146	0.07403946	0.06778010	0.05876
4	0.07580589	0.06600489	0.06080289	0.05454353	0.04734
6	0.06872800	0.05892700	0.05372500	0.04746564	0.03748
8	0.06597785	0.05617685	0.05097485	0.04471549	0.03471
10	0.06439402	0.05459302	0.04939102	0.04313166	0.03368
12	0.063298018	0.053497018	0.048295018	0.042035658	0.03206
14	0.062187785	0.052386785	0.047184785	0.040925425	0.03095

The suggested RBM-CNN method provides greater accuracy when taking into account two error measurements like RMSE and MAE, according to an analysis and comparison of all the methodologies. When an RBM and CNN are integrated in a deep learning environment, the suggestion quality for selecting a hospital for a specific patient is improved.

5. CONCLUSION

One of the newest and most popular methods for extracting additional information about a patient from medical data is the health recommender system. These systems use the similarity of patients' choices to determine which hospitals are suggested. As a result, they are crucial to the medical industry. Modern, cutting-edge solutions are needed to address the data security and privacy problems with CF-based health recommendation systems.

This research compares the deep learning approach with other privacy-preserving shared filtering techniques. When compared to other health recommender systems, the suggested RBM-

CNN shows superior accuracy. We'll work to improve our algorithm in the future to deliver greater accuracy while maintaining a high degree of privacy.

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